Master Thesis

Do Dominant Founders Receive Better Funding? – An Emotion Analysis of Founder Twitter Activity

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Abstract

Venture capital investments are an important driver of economic activity and innovation. Based on an integration of signaling theory and Emotions as Social Information (EASI) theory, this paper investigates the effect of founder dominance signaling on Twitter on venture funding amount. This study introduces two channels of emotional signaling via social media, verbal content and facial expressions in images, along with measures to assess them. Only dominance signaling in verbal tweet content predicts funding amount (b = 394.84, SE = 123.20, $p < .01$), increasingly so with larger follower count (b = .0047, SE = .0023, $p < .05$). These findings extend traditional signaling theory to signals with low cost of imitation, challenging the assumption of rational actors. This study is the first to apply EASI theory in a virtual context, providing evidence for the effect of emotional signaling in a digital world. It showcases the value of machine learning techniques and social media data for social scientists. Though causal conclusions are not warranted, founders should take notice that their online presence does matter. At the same time, as investors increasingly leverage information from social media, they need to consider that signals like dominance on Twitter may affect investment decision-making without necessarily indicating investment quality.

Content

Introduction

In 2021, the venture capital (VC) sector invested a total of USD 621bn into startups across the world (CB Insights, 2022). VC investments have a strong influence on economic activity: While in a given year only 0.5% of companies incorporated are backed by VC firms, that ratio increases to 50% when looking at companies that go public (Lerner & Nanda, 2020). Indeed, there seems to be a causal relationship between VC investment and company success (Bernstein et al., 2016; Chemmanur et al., 2011; Puri & Zarutskie, 2012; Kortum & Lerner, 2001). VC investments have also been connected to waves of innovation in specific technologies: The portion of VC-backed companies is much larger among companies with larger spend on research and development (Lerner & Nanda, 2020) and VC-backed companies are at least twice as likely to file patents in the top percentile of influence (Howell et al., 2020).

As an important driver of economic activity and innovation, it is important to understand how venture investments are made. A core characteristic of venture investments is the selection and assessment process VC investors undertake before deciding to invest in a venture (Lerner & Nanda, 2020). This process is important due to the high information asymmetry between the two parties. According to signaling theory (Connelly et al., 2011; Spence, 1978), economic actors use signaling behavior to convey information about underlying qualities and reduce information asymmetry. In line with this, the investment selection process is strongly influenced by signals such as the characteristics of a founding or management team. In fact, most investors view the founding team as the most important factor (Gompers et al., 2020), likely because management risks, like difficult founder personalities, are among the most common sources of uncertainty (Kaplan & Stromberg, 2001).

Founder characteristics influencing investment decisions include relatively objective factors like educational background, industry experience, and entrepreneurial experience (Gompers et al., 2020), as well as more subjective factors like founders' passion (Cardon, Glauser, et al., 2017; Chen et al., 2009; Li et al., 2017), rhetorics (Steigenberger & Wilhelm, 2018), and joy (Jiang et al., 2019). Studies considering the influence of emotional display, including passion and joy, have thus far focused mainly on the display of positive emotions. However, according to the three-factor model of emotions (Russell & Mehrabian, 1977), emotions are more complex and can be mapped onto three dimensions, not just one. These dimensions are valence, arousal, and dominance. Most discrete emotions like Ekman's (1971) basic emotions – anger, surprise, disgust, enjoyment, fear, and sadness – can be mapped onto this three-dimensional space of emotions (Buechel & Hahn, 2017) which makes it a holistic framework for analyzing emotions.

In this study, I focus on the influence of the emotional dimension of dominance on investment decisions. Dominance is defined as the feeling of having control or influence over one's environment (Russell & Mehrabian, 1977). Following Emotions as Social Influence (EASI) theory, founders' signals of dominance are expected to convey important information about founders' underlying qualities. Given the stressful and uncertain nature of the job (Boyd & Gumpert, 1983), a general feeling of control may indicate a founder's competence and coping abilities. Since investors increasingly use online resources such as social media to reduce information asymmetries (Aggarwal et al., 2012; Antretter et al., 2019; Jin et al., 2017), this study examines dominance signaling via social media.

Theoretical contributions of this study include the integration of traditional signaling theory which views economic actors as purely rational with EASI theory, a social-functional account of emotions explaining the influence of emotional signals on receivers' behavior. It further extends EASI theory by examining the effects of emotional signaling in virtual contexts. Lastly, this study introduces two new measures of online behavior and emotional signaling.

Theoretical Background

Signaling Theory

Signaling theory describes the process in which one party engages in certain activities which signal underlying qualities to another party (Connelly et al., 2011; Spence, 2002). This process is an important mechanism in economic markets characterized by information asymmetries in which, simply put, “different people know different things” (Stiglitz, 2002, p. 469). Information asymmetries exist in relationships in which one party holds information which would help another party make better decisions (Connelly et al., 2011). Signaling theory explains how economic actors leverage a broad range of signals in order to convey information to relevant stakeholders and reduce information asymmetries. Investor decision-making is a prime example of situations characterized by information asymmetry: The venture founding team holds much more information about the investment opportunity – their own business – than the potential investor. Indeed, investors’ decision-making is, to a large extent, guided by the signals sent by the venture and its founders (Busenitz et al., 2005; Lester et al., 2006; Zhang & Wiersema, 2009).

In their review, Connelly and colleagues (2011) define the key concepts involved in the signaling process: The *signaler* is an insider (or multiple insiders) with private information which could be useful to (certain) outsiders. In the venture capital investment process, entrepreneurs, management teams, or the ventures themselves are signalers. These signalers send the *signals,* primarily defined as deliberate actions with the purpose of conveying positive information about underlying, hard-to-observe qualities. For example, a founding team can send a signal communicating its competence and potential by participating in and winning a startup pitch competition. Signals differ in terms of their *observability* (i.e., how easy it is for outsiders to notice the signal) and *cost* (i.e., how difficult it is for the insider to produce the signal, given their underlying qualities), which influence the effectiveness and reliability of a signal, respectively. *Receivers* are those who notice, process, and then take action informed by the signal – in this case, potential investors taking notice of and making inferences based on the team’s accomplishment. Signaling takes place when the signaler benefits from an action taken by the receiver which the receiver would not have undertaken without the signal (Bliege Bird & Smith, 2005; Connelly et al., 2011). Signalers’ and receivers’ interests are partially at conflict as successful deceit benefits the signaler at the expense of the receiver.

Signals Influencing Investment Decision-Making

There are almost unlimited ways in which a venture and its founders can signal their qualities to investors. A popular metaphor provides a distinction between two important groups of signals: When making an investment, investors can bet on “the jockey” or “the horse” (Kaplan et al., 2009): Some signals convey information about the founding or management team (the jockey), others provide information about the business (the horse). Professional investors tend to place emphasis on the qualities of the founding team. In fact, they rank the management team as the most important factor influencing investment decisions (Gompers et al., 2020). This tendency is even more pronounced in the technology and software sector. Some traditional “jockey” signals include team composition, industry experience, entrepreneurial experience, and education (Gompers et al., 2020; Kaplan et al., 2009), but also “soft” factors like personality (Murnieks et al., 2015), passion (Cardon, Mitteness, et al., 2017; Chen et al., 2009; Li et al., 2017; Warnick et al., 2018), or rhetorics (Steigenberger & Wilhelm, 2018).

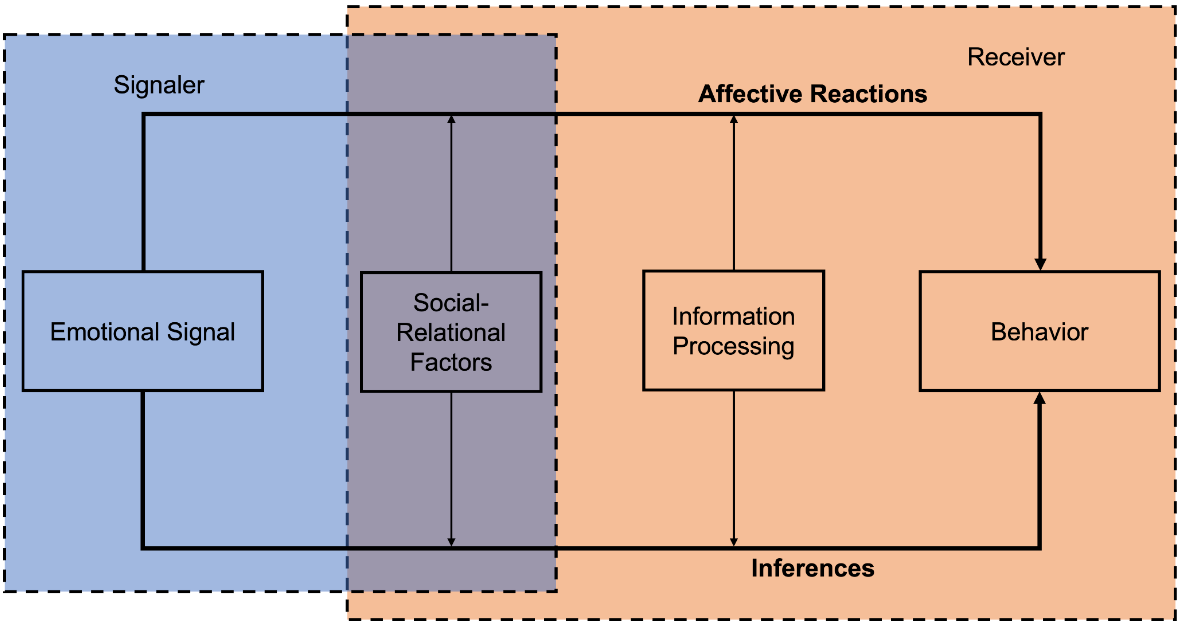
Steigenberger and Wilhelm (2018) showed that rhetorical signals sent by founders during their pitch, including emotional signals, complemented more ‘substantive’ signals of a company’s quality such as technical specifications of the product. These weak signals tended to draw more attention to substantive signals, but also provided additional information, reducing information asymmetry. Other exemplary studies have examined how founders convey passion by expressing enthusiasm when presenting their venture to potential investors in pitch situations (Cardon, Mitteness, et al., 2017; Li et al., 2017). Researchers assume that passion is a relevant quality for investors because it indicates the founders’ willingness to invest time and effort in order to ensure the venture’s success (Cardon et al., 2009). Expressions of emotions can be powerful signals but they can convey much more than just positive or negative attitudes (Clark & Taraban, 1991; Keltner & Haidt, 1999; Niedenthal et al., 2010; Rychlowska et al., 2017; Shariff & Tracy, 2011). The present study aims to expand the focus of founder emotional display research beyond the effects of positive versus negative emotions. Based on the three-factor theory of emotions proposed by Russel and Merhabian (1977), this study focuses on the emotional dimension of dominance, defined as the feeling of having (or, in case of low dominance, lacking) control or influence on events. Given the stressful and uncertain nature of entrepreneurship (Boyd & Gumpert, 1983; Shepherd et al., 2010), I assume dominance to be an important emotional signal for investors because founders who signal that they are in control of their situation likely convey an underlying quality of competence and coping ability. Indeed, being well-prepared – though not emotional in nature – has been found to be a more important signal than positive emotionality (Chen et al., 2009), likely because it indicates competence. This study also considers founders' network size as a moderating factor since it relates to the signal's observability: Dominance signals sent within a large network are more likely to be noticed by investors than those sent within small networks.

