Complementor Reactions to Platform Control – Evidence from the YouTube "Adpocalypse"

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Abstract

Effective governance in an important determinant of a platform's ability to ensure the provision of high-quality complements and – by extension – its performance in the market. A key aspect is to prevent the presence of low-quality or "bad-faith" actors who can otherwise harm the health of the ecosystem. However, platform's attempts at exerting control over complementors' activities is subject to trade-offs and may entail unintended consequences and reactions. We therefore investigate how complementors react to an increase in platform control over their activities. We study a rule change on Youtube that removed a subset of complementors from its partner program and made it impossible for them to monetize their videos on the platform. Using a regression discontinuity design we provide causal evidence that they subsequently left the platform at higher rates. In addition, those who did not leave still reduced the frequency of their uploads and provided content of lower quality and diversity. We also investigate and discuss effect heterogeneity between mainstream and niche Youtubers to learn about the underlying financial and non-pecuniary incentives.

1 Introduction

Multi-sided platforms create value by enabling interactions between consumers and suppliers of complements (Kretschmer et al., 2021; McIntyre and Srinivasan, 2017). To govern these interactions, platforms implement rules and design features to coordinate the activities of its complementors towards a joint value creation (Jacobides et al., 2018; Tiwana, 2013; Wareham et al., 2014). While successful governance can ensure the provision of high-quality complements (Cennamo, 2018; Claussen et al., 2013), identifying and effectively implementing appropriate incentive mechanisms presents several challenges for the platform owner (Boudreau and Hagiu, 2009). First, as a platform grows large it becomes infeasible to manage individual interactions and relationships. Instead, platform owners usually maintain an arm's length relationship with its complementors (Ghazawneh and Henfridsson, 2013). Second, complementors are heterogeneous in their characteristics and preferences (Afuah, 2013; Rietveld and Eggers, 2018). Therefore, rules that are applied indiscriminately can have detrimental consequences for them (Gawer and Henderson, 2007; Jacobides et al., 2018) and lead to unintended and undesirable reactions (Tiwana, 2015; Zhang et al., 2020).

As most owners impose little restrictions as to who can join their platform, a key governance challenge is to prevent an inflow of low-quality or "bad-faith" actors. Failing to do so can have serious consequences for the health and integrity of its ecosystem (Geva et al., 2019). For instance, the crash of the video game industry in the early 1980s has been attributed to the high number of games with low quality or obscene content (Pursey, 2022). In 2022, social media platform Twitter is rolling out its crowd-sourced fact-checking project "Birdwatch" to deal with false information (Perez, 2022). And YouTube has faced intense public backlash and advertiser boycotts in 2017 due to the presence of hate-speech and other problematic content (Statt, 2017). Therefore, unrestricted access to the platform without exerting some degree of control over complementors' activities can be harmful.

However, platform control is connected to trade-offs (Boudreau, 2010; Benlian et al., 2015). On the one hand, if a platform grants unrestricted access to its features and participants, it likely benefits from larger, more diverse, and more innovative set of complementors (Boudreau, 2012). On the other hand, this may lead to uncontrolled creativity and a deterioration of incentives to provide complements of high-quality (Geva et al., 2019) or threaten the integrity of the platform's offerings (Eaton et al., 2015). In addition, as a platform evolves, its optimal governance strategy may change as well (Rietveld et al., 2020). In particular, the examples above illustrate that an inflow of harmful actors may make a higher degree of control necessary. However, little is known about how a platform's complementors react to such a change. Especially in large ecosystems, the “rules of the game” are often applied indiscriminately. As a result, increased control does not only affect the actors it is aimed at, but also those complementors who are actually not the cause of concern. We therefore ask the following research question: *How do complementors react to an change in platform control?*

We study an increase in control over its complementors’ activities on YouTube. In reaction to backlash and advertiser boycotts as part of the “Adpocalypse”, the platform increased the eligibility criteria for its partner program in February 2018. While the platform largely relies on user-generated content, the program presents a means for video creators, or “Youtubers”, to monetize their content by receiving a share of the generated advertising revenue. The increased criteria made if not only harder for new creators to become “YouTube partners”, but it also removed all former program participants that did not meet them at the time of the rule change. This presents an increase in platform control, because it enabled more manual curation of the content by limiting the number of advertising Youtubers.