Emotional Signaling

To account for the non-rational influence of emotional signals in the economic context of venture investing, I am integrating traditional signaling theory with Emotions as Social Information (EASI) theory (Van Kleef, 2009), a social-functional account of emotions. One stream of research in social-functional theory of emotions proposes that a primary function of emotion at the interpersonal level is to grant the emoter (i.e., the person displaying the emotion) with social influence (Keltner & Haidt, 1999; Van Kleef et al., 2011). Specifically, emotional signaling is assumed to serve the purpose of transmitting information which in turn may influence others' behavior. This aligns with the general process of signaling as described in signaling theory (Connelly et al., 2011; Spence, 2002). For the sake of consistency, I will continue using signal theory's terminology of signalers and receivers, which in social-functional accounts of emotions are often referred to as senders or emoters and observers, respectively. EASI theory provides a conceptual framework of the process by which emotional signals sent by a signaler might influence a receiver's behavior. The model as depicted in Figure 1 provides two distinct but mutually influential pathways of information flow: inference and affective reaction.

Figure 1

Emotions as Social Information (EASI) model



Note. Adjusted from van Kleef (2009).

In the context of social interaction, inference describes the process in which the receiver infers information about the signaler's internal state based on their emotional signal, including attitudes, relational orientation, and (behavioral) intentions (Van Kleef, 2009). This extended understanding of the signaler in turn informs the receiver's own behavior. For example, an investor may refrain from investing in a founder signaling low dominance because they infer that this founder lacks control, or agency, and competence. Next to inference, the receiver's behavior is also influenced by their own affective reaction to the signaler's emotional signal (Van Kleef, 2009). One type of affective reaction has been described as emotional contagion, a form of mimicry in which a sender's emotion elicits that same emotion in the observer (Hatfield et al., 1992). The other type of affective reaction is a change in interpersonal liking: For example, it has been shown that signals of joy lead to increased interpersonal liking, while anger leads to decreased interpersonal liking (Clark & Taraban, 1991). Both reactions will in turn influence the range of behaviors activated or deemed appropriate by the observer (Van Kleef, 2009). Both pathways are moderated by information processing (motivation and ability) as well as social-relational factors (such as cultural norms and the nature of the relationship between signaler and receiver), further establishing the non-rational nature of the signaling process. One potential social-relational factor moderating the relationship between founders' dominance signaling and investors' investment decisions is founders' network size. Depending on a founder's network size, investors may apply different social norms. Network size may also provide an indication of the interpersonal relationship between founder and investor: A small network size may indicate that both parties are acquainted which could be related to reduced information asymmetry, while a large network may indicate the opposite.

Social-functional theories of emotion are supported by empirical evidence of individuals' emotions affecting others' behavior. A meta-analysis by Chervonsky and Hunt (2017) found a reliable connection between the expression of emotions (i.e., emotional signaling) and better social outcomes when the expressed emotion was positive in valence. Some outcomes influenced by emotional signaling are first impressions and liking, both of which can be placed along the more intuitive affective reaction pathway of information flow in investor decision-making. Similar effects are found in virtual environments: A meta-analysis by Geiger and Moore (2022) showed that positive valence in online communications between ventures and potential investors increased the venture's likelihood of funding success by attracting more investors. Though these findings support the notion of founder emotions affecting investor decision-making, it is important to note that Geiger and Moore (2022) investigated these effects in the context of crowdfunding. Positive tone here relates to the content provided by the *venture,* not the founder, on a specific *crowdfunding platform,* not on social media, to *typically amateur investors investing small amounts,* not professional investors. Funding rounds of the size investigated in the present research are more likely to be decided on by professional investors like venture capitalists and private equity firms. The analysis also fails to provide information about the effect of the other dimensions of emotion, dominance and arousal, on investment success. As of yet and to my knowledge, there is only limited empirical research on the effect of founder emotional signaling on investment success, let alone dominance signaling via social media. Given that investors increasingly use social media to gain information about ventures and their founders (Tumasjan et al., 2021), the present study aims to close an important gap in the research by investigating the effects of online emotional signaling. Because VC investments are an important driver of economic growth and innovation (Lerner & Nanda, 2020) it is important to understand the factors influencing the decision-making behind these fund allocations. Investors self-report (Gompers et al., 2020) as well as empirical evidence (Cardon, Mitteness, et al., 2017; Jiang et al., 2019; Steigenberger & Wilhelm, 2018) indicate that founders' emotional signaling may be one of these factors.

Emotional Signaling of Dominance on Social Media

Online behavior is an increasingly important area of research for behavioral science as more and more important societal conversations, cultural movements, and, as investigated here, economic transactions, largely take place online. In fact, consumers, businesses, founders, and investors are already using social media as an important means of communicating and receiving important information. For example, young ventures have started establishing their legitimacy among consumers via their online presence (Antretter et al., 2019), which has turned venture online presence and legitimacy into a relevant signal for investors. Because of the scarcity of information in venture investing (Courtney et al., 2017), investors use social media as an additional source of information (Tumasjan et al., 2021). Specifically Twitter plays an important role for investors as it has become the leading platform when it comes to information exchange about technology, trends, and business: new technology and business models are among the most prominent topics on the platform (Tumasjan et al., 2021). Underscoring the platform's relevance in the investment context, the US Security and Exchange Commission (SEC) changed its policy in 2015 and allowed ventures to explicitly attract potential investors via Twitter (Jin et al., 2017). As a consequence, ventures' social media presence has been associated with higher likelihood of closing a larger investment round because it enables discovery and information sharing.

This research focuses on founders' displays of dominance on Twitter as signals of competence towards potential investors. As per constraints and/or common usage of the platform, signalers can convey dominance verbally, in the emotional tone of their written posts (tweets), and visually, via their facial expression in their profile pictures. Based on the work of Margaret Bradley and Peter Lang (Bradley & Lang, 1999a, 1999b; Lang et al., 1999), I assume both channels to be viable means of expressing emotionality. Bradley and Lang produced three datasets of normative emotional ratings of data of varying modality. Specifically, human raters were reliably able to rate emotions on the three dimensions of valence, arousal, and dominance, when the emotions were expressed in written form (Bradley & Lang, 1999b), in facial expressions (Lang et al., 1999), and also in auditory signals (Bradley & Lang, 1999a). Since Twitter is a text-focused platform which also frequently presents users' profile pictures (namely, with every single post), I decided to focus on these two channels. Users tend to use profile pictures that show them with a smiling facial expression, but these smiles are necessarily signals of joy. The simulation of smiles (SIMS) theory (Niedenthal et al., 2010) establishes that there are three types of smiles, communicating different information to observers. One type of smile is associated with signaling dominance and can be reliably detected by human observers, even in virtual representations (Rychlowska et al., 2017).

Though some studies have started analyzing the effects of founder and/or venture online presence on business and/or funding success (e.g., Antretter et al., 2019; Jin et al., 2017; Tumasjan et al., 2021), the evidence is still limited. Partially this is caused by a relatively high technical entry barrier to analyzing online activity. This is changing, and some tools provide very easy access to this form of data analysis (e.g., LIWC[1]; Boyd et al., 2022). However, these tools tend to be very constrained in terms of which topics and methods they allow their users to investigate. Thus, targeted analysis of online behavior still requires behavioral scientists to acquire relatively strong technical skills which are not part of the typical methodological curriculum in these fields. Still, advancements in tooling as well as

[1] https://www.liwc.app/

data science and machine learning have made a set of extremely powerful methodologies much more accessible. Specifically, the spread of transformer models, most notably Google's powerful and open source large language model BERT (Devlin et al., 2018), as well as open source computer vision models like OpenFace 2.0 (Baltrusaitis et al., 2018) and APIs allowing access to such models at no cost (e.g., TensorFlow Hub[2], Huggingface API[3], or Keras Applications[4]) allow highly complex analyses on very large datasets.

Theoretical Contributions

Pooling Equilibria in Signaling Theory. Signaling theory generally requires signals to create a separating equilibrium (Bergh et al., 2014): A signal must allow receivers to distinguish between high and low quality signals. For this to be true, the signal used to reduce the information asymmetry must be more costly to realize for low-quality signalers. This is not necessarily the case for dominance signals on social media, as it is quite easy to create a dominant online persona, even if one is not really a dominant person. Dominance signals are more likely to create a pooling equilibrium. In a pooling equilibrium, signaling costs are equal irrespective of signaler quality (Bergh et al., 2014), which brings with it the threat of imitation and deceit. In their research agenda, Bergh and colleagues (2014) conclude that research on such signals can still contribute to signaling theory, especially in combination with other relevant theories: One important limitation of the original signaling theory is its assumption of rational agents. Vast bodies of research have confirmed that humans make irrational decisions, especially in noisy environments like venture investing (for a review, see Thaler, 2016). In fact, many investors admit to making investment decisions partially based on gut-feeling, precisely because of information asymmetries (Gompers et al., 2020). This is remarkable because at the same time, deal selection is viewed as one of the most important factors determining success of an investment portfolio (i.e., high returns on investment).

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[2] https://www.tensorflow.org/hub
[3] https://huggingface.co/models
[4] https://keras.io/api/applications/

Similar to Steigenberger and Wilhelm (2018)'s findings on rhetorical signaling, I assume online displays of dominance draw attention to a founder and their startup, as well as provide additional information otherwise not accessible to potential investors. EASI theory explains how signals which fail to produce separating equilibria can still have an influence on receivers' information processing: Considering the affective reaction pathway extends traditional signaling theory by recognizing that receivers are not completely rational actors but instead are also influenced by their own, automatic affective reactions – an addition to the original theory much in line with Bergh and colleagues' (2014) research agenda.

New Signaling Channels for EASI Theory. The present research extends EASI theory by applying it to new channels of emotional signaling. To my knowledge, the framework has not been explored in a virtual context. Though emotional signals tend to have similar effects across different channels (Van Kleef et al., 2011), it has not been examined whether emotional signaling also takes place in an online context. Emotional signaling via social media affects some of the pathways important to EASI theory. Social-relational factors differ in terms of what is appropriate, and receivers' information processing is highly affected by the rate and amount of information on social media (Rodriguez et al., 2014). Further, this research considers two distinct channels of virtual emotional signaling, written tweet content and facial expression in profile pictures. The verbal channel (tweet content) is based on the three-factor model of emotions (Russell & Mehrabian, 1977) while the visual channel is informed by SIMS theory (Niedenthal et al., 2010). The integration of these two accounts of emotional expression provide an important extension to traditional EASI theory as both accounts allow for the examination of dominance signaling. Given the emphasis of EASI theory on social influence (Van Kleef et al., 2011), dominance is an obvious emotional dimension to explore using this framework.

Hypotheses

Founders' signals of dominance are likely to convey relevant information about the founders' competence – their ability to be in control of their situation. Perceived competence has been shown to positively affect founders' success at securing investments from professional investors (Chen et al., 2009). Thus, I expect founders' dominance displays on social media to also be positively related to the amount of funding they receive for their venture.

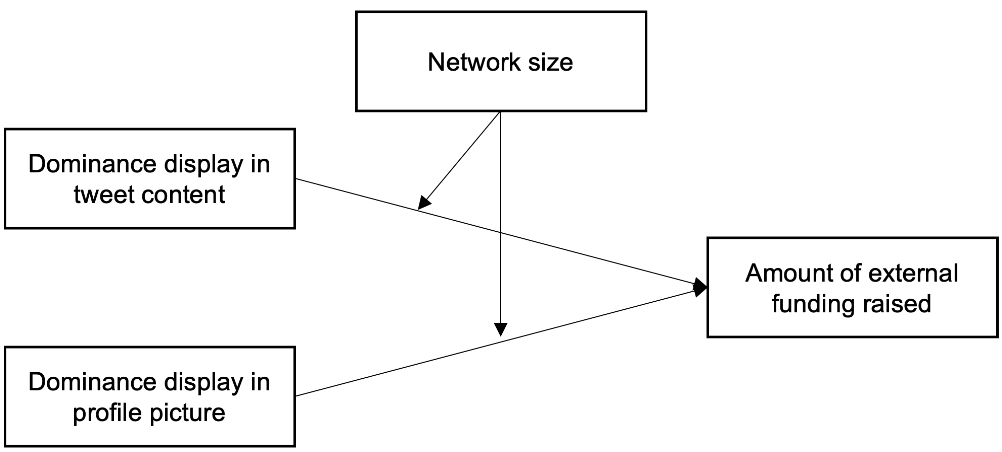
H1: Founders who signal more dominance in the written content of their tweets during the year before the close of an investment round[5] receive higher funding.

H2: Founders who signal more dominance via the facial expression in their Twitter profile pictures receive higher amounts of investment in their venture.

The effect of dominance signals likely depends on the size of founders' Twitter networks. Not only have network size and interaction themselves have been shown to be predictors of financial success (Albrecht et al., 2020; Banerji & Reimer, 2019; Chahine & Malhotra, 2018), founders also need a reasonably sized online network in order for their signals to reach any receivers. After all, observability is a key feature of effective signals (Connelly et al., 2011): The larger the network, the more visible the signal, the more likely it is to affect investors' decision-making. Thus, I expect network size to moderate the relationship between dominance and funding. The hypothesized model is shown in Figure 2.

Figure 2

Hypothesized Model



[5] The research proposal associated with this study stated that only the three months leading up to the close of the round will be taken into account. I decided to include a longer time period in the analysis since, in 2021, ventures typically took 15 to 17 months to close a new round at the stages of interest (Series A to D; CB Insights, 2022).

H3: Network size serves as a contingent moderator of the relationship between dominance signals in founders' written tweet content and funding amount such that the positive relationship becomes significant only with larger network size.

H4: Network size serves as a contingent moderator of the relationship between dominance signals in founders' profile picture facial expressions and funding amount such that the positive relationship becomes significant only with larger network size.

Methods

Study Design

This study uses an observational design in which data is collected from a single group of participants who are not assigned to any treatment. There is no blinding involved in this study. This study design does not allow for conclusions about the causal nature of any relationships between variables.

Sample

The studied sample consists of founder-CEOs of US-based tech startups who have raised a Series A-D funding round in 2021. According to PitchBook[6], a total of 2,852 such deals were made in 2021. Some ventures have received multiple rounds of funding during the selected period. After dropping cases in which the same venture was listed multiple times and applying the inclusion criteria, the final analysis was run on n = 720 individual cases (25%). The three inclusion criteria are (1) twitter presence, (2) base tweet activity, (3) human profile picture. (1) Subjects need to have a Twitter profile unambiguously associated with their identity. Twitter profiles were searched and verified manually. Because the only information available to search for the profiles were subject name, venture name, and some additional information about both, profiles were accepted if, apart from its screen name, the content in some way pointed to the fact that this is the profile of the person in question. One

[6] https://www.pitchbook.com

example of this would be the user mentioning their company and/or role within that company in their profile description. This strategy does not account for potential impersonations, though in ambiguous cases where more than one profile could be potentially tied to the subject, that subject was also excluded from the analysis. After this step, any personal information was deleted from the dataset. (2) Subjects' twitter profiles must show a minimum of 1 tweet per month[7] in the period of interest (i.e., one year prior to funding), excluding retweets. (3) Subjects' twitter profile picture must show a human face.

A power analysis in G*Power reveals a minimum sample size of $n = 92$. The selected test is an F-test of linear multiple regression (fixed model, testing for an R^2 deviation from zero). The same minimum sample size is confirmed by an additional power analysis in R using the pwr package. The model includes five predictors: tweet dominance, profile picture dominance, network size, and the two interaction terms tweet dominance x network size and profile picture dominance x network size. G*Power analysis for two-tailed t-tests to determine the significance of single predictors reveals smaller required sample sizes. In line with common practice, the larger required sample size ($n = 92$) is used as the minimum sample size for this study.