To estimate the causal effect of losing access to the partner program, we use a regression discontinuity design. The new criteria provide a clear threshold in former program participants’ subscriber count at the time of the rule change. We therefore compare the subsequent supply of videos between those who are just below (lost access) and just above (remained in the program) that threshold. In our empirical analysis of German Youtubers, we find that those who lost access to the program subsequently exited the platform at higher rates. Further, those who did not leave altogether still reduced their frequency of video uploads, and their content was of both lower quality and diversity. We also provide evidence for and discuss heterogeneity in these effects between mainstream and niche Youtubers to learn about how the rule change impacted financial and non-pecuniary supply incentives.

These findings provide novel insights about how changes in platforms’ governance strategies affect its complementors. In particular, we provide causal evidence of how increased control affects their supply incentives, and how this can entail unintended and perhaps undesirable consequences for the platform. In addition, our study contains contributions to the literature on incentives underlying user-generated content. Complementors on YouTube are likely driven by a mix of financial and non-pecuniary incentives (Ma and Agarwal, 2007). We add to this discussion by showing that different type of complementors (mainstream vs. niche) likely draw on different motivational sources, and that this can drive differences in behavior.

2 Related Literature

2.1 Platform Governance

Platform governance broadly refers to the set of rules and design features put into place by the platform owner to coordinate and facilitate complementors' value creation processes (Boudreau and Hagiu, 2009; O'Mahony and Karp, 2020; Wareham et al., 2014). While the implementations of such "rules of the game" (Jacobides et al., 2018) can motivate the provision of diversity and quality in complements (Cennamo, 2018), failing to do so effectively can inhibit effective and desirable participation and even lead to complementors leaving the platform altogether (Gawer and Henderson, 2007; Niedermayer, 2013; Tiwana, 2015; Zhu and Liu, 2018).

Platform owners use a wide range of tools to facilitate the production of complements (Chen et al., 2022; Rietveld and Schilling, 2020). They provide boundary resources or interface features (such as APIs for app developers) (Ghazawneh and Henfridsson, 2013; Tae et al., 2020), use selective promotion of complements (Rietveld et al., 2019), and put into place algorithmic or ranking-based recommendation systems to guide and facilitate interactions between consumers and complementors (e.g. Dinerstein et al., 2018; Kapoor and Agarwal, 2017; Oestreicher-Singer and Sundararajan, 2012). A key governance challenge faced by platform owners is to what extend they should exert control over complementor activities (Tiwana, 2013). In particular, the question whether or not access to the platform should be restricted received scholarly attention (Benlian et al., 2015). Controlling how many and which complementors can join is connected to a trade-off (Parker and Van Alstyne, 2018). On the one hand, an open platform with unrestricted access is likely to benefit from a larger number of complementors providing a diverse set of products and services (Boudreau, 2010). As a result, its value to consumers may be higher due to the facilitation of indirect network benefits (Eisenmann et al., 2006) and the possibility to satisfy idiosyncratic preferences (Brynjolfsson et al., 2010; Crain and Tollison, 2002). On the other hand, unrestricted access can deteriorate complementors' incentives to supply innovative or high-quality products (Boudreau, 2012; Parker and Van Alstyne, 2018), lead to uncontrolled creativity (Geva et al., 2019), and can threaten the integrity of the platform as a whole (Eaton et al., 2015).

In addition, platforms' ability to influence complementor behavior goes beyond restricting access (Chen et al., 2022). They can be steered towards desirable actions via rules that incentivize certain behaviors (Claussen et al., 2013), certification systems (Rietveld et al., 2021), sending signals (Hukal et al., 2020), or by regulating access to boundary resources and other platform participants (Constantinides et al., 2018). For example, Twitch and YouTube impose few restrictions in terms of who can become an creator, but they do restrict access to advertisers via partnership programs. TaskRabbit requires proper skill certifications in some categories before allowing workers to offer their services. And most video game console manufacturers provide tools that aid in the development of compatible games only to selected developers. While neither of these examples outright prevent access, they likely affect complementors' ability to both create and capture value on the platform, hence providing a means for the platform to regulate their behavior.