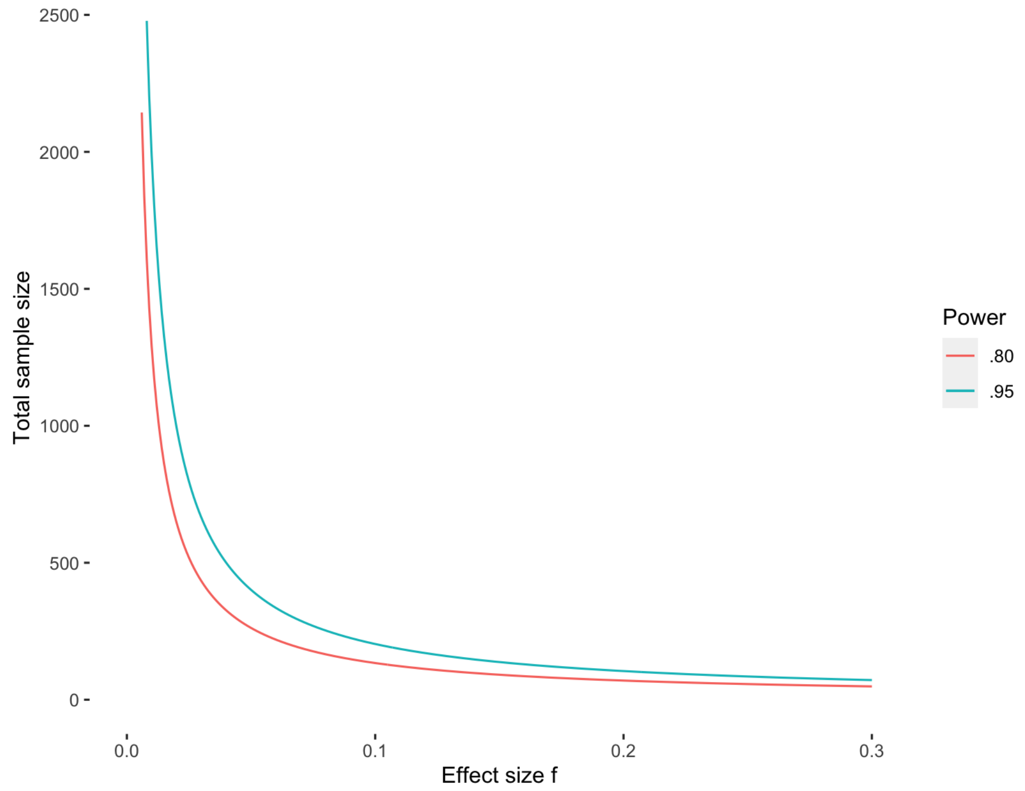
As of yet, there are no meta-analyses of the effects examined in this study, so the assumed medium effect size $f^2 = .15$ (Cohen, 1988) is based on findings of medium effect sizes for relationships between other founder signals and funding outcomes (see Albrecht et al., 2020; Banerji & Reimer, 2019; 2017; Chen et al., 2009). One meta-analysis by Chervonsky and Hunt (2017) finds smaller effect sizes for the relationship between positive emotional signaling and social wellbeing outcomes ($d = .173$, $p > .001$, 95% CI [.095, .248]). Though the type of emotional signal and the outcome in this meta-analysis differ from the present analysis, it may indicate that emotional signals in general potentially have smaller effects than other signals. Thus, I conducted an additional sensitivity analysis as suggested by Perugini and colleagues (2018) in the case of a moderated multiple regression where

[7] Due to the longer time period under consideration, this criterion was adjusted from the original research proposal (before: one tweet per week in a three-month period). In both cases, the minimum number of tweets required was 12.

there is limited basis for estimating effect sizes. The results modeling sample size as a function of different effect sizes *(f^2)* are shown for two levels of power (.80 and .95) in Figure 3. According to this analysis, the achieved sample size allows for detection of sample sizes as small as f^2 = .018 or 0.028 at .80 or .95 power, respectively.

Figure 3

Sensitivity Analysis



Note. Effect size denoted as Cohen's (1988) f^2.

Data Collection & Measurement

Data on timing and amount of funding, as well as subject name (only for identification of the correct Twitter profile) is collected from the investor data platform PitchBook[8]. The remaining data is scraped from the subjects' Twitter[9] profiles using Twitter's Research API

[8] https://pitchbook.com/
[9] https://www.twitter.com

(Application Programming Interface). The outcome variable, funding amount, is retrieved directly from PitchBook. It is defined as the size of the funding round which took place during the period of interest, measured in USD.

Dominance signaling in written tweet content (tweet dominance) is measured on a scale of 0 to 1, using a natural language processing (NLP) model trained specifically for this purpose. This model is based on the large language model BERT (Devlin et al., 2018) and has been trained to the task with transfer learning using EmoBank, a human-labeled linguistic dataset (Buechel & Hahn, 2017). Dominance signaling in facial expression (picture dominance) was measured as a dichotomous variable using the open source software OpenFace 2.0 (Baltrusaitis et al., 2018) based on characteristic facial muscle activity patterns identified by Rychlowska and colleagues (2017).

Apart from dominant smiles, the facial expression measure additionally measures whether a facial expression is a smile in general and whether that smile is of the affiliative or rewarding type as specified by Rychlowska and colleagues (2017). The NLP model additionally measures the two remaining dimensions of emotional space defined by Russel and Mehrabian (1977), valence and arousal. These measures are not included in the statistical analysis. All code used for data collection, processing, and analysis is available on GitHub[10].

Measure Development

Emotion Analysis of User-Generated Writing: EmoBERT. First introduced in 2017 (Vaswani et al., 2017), transformer models have become the gold standard in NLP (Rogers et al., 2020). Transformer model architectures consist of encoders and decoders, with encoders learning about language meaning and decoders learning how those word meanings relate to a certain output. The reason transformer models are so powerful in NLP is that encoders process all words within a sequence (i.e., one or multiple sentences) simultaneously. This allows the model to account for word context and ordering which play a very important role in accurately assessing word meaning (Acheampong et al., 2021). For

[10] https://github.com/carlaost/fundingdominance

example, the word “bank” can have two completely unrelated meanings, depending on whether it is preceded by the word “river” or followed by the word “robbery.” This nuanced language understanding makes transformer models interesting for emotion analysis.

One of the most powerful transformer-based models is BERT (Devlin et al., 2018) which consists of a stack of transformer blocks. BERT is conventionally used in a two-stage workflow of pre-training and fine-tuning or transfer learning (Rogers et al., 2020). During pre-training, the model obtains natural language understanding (NLU). In fine-tuning and transfer learning, this general knowledge is then applied towards solving a specific NLP task. EmoBERT was developed using a BERT model that had already been pre-trained which was then trained to determine emotional signaling in writing. Though fine-tuning and transfer learning tend to be used interchangeably in the literature, I will make a distinction to highlight the training strategy used in this study. Both processes are used to train a general model towards solving a specific task by training it on a dataset specific to that task. I refer to transfer learning as the process of freezing the base model parameters, adding new layers on top of the base model and training only the new layers on a task-specific dataset. Freezing model parameters means that the weights and biases – those parameters typically adjusted during model training – are fixed, which preserves the knowledge encoded in them during pre-training. In fine-tuning, new layers are added to the base model but the base model parameters are not frozen. All model parameters are then trained on the task-specific dataset. One common issue in fine-tuning is catastrophic forgetting in which pre-trained knowledge is lost during fine-tuning (McCloskey & Cohen, 1989). This can be circumvented by lowering the learning rate during fine-tuning (Sun et al., 2019). At lower learning rates, model parameters are adjusted more gradually during training. This means that a model must be trained for more epochs to arrive at the right parameter configuration, which requires more computational resources. Transfer learning requires less computational resources and tends to quickly yield good model performance on complex tasks, even with relatively small datasets (Zhuang et al., 2021). For these reasons, EmoBERT is developed using only transfer learning.

Pre-training of BERT is described in detail in the original paper (Devlin et al., 2018). This pre-trained model was used as the base model for EmoBERT. It produces word embeddings, which are vector-representations of each word whose coordinates depend on the word's meaning and form clusters corresponding to word senses (Wiedemann et al., 2019). Because of the contextualization of words, the two "banks" from the example above would result in very different vectors, corresponding to their very different meanings. The base model used for transfer learning on emotional signaling was obtained from TensorFlow Hub[11]. It uses L = 12 hidden layers (i.e., transformer blocks), a hidden size of H = 768, and A = 12 attention heads. This architecture as well as the model weights are identical to those of the BERT base model published in the original paper (Devlin et al., 2018). EmoBERT's model head (i.e., the trainable layers added on top of the base model) uses L = 2 hidden layers with a hidden size of H = 64, and three output layers. The final model architecture is shown in Figure 4. The model uses the RMSprop optimizer since it performed best during hyperparameter tuning. During training, parameters were adjusted using the mean squared error (MSE) loss function because it punishes large mistakes more than small ones. The chosen model performance metric is the mean absolute error (MAE) as it is easy to interpret.

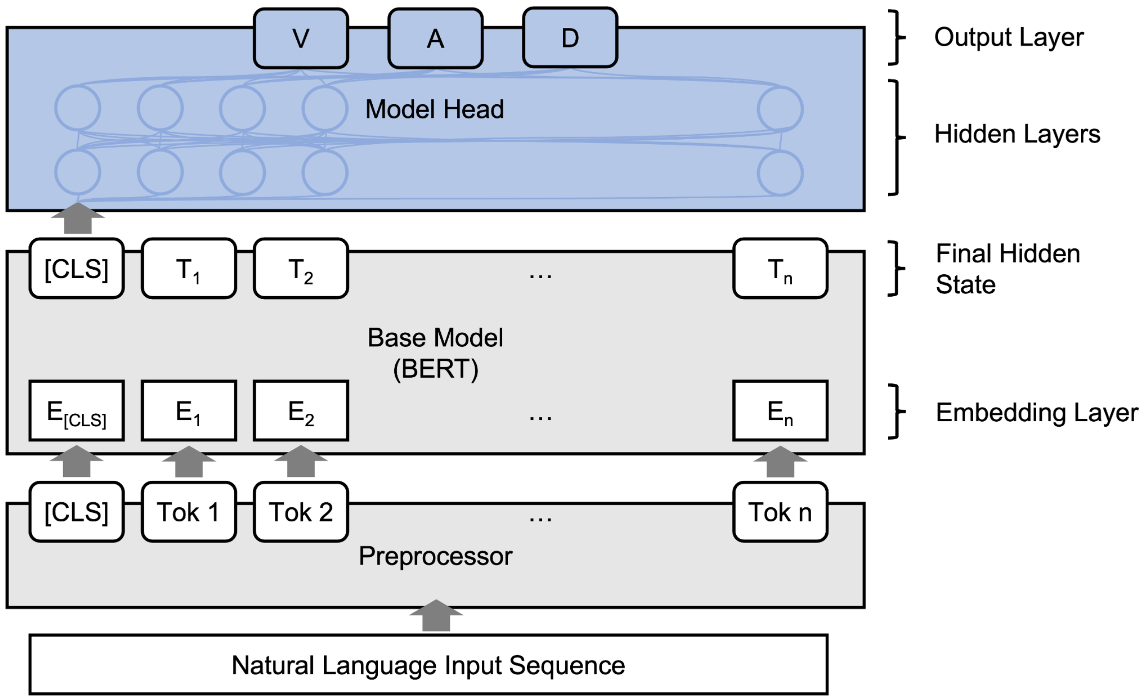
The transfer learning process uses the EmoBank "writer" dataset which has been made publicly available[12] (Buechel & Hahn, 2017). The text data originates from several categories of the Manually Annotated Sub-Corpus of the American National Corpus (MASC; Ide et al., 2008, 2010) and the corpus of SemEval-2007 Task 14 Affective Text (SE07; Strapparava & Mihalcea, 2007).The dataset contains 10,062 text sequences which have been labeled with regards to the emotion expressed by the writer on the dimensions of valence, arousal, and dominance. In its original form, emotion is rated on a range between 1 (low) and 5 (high). For transfer learning, these values are transformed to a range between 0 (low) and 1 (high). The final model architecture was determined via automated hyperparameter tuning using the Keras library. EmoBERT was tuned, trained, and deployed

[11] https://tfhub.dev/tensorflow/bert_en_cased_L-12_H-768_A-12/4
[12] https://github.com/JULIELab/EmoBank

on Google Colaboratory because the platform provides GPU-assisted training, speeding up training times significantly.

Figure 4

EmoBERT Model Architecture



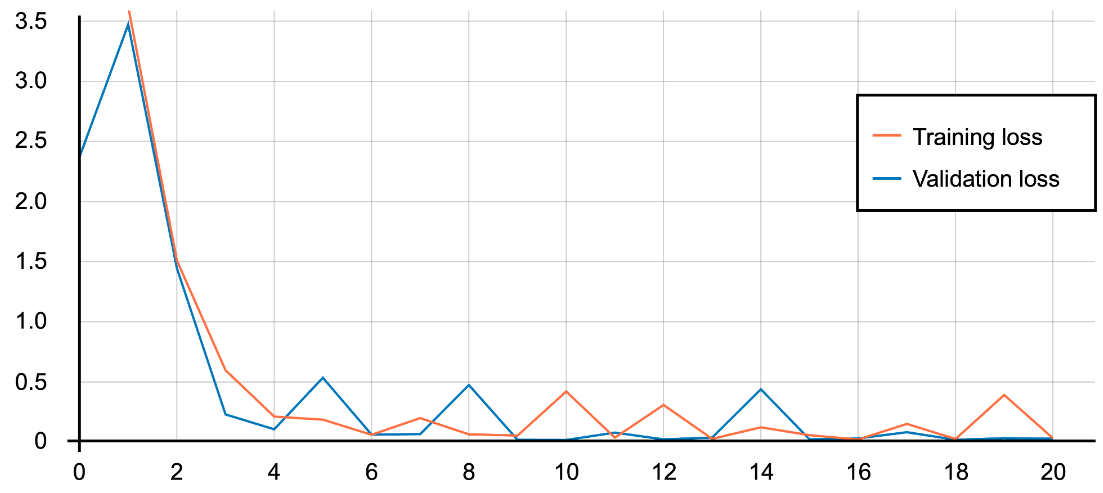
Note. Blue layers are added and trained during transfer learning. Total parameters: 108,363,844. Trainable parameters: 53,71; non-trainable parameters: 108,310,273

An input sequence is passed to the base model's preprocessor which transforms natural language into numeric sequences (tokens) as input for the encoder. The final encoder layer outputs a sequence of vectors in which each vector is the final hidden state representing a specific input token, as well as a special token, the [CLS] token. This special token is a representation of the entire sequence (Sun et al., 2019). It is then passed to the first layer of model head, the part of the model trained specifically to the emotion detection task during transfer learning. The three final layers of the model head have each been trained to predict one of the three emotional dimensions (valence, arousal, and dominance).

During transfer learning, EmoBERT was trained on a regression task using the EmoBank dataset. Using the Early Stopping technique, training was interrupted once the model metrics did not improve for 10 epochs, which occurred after 21 epochs of training. This saves computational resources as it can be assumed that model predictions do not significantly improve after this point (Chollet, 2021). Fig 5. shows the loss function over the entire training process. During training, model parameters are adjusted in order to minimize the loss, meaning that the predicted values are very close to the true values.

Figure 5

EmoBERT Loss Functions During Transfer Learning



Note. Training was stopped after epoch 20 since validation metrics did not improve meaningfully in the previous epochs.

During the best training epoch, EmoBERT achieved a training loss of *MSE* = .0369, and a validation loss of *MSE* = .0791. The final evaluation metrics are shown in Table 1. The model is able to predict dominance expressed in text with an average absolute error of *MAE* = .046. Given the dataset's distribution, this means that EmoBERT makes predictions within a .7 *SD* range of the true value (1 *SD* = .064).

Table 1

EmoBERT Evaluation Metrics

Variable	Loss *(MSE)*	Performance *(MAE)*
Overall Model	.0166	
Valence	.0066	.0560
Arousal	.0064	.0595
Dominance	.0036	.0455

Note. MSE: mean squared error. *MAE:* mean absolute error.

The final, fully trained EmoBERT model is used to assess emotional signaling in subjects' tweets. This text-based emotional signaling was analyzed in a multi-step approach. Per subject, EmoBERT makes a prediction of the emotional signal sent in each tweet posted in the relevant timeframe. A composite score of emotional signaling is computed across all tweets. This composite score is simply the mean for each of the three dimensions. I assume an average score to be a reasonable approximation of an overall image of the founder received by investors.

Emotion Analysis in Facial Expressions: Facial Expression Classifier. The analysis of dominance signaling in Twitter profile pictures is based on the open source computer vision algorithm OpenFace 2.0[13] (Baltrusaitis et al., 2018). OpenFace 2.0 provides functionalities that are useful to a broad range of computer vision problems. The automated profile picture analysis uses its feature extraction functionality. In computer vision, feature extraction refers to the process of transforming (extracting) image data into numerical representations (features) of that data which contain all the relevant information. With OpenFace 2.0, researchers can extract important features for facial recognition, like facial landmark detection, head pose estimation, eye-gaze estimation, and, importantly, facial

[13] https://github.com/TadasBaltrusaitis/OpenFace

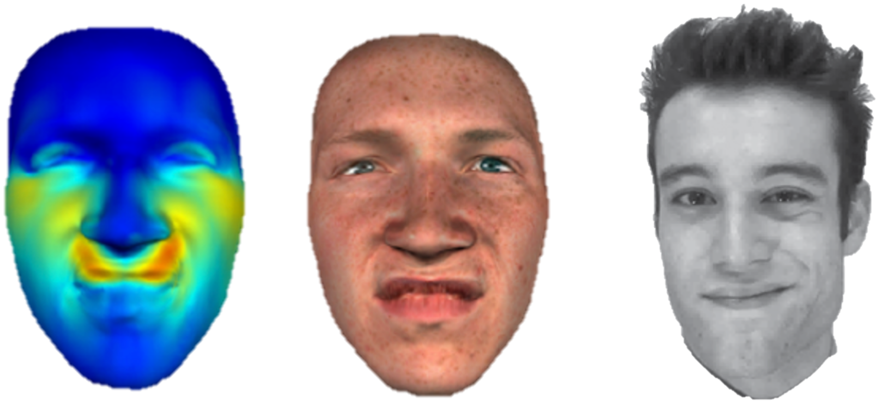
action unit recognition (Baltrušaitis et al., 2015; Baltrusaitis & Robinson, 2013; Wood et al., 2015; Zadeh et al., 2017).

Using Twitter's Research API, URLs pointing to subjects' profile pictures are identified, which are then used to download the pictures themselves. The downloaded images are passed into OpenFace 2.0 for feature extraction. Among other features like facial landmark positions, the feature extractor provides information on the activation of 18 action units (AUs). Action units are groups of facial muscles which, when activated, result in a characteristic facial expression, like raised brows or closed lips (Ekman & Friesen, 1978). These activation patterns were then used as input for the facial expression classifier which categorizes these activation patterns based on the three prototypical activation patterns of dominant, affiliative, and rewarding smiles as identified by Rychlowska and colleagues (2017). Dominant smiles are characterized most prominently by the activation of the following combination of AUs: the Upper Lid Raiser (AU5), Cheek Raiser (AU6), Nose Wrinkler (AU9), Upper Lip Raiser (AU10), and the Nasolabial Deepener (AU11) as well as a unilateral activation of the Lip Corner Puller (AU12; Rychlowska et al., 2017). An exemplary representation of a dominant smile is shown in Figure 6.

For the dominance score, the classifier weights each AU's activation score (0 or 1, inactive or active; provided by the feature extractor) based on the percentage of raters from Rychlowska's study (2017), who rated a facial expression involving this AU as dominant. This process is the same for all smile types. Finally, the program classifies a profile image as showing that expression which has received the highest score. Weighting the activation scores results in AUs having a stronger impact on the score – i.e., being a stronger indicator for a certain smile type – when that AU's activation is more likely to result in observers perceiving a facial expression as that smile type. The feature extractor does not provide information about the activation of all of these AUs. The only AUs relevant for dominant smiles that are reported by the feature extractor are AU5, 6, 9, and 12. Thus, not all AUs identified as important for the different smile types could be taken into account.