In addition, as a platform grows, the level of control a platform exerts may need to change (Rietveld et al., 2020). As the number of complementors grows larger, continuously eliciting desirable contributions that are aligned with the owner's expectations becomes increasingly challenging (Hukal et al., 2020). The underlying tension lies in the necessity of maintaining arm's length relationships with complementors (Ghazawneh and Henfridsson, 2013) which however makes it hard to establish governance practices that fit an increasingly heterogeneous set of needs and preferences (Afuah, 2013; Kapoor and Agarwal, 2017; Rietveld and Eggers, 2018). As a result, it becomes difficult to predict complementor reactions to changes in the "rules of the game" (Boudreau and Hagiu, 2009), which can disrupt their competitive landscape (Jacobides et al., 2018), entail confusion and anxiety (Jhaver et al., 2018), and interpretation challenges (Koo and Eesley, 2020). As a result, they often lead unanticipated reactions, such as decreased subsequent performance and exit (Gawer and Henderson, 2007; Tiwana, 2015).

2.2 Motivating Creative and User-Generated Content

Our study also relates to the literature about the motivation and incentives underlying user-generated content and the creator economy. In contrast to many platforms that exclusively rely professionals complement supply – e.g. video games for consoles or apps for smartphone operating systems –, much of the content on YouTube is created by nonprofessionals (Kerkhof, 2020) who are not purely driven by pecuniary incentives (Luca, 2015), but by intrinsic or reputation-based motivations (Ma and Agarwal, 2007; Toubia and Stephen, 2013).

Prior literature has investigated several potential nudges to stimulate the generation of user content. The effectiveness of financial incentives has been studied in the context of online reviews, providing nuanced insights. Cabral and Li (2015) find only a small positive influence on the likelihood of leaving a review. Similarly, Burtch et al. (2018) find that they increase the frequency of reviews, but are most effective in combination with other nudges, such as social norms. Others find that the effectiveness of financial rewards is subject to heterogeneity across different user types: Sun et al. (2017) document a stifling effect on review provision among well-connected users, but a stimulating effect for others. Similarly, Khern-am nuai et al. (2018) find that the platform experienced an inflow of new reviewers after financial incentive had been put into place, but that existing reviewers decreased their activity. The mixed findings not only illustrate that financial payments are limited in their effectiveness, but also that users are subject to multiple, complex motivational sources.

In addition, platforms organized around the production of creative or user-generated content commonly use advertising-based models (Bhargava, 2021; Jain and Qian, 2021). YouTube, Twitch, and WordPress are popular examples of platforms that create financial incentives by sharing parts of the generated ad-revenues with their complementors. Three recent empirical studies investigate how this affects the creation of content. First, Sun and Zhu (2013) find that bloggers increased the quality of their content and shifted production towards more popular topics after they adopted such a model. This is consistent with early studies noting that advertising creates an incentive to shift production towards popular content in an effort to maximize "eyeballs" (Steiner, 1952; Wilbur, 2008), which leads to a duplication of mainstream at the expense of niche content (Anderson and Gabszewicz, 2006). Second and in contrast, Kerkhof (2020) finds that an increase in the amount of advertising that creators on YouTube include in their videos *decreases* their tendency to duplicate mainstream content. This is attributed to increased competitive pressure in this market segment. Third, Wu and Zhu (2022) show that authors on a creative writing platform react more strongly – in terms of effort provision and novelty – to increased competition when they earn a share of advertising revenue.

As an alternative incentive device, awards or community badges are commonly in place to reward user activity by helping them build an online reputation. Prior research largely found positive effects, with reputation-based nudges stimulating user participation on StackOverflow (Anderson et al., 2013) and increasing newcomer retention on Wikipedia (Gallus, 2017). At the same time, Burtch et al. (2020) – while finding a positive effect on activity – also document that (peer) awards tend to decrease novelty, thus demonstrating a potential downside in the context of the generation of creative content. Goes et al. (2016) highlight an additional limitation in the context of milestone-based incentive hierarchies: Consistent with motivation stemming from the pursuit of a goal (Locke and Latham, 2002), they find that milestones initially stimulate activity, but that motivations decrease immediately after the successful accomplishment.