Figure 6

Prototypical Dominant Smile



Note. Adapted from Rychlowska et al. (2017). Relative activity of action units (left), virtual simulation (middle), and real life example (right) of a prototypical dominant smile.

Statistical Analysis

The hypotheses are tested using a linear multiple regression of a fixed model testing for an R^2 deviation from zero. There are five predictor variables: tweet dominance (continuous), profile picture dominance (dichotomous), network size (continuous), and the two interaction terms tweet dominance x network size and profile picture dominance x network size. The criterion variable is funding amount. Since profile picture dominance is a dichotomous variable, it will be dummy coded with 0 = non-dominant and 1 = dominant. Statistical significance of each individual predictor is tested using individual t-tests of the single regression coefficients in the fixed model, at the convention of $p < .05$. Because the ordinary least squares (OLS) regression initially computed violates multiple assumptions (see Appendix A), including the normal distribution of residuals, I compute a robust regression using M-estimation with Huber weighting (Huber, 1973). Due to the adjustment of residuals in robust regression, model fit cannot be inferred from R^2 in a straightforward manner[14]. Individual effect sizes *b* for all individual predictors are provided based on the robust regression, overall model fit R^2 is provided only for the OLS model. All statistical analyses are done in R (version 4.1.2) and the code can be found on GitHub[15].

Results

Descriptive Statistics

A total of n = 720 cases met all inclusion criteria. Because PitchBook does not offer any demographic data about individuals, these cannot be analyzed or used as control variables. The 720 deals included in the analysis ranged in size from USD .22m to USD 788.26m. However, there are only very few very large deals in the dataset: 90% of deals had a size of USD 84.3m or lower. The mean deal size was USD 37.86m, the median USD 17.53m, *SD* = 68.03m. The mean and median score of tweet dominance were both .536 *(SD* = .005) and the range of scores in the dataset was very constrained with a minimum score of *Min* = .512 and a maximum of *Max* = .552. In the original EmoBank training set, the mean was .521 *(SD* = .060), and scores were more dispersed *(Min* = .200, *Max* = .850). The full range of tweet dominance in this sample is a smaller interval than one standard deviation of dominance scores in the training dataset. Comparisons between the two datasets are difficult though, because the text data in EmoBank was obtained from domains outside of social media like news headlines, blogs, letters, and travel guides (Buechel & Hahn, 2017), which indicates different norms for emotion expression. Out of the 720 analyzed profile images, 234 (33%) showed a dominant smile. The minimum network size was 10 followers, the maximum 5,265,944, though 90% of subjects had less than 13,078 followers. The median network size was 1,385, *SD* = 205,471. The correlation matrix of deal size, tweet dominance, and network size reveals no correlations between the variables (see Table 2).

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[14] For a discussion, see https://stackoverflow.com/questions/31655196/how-to-get-r-squared-for-robust-regression-rlm-in-statsmodels

[15] https://github.com/carlaost/fundingdominance

Table 2

Descriptive Statistics and Correlations

Variable	*M*	*SD*	1	2	3	4
1. Deal Size	37.86	68.03	—	.82	.64	1.00
2. Tweet Dominance	0.54	.01	.05	—	1.00	.82
3. Profile Picture Dominance	—	—	.06	.01	—	.82
4. Network Size	17,086	205,471.1	.01	-.01	.05	—

Note. Deal Size measured in USD million. Values above the diagonal of the correlation matrix show probability values adjusted for multiple tests.

Hypothesis Testing

An initial OLS linear multiple regression model revealed that network size negatively predicts funding amount and moderates the relationships between funding and the two ways of dominance signaling as reported in Table A1. However, this model violates a number of assumptions (see Figure A1). The results reported in the following section are thus based on a robust regression model using M-estimators with Huber weighting (Huber, 1973). The results are listed in Table 3. Dominance signaling in written tweet content positively predicts funding amount (b = 394.84, *SE* = 123.20, $p < .01$) as predicted by *H1*. Network size negatively predicts funding amount (b = -.0025, *SE* = .0012, $p < .05$) and serves as a contingent positive moderator of the relationship between tweet dominance and funding (b = .0047, *SE* = .0023, $p < .05$), technically supporting *H3. H2* and *H4* are not supported by the model: Dominance signaling in profile pictures does not predict funding amount (b = 1.44, *SE* = 1.70, p = .40) and this relationship is not moderated by network size (b = .00, *SE* = .00, p = .30). R does not provide an R^2 of robust regression models which either way, as discussed in the methods section, would only have limited interpretability. As a proxy, the OLS regression (which violated critical assumptions) has a fit of R^2 = 0.0182 (adj. R^2 = 0.0113), indicating an effect size of f^2 = .02, a small effect size according to Cohen (1988).

Table 3

Robust Regression Results

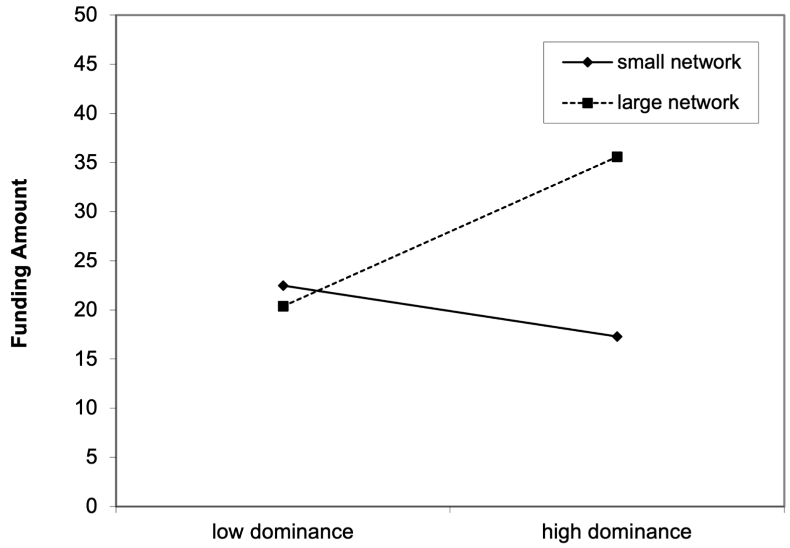
Variable	*B*	*SE*	*t*	*p*		95% CI
Constant	-188.0768	81.3530	-2.3119	.0207	*	[-348.0000, -28.6000]
Tweet Dominance	394.8388	151.7513	2.6019	.0092	**	[97.4000, 692.0000]
Picture Dominance	1.4368	1.7026	0.8439	.3985		[-1.9000, 4.7700]
Network	-.0025	.0012	-1.9924	.0438	*	[-.0049, -.0000]
Tweet Dominance * Network	.0047	.0023	2.0036	.0426	*	[.0001, .0092]
Picture Dominance * Network	.0000	.0000	1.0060	.3039		[-.0000, .0000]

Note. p-values: 0.000 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Figure 7a shows the moderating effect of network size on the relationship between tweet dominance and funding amount at one standard deviation above and below the average network size. According to this view, network size indeed is a positive contingent moderator as predicted in *H3.* There is no significant effect of tweet dominance on funding amount for small network sizes (b = -490.57, p = .31), but there is a positive effect for large network sizes (b = 1440.86, p < .01). However, given the large standard deviation of network size, small networks defined as one standard deviation below the mean would count -188,385 followers, a practically impossible number. Following this logic, the relationship between tweet dominance and funding amount becomes significant at a network size of -16,460. The realistically smallest achievable network size is 0, a point at which the relationship is already significant, b = 394.84, p < .01.

Figure 7a

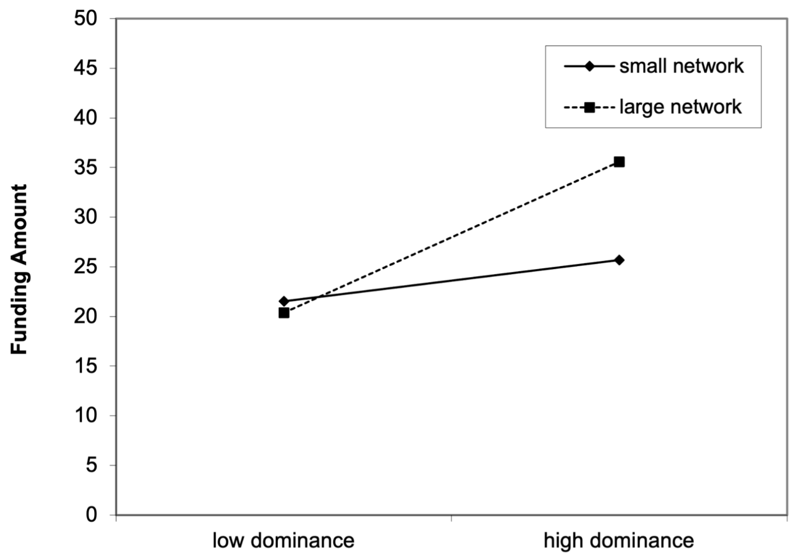
Interaction Pattern at +/- 1 SD of Network Size



Note. Small network size = -188,385.1. Large network size = 222,557.1.

Figure 7b

Interaction Pattern at realistic values of Network Size



Note. Small network size = 0. Large network size = 222,557.1.

Figure 7b shows the interaction pattern for small networks defined as the minimum achievable network size of 0 and large networks defined as one standard deviation above the mean. If one only considers practically achievable values, network size is, in fact, a *contributory* divergent positive moderator, such that the relationship is already positive and significant for small networks, but becomes stronger for large networks. Thus, *H3* is only partially supported by the findings: The interaction pattern technically confirms the assumption of contingent moderation, but under all realistic conditions (i.e., minimum network size of 0), the effect is already significant and network size only serves as a contributory moderator.

Discussion

Based on an integration of the social-functional account of emotions provided by EASI theory (Van Kleef, 2009) with the economic perspective of signaling theory (Connelly et al., 2011; Spence, 1978), this study draws on theoretical considerations on non-rational effects of founder signaling on investor decision-making as well as the practical observation that VC investors increasingly use information based on social media to reduce information asymmetries (Tumasjan et al., 2021). I investigate the effects of emotional signals by startup founders on the amounts of investments they receive. Specifically, I introduce two new mechanisms to examine the effects of founders' dominance signaling on Twitter via written tweet content (based on the three-factor theory of emotions by Russel and Mehrabian, 1977) and profile pictures (based on SIMS theory; Niedenthal et al., 2010) on funding amount. The findings indicate that dominance signaling in tweet content does predict funding amount, while profile picture signaling does not. Founders' network size moderates the relationship between tweet dominance and funding amount such that the positive effect becomes stronger for larger networks. Network size does not moderate the relationship between profile picture dominance and funding amount.

Implications

This study focuses on dominance as an emotional signal because it transmits information about whether the signaler feels like they are in control of their surroundings or not (Russell & Mehrabian, 1977). Founders' dominance is assumed to be a relevant signal for investors as it allows for inference about a founder's competence and agency: A founder who expresses high dominance has a feeling of agency and control over their situation, including the process of scaling their venture. This may increase investors' confidence in the founder's competence, which has been shown to influence investment decisions in favor of the founder (Chen et al., 2009). This study found that tweet dominance predicts funding amount, providing initial support for this idea. The feeling of agency and control may also signal a decreased risk of founder burnout: Entrepreneurship is widely recognized as a stressful occupation with high risks of burnout (Boyd & Gumpert, 1983; De Mol et al., 2015; Shepherd et al., 2010). A founder who continuously signals dominance also signals that they are successfully coping with the stressors accompanying their work, reducing the perceived risk of an investment. Next to, and potentially supported by, these inferences, the signal may also affect investors' affective reaction towards the founder: A founder who feels in control of their surroundings might create a sense of trust and reduced anxiety in investors. Feelings of trust have been shown to lead to larger venture investments (Maxwell & Lévesque, 2014).

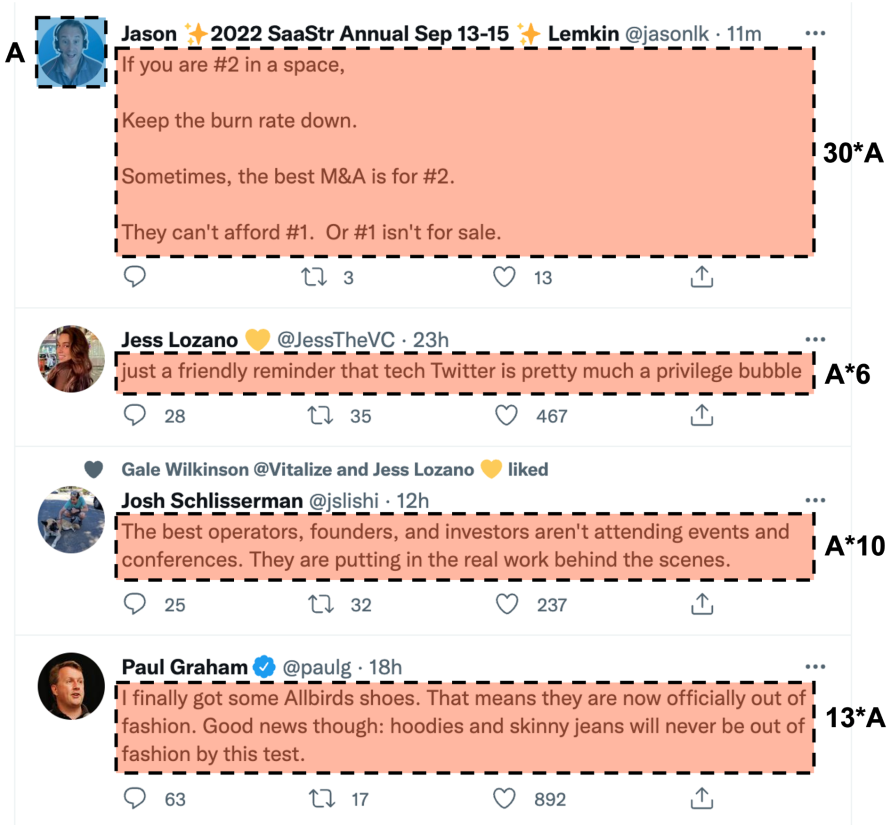
Emotional signals have been shown to have similar effects across channels (Van Kleef et al., 2011). Thus, it seems surprising that the above mechanisms seem to apply to dominance signals in tweet content but not profile pictures. Signaling theory (Connelly et al., 2011; Spence, 1978), EASI theory (Van Kleef, 2009; Van Kleef et al., 2011), and methodological considerations offer three potential explanations for this inconsistency. First, signaling theory suggests that the difference in cost of signaling for imitative compared with genuine signalers c may differ between the two signals (Bergh et al., 2014). Both signals have very low cost of imitation, but the cost is presumably not zero as it does require some effort from the imitative signaler to adjust their emotional expression towards a dominant one in a process known as impression construction (Leary & Kowalski, 1990). For simplicity, we can assume that the cost of imitating one dominant tweet c_t is equal to the cost of imitating one dominant profile picture c_p, or $c_t = c_p$. However, due to inclusion criterion 2 (a minimum of 1 tweet per month in the relevant timespan), the tweet dominance measure T used in this study is composed of a minimum of 12 individual signals, meaning $c_T > 12 * c_t$ or $c_T > 12 * c_p$. The reliability of a signal is a function of *c (Bergh et al., 2014; Connelly et al., 2011)*. Thus, the inconsistency may be caused by measure design choices and a resulting difference in signal reliability.

Second, EASI theory suggests that the inconsistency may be caused by differences in moderating forces between the two signaling channels: The effects of a signal depend on receivers' information processing (Van Kleef, 2009). There may be a difference in the way receivers process the two signals, causing tweet dominance signaling to have stronger effects. In fact, tweet dominance signals differ from profile picture dominance signals in size and novelty, both important aspects of information processing (Herrmann et al., 2010; Rangel-Gomez & Meeter, 2016). As shown in Figure 8, tweet signals take up more space in the visual field of receivers which may make the signal more salient and thus increase its effect. This consideration is also in line with signaling theory which claims that the observability of a signal moderates its effectiveness (Connelly et al., 2011). Information processing may further differ due to differences in signal novelty. Both signals are sent to receivers at the same frequency – whenever the signaler makes a post. However, users tend to change their profile pictures less often as they post new content. Thus, the content of the tweet signal is new every time while the profile picture signal mostly stays consistent. Thus, tweet signals are typically more novel, further increasing their salience.

Lastly, the inconsistency may be explained by differences in measurement of the two signals. Both measures have yet to be extensively validated, but EmoBERT already undergone basic tests and validations common in the field of machine learning. The validity of the facial expression classifier has yet to be confirmed. Profile picture dominance signaling may indeed have an effect on funding, but the classifier may require further improvement to allow for this effect to be detected.

Figure 8

Size of Profile Pictures vs Tweets In Exemplary Twitter Feed



Note. A = 400 * 400 pixels.

Based on previous findings which have detected a positive relationship between network size and financial success (Albrecht et al., 2020; Banerji & Reimer, 2019; Chahine & Malhotra, 2018) as well as signaling theory in which a signal becomes more effective with increased observability (Connelly et al., 2011), I assumed network size to be a contingent moderator of the relationship between tweet dominance and funding amount. The findings of this study only partially support that assumption as the moderation effect is contributory under all realistics conditions (positive network sizes). Still, the empirical and theoretical considerations that led to the original assumption do not contradict this pattern. EASI theory’s moderating forces provide additional potential explanations of the interaction.

Social-relational factors, including the nature of the personal relationship between signaler and receiver as well as context-specific norms, moderate signaling effects (Van Kleef, 2009). Network size can be interpreted as one such social-relational factor. The personal relationship between founder and investor may be different when founders have a small rather than a large network: In a small network, it is more likely that both parties do have a personal relationship, or that they at least have a shared connection with someone else. This could mean that the information asymmetry between investors and founders in small networks is smaller than in large networks, providing less need for investors to rely on signals such as dominance (Connelly et al., 2011). Further, the norms for founders' emotional signaling may differ as a function of their network size. Founders with large networks may be perceived as public personas who tend to be judged by different criteria than "ordinary" people (Strumska-Cylwik & Olivier, 2018). The effect of dominance signaling may be stronger here as low dominance may be judged more harshly by investors for founders with large networks.

This study carries implications for signaling theory, EASI theory, and studies of online behavior. The findings of this study indicate, in line with behavioral economics (Thaler, 2016) but contrary to signaling theory assumptions (Bergh et al., 2014; Spence, 1978), that economic actors are not completely rational. It also suggests that the equilibria created by signals may be exist on a continuum rather than in two distinct categories (separating and pooling; Bergh et al., 2014): The larger a signal's differential cost *c*, the stronger its signaling effect, the more the equilibrium becomes separating rather than pooling. Further, this study presents an extension to traditional EASI theory (Van Kleef, 2009) by applying it to emotional signaling via social media and integrating different theoretical accounts of emotionality – SIMS theory (Niedenthal et al., 2010) and the three-factor theory of emotions (Russell & Mehrabian, 1977). This creates a larger design space for research on the effects and mechanisms of emotional signaling across channels (offline vs. online, verbal vs. facial) and emotions (degree of valence, arousal, and dominance; expression of dominant, affective, and rewarding motives). Lastly, this study is an example of social science using the breadth of data available online. Data sources such as social media are a valuable addition to social science as they provide the opportunity to observe natural behavior not influenced by experimental or other research settings. The opportunities for researchers interested in the effects and patterns of human behavior are almost unlimited given the richness of data available. For example, this study integrated two very different and seemingly unrelated data bases, Twitter and Pitchbook, to make observations on the effect of human's emotions on economic outcomes.

The relationship between dominance and funding needs further examination before true conclusions relevant to practice can be made, as discussed in the next section. As of now, there is one major implication of the findings in this study for the practice of venture investing: Investors are not completely rational and their investment decisions are likely influenced by weak signals which fail to create true separating equilibria. This provides additional support to findings of investors reporting gut-based decision-making (Gompers et al., 2020) and the influence of weak signals on investment decisions (Steigenberger & Wilhelm, 2018). Given the impact of venture investing on economic activity and innovation, investors should be aware of the factors influencing how they allocate their funds. As investors increasingly leverage social media-based information to learn more about ventures and founders (Tumasjan et al., 2021), they need to consider that signals like dominance on Twitter may affect investment decision-making without necessarily indicating investment quality. For founders, the findings of this study imply that building a dominant presence on Twitter, or otherwise creating a competent image, may help with raising investments. At the very least, founders should be aware that their online presence is a factor when it comes to fundraising and their choice of words in posts may influence investors' decision-making. Previous findings (Cardon, Mitteness, et al., 2017; Chen et al., 2009; Jin et al., 2017) have highlighted the importance of positive emotional signaling for founders when it comes to securing investments. This study expands the "emotional playing field" available to founders by establishing the relevance of dominance signaling for investment success.

Limitations and Future Research Avenues

The two new measures introduced in this study have yet to be systematically validated in line with psychometric standards, including tests for reliability as well as discriminatory and convergent validity. As of yet, EmoBERT has only been tested in accordance with basic best practices in machine learning while the facial expression classifier fully relies on insights from studies on SIMS theory (Niedenthal et al., 2010; Rychlowska et al., 2017). More research needs to be done to establish the validity of these measures by incorporating standard psychometric procedures for measure validation (El-Den et al., 2020). For example, convergent validity of the facial expression classifier may be measured using techniques similar to those used by Rychlowska and colleagues (2017). Both measures' should also be tested on interrater reliability by comparing the measures' with human-rated (ideally including experts and non-experts) scores.

Further, the sample used in this study was kept relatively homogeneous in order to increase internal validity of the study, resulting in a trade-off in generalizability. The relationship between dominance signaling and funding needs to be examined across different industries, geographies, and occupations as norms defining appropriate or desirable levels of dominance may differ (Safdar et al., n.d.). For example, founding a venture requires a strong sense of agency, indicating that founders may generally show more dominance than the general population.

Even within the specific population examined in the study, there is much left to examine. The study design does not allow for conclusions about the causal nature of the relationship. This study only meets one of the criteria of causal inference by accounting for temporal sequence. Studies using experimental designs, including manipulation of the predictor variable randomized control trials, need to be conducted to understand the true nature of the relationship. For example, an experimental study could generate artificial twitter presences of founders signaling different levels of dominance in their tweets and profile pictures. Profile pictures could be generated in the same manner in which Rychlowska and colleagues (2017) modeled the prototypical smile types. Dominant tweets could be generated using text-generating NLP models like OpenAI's GPT models (Polu & Sutskever, 2020). Such studies would allow conclusions about the causal nature and direction of the relationship (Podsakoff & Podsakoff, 2019). They may also reveal that the relationship detected in this study is purely correlational or caused by confounding variables or alternate pathways. A third variable not directly accounted for in this study, like venture revenue (Zhang & Wiersema, 2009) or a founders' connections to potential investors (Banerji & Reimer, 2019), may affect both measures, resulting in an apparent relationship between the two. Future studies should include such control variables to determine whether there are mechanisms outside of emotional signaling that may account for the relationship between dominance and funding.

Lastly, this study lacks depth of analysis on both the signaler and the receiver side. Traditional signaling theory assumes that signalers take deliberate action to communicate underlying qualities to receivers (Connelly et al., 2011) but this may not apply to online emotional signaling: Future studies should examine whether founders intentionally use Twitter as a means for emotional signaling. In the same sense, the exact mechanisms by which these emotional signals affect receivers have not been examined here. EASI theory provides multiple avenues for further research on exactly how investors receive emotional signals and how these affect their inference and affective reactions (Van Kleef, 2009). This study did not explicitly distinguish between the inferential and affective pathways of information flow. Apart from network size, this study also failed to include potentially meaningful moderating variables like social-relational factors and differences in information processing. To fully understand the mechanisms creating the detected relationship between dominance and funding, these factors need to be considered in future studies.

Conclusions

This research shows that dominant founders do get better funding: Founders who signal more dominance in their tweet content raise larger investment rounds. This effect is moderated by their network size such that the effect becomes stronger for founders with larger networks. Thus, founders' dominance seems to be a relevant signal that is connected to investments in their venture. The exact nature of this relationship and its implications for investors' decision making have yet to be explored. This study contributes two new ways of analyzing emotional signaling in online contexts, expanding the tool set of social scientists. Further, this study first integrates signaling theory with Emotions as Social Information theory, allowing for considerations of the signaling effect of emotions in economic contexts.

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Appendix A

The OLS regression model does not provide support for *H1* and *H2.* According to this model, neither tweet dominance *(b* = 457.50, *SE* = 484.50, *p* = .345) nor profile picture dominance *(b* = 7.40, *SE* = 5.44, *p* = .174) predicts funding amount. *H3* and *H4* seem to be at least partially supported by this model as network size moderates the relationship between funding amount and both tweet dominance *(b* = 0.022, *SE* = 0.007, *p* < .01) and profile picture dominance *(b* = 0.0002, *SE* = 0.00007, *p* < .05). All results are shown in Table A1. However, the OLS model violates the basic assumptions of linear regression models, including residual independence and multicollinearity. Figure A1 shows plots of the residuals further indicating that they are not normally distributed.

Table A1

OLS Regression Results

Variable	*B*	*SE*	*t*	*p*		95% CI
Constant	-210.50	259.800	-.811	.417		[-720.5076, 299.4298]
Tweet Dominance	457.50	484.500	0.944	.345		[-493.7452, 1408.7870]
Picture Dominance	7.40	5.440	1.362	.173		[-3.2682, 1.8077]
Network	-.017	.004	-2.926	.004	**	[-.01949, -.0036]
Tweet Dominance * Network	.0218	.007	2.0036	.004	**	[.0072, .0364]
Picture Dominance * Network	.0002	.000	1.0060	.034	*	[.0000, .0003]

Note. R^2 = .0182, *adj.* R^2 = .0113
p-values: 0.000 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Figure A1 a

Residuals vs Fitted Values

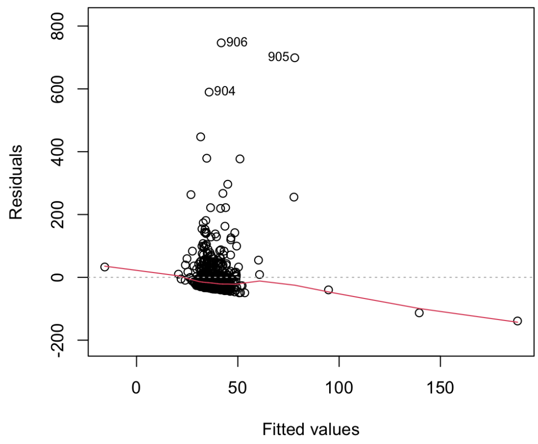

Figure A1 b

Normal Q-Q Plot

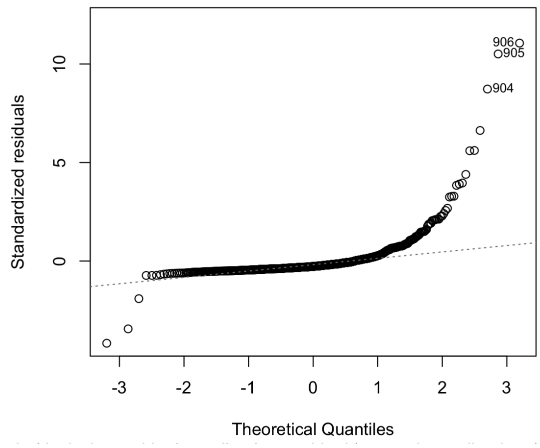

Figure A1 c

Scale-Location Plot

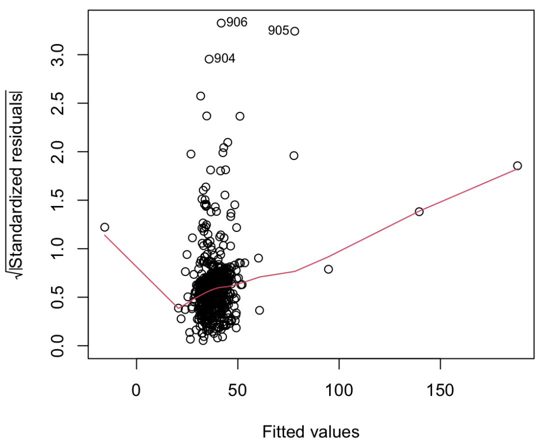

Figure A1 d

Residuals vs Leverage