3 Institutional Background

3.1 YouTube Partner Program

We study a rule change to the YouTube Partner Program that occurred in early 2018. YouTube is the world's largest video sharing platform, and – as of February 2021 – the second-largest website in terms of overall traffic behind Google[1]. In addition, it has more than 2 billion monthly users, and more than 500 hours of video are uploaded every minute[2]. These videos are created by registered users and can be viewed by anyone for free. While also offering paid premium memberships for viewers[3], YouTube's main source of revenue is advertisements that are played before and during videos. Its supply of complements (the videos) is organized around user-generated content, the creators of which are commonly referred to and self-identify as "Youtubers" (Kerkhof, 2020). Youtubers upload videos to their own "channels", which can be subscribed to by viewers, who will subsequently become informed about the release of new content.

Youtubers have the possibility to earn money with their content by participating in the YouTube Partner Program (YPP).[4] This program mainly serves two purposes. For the platform, it provides a means of quality control. Its ads only run with videos uploaded by Youtubers

[1]See https://www.alexa.com/siteinfo/youtube.com, accessed on 12 February 2021
[2]See https://blog.youtube/press, accessed on 12 February 2021
[3]See https://www.youtube.com/premium, accessed on 12 February 2021
[4]See https://creatoracademy.youtube.com/page/lesson/ypp_what-is-ypp_video, accessed on 12 February 2021

who are part of this program[5] as to ensure that they are not shown alongside inappropriate content. In addition, Youtubers cannot freely join the program, but they have to fulfill certain criteria – changes to which are the subject of this study – before they are eligible to apply for membership. As part of the application process, they then undergo a (partly automated, partly manual) review process to ensure that their videos follow the platform's guidelines. In turn, for the Youtuber, it provides a means to monetize their videos as YouTube shares part of the generated revenue. However, while Youtubers have agency about *whether or not* and *how many* ads may be shown during a video, the platform determines *which* ads are actually shown via an algorithm. Accordingly, advertisers and Youtubers have no way of directly interacting with one another. In terms of the attractiveness of the YPP, anecdotal evidence – official statistics do not exist – suggests that Youtubers can earn about three to five USD per 1,000 ad views per video[6]. As a result, YouTube relies on two tiers of complementors: First, Youtubers in the YPP are vetted and they can earn money by allowing the platform to run ads before and during their videos. Second, Youtubers outside the program cannot earn money, and no advertisements are shown with their videos. In addition, through the eligibility criteria and application process the platform limits the access to the program and actively controls who can move from the latter to the former tier.

The eligibility criteria for the YPP changed several times since its launch in 2007. While having been quite selective in the beginning, YouTube opened it up in 2012 by removing virtually all access barriers (YouTube Official Blog, 2012). However, this entailed an inflow of "bad actors", threatening the platform's integrity. In response, in early 2017, it put into place the restriction that Youtubers have to have accumulated a minimum of 10,000 lifetime views before being able to apply (Popper, 2017). In this study, we analyze the subsequent rule change put

[5]Following a change in the platform's policy in late 2020, YouTube now also holds the option to run ads with videos outside the program as well (Koetsier, 2020). This, however, has no implications for the present study as it falls outside our sample period.

[6]See https://influencermarketinghub.com/how-much-do-Youtubers-make/, accessed on 12 February 2021

into place in early 2018, which instituted an additional and much more significant increase in the eligibility criteria.

3.2 YouTube "Adpocalypse" and the Rule Change in 2018

We study a change to the eligibility criteria for the YPP that occurred in February 2018. This change was preceded by YouTube facing considerable backlash and, ultimately, a large-scale boycott by its advertisers (Nicas, 2017) – commonly referred to as the YouTube ”Adpocalypse” (Alexander, 2018). Despite existing access requirements, advertisements routinely appeared alongside hate speech as well as racist and anti-Semitic content. In addition, YouTube faced criticism more broadly for its lack of restrictions as to what type of content is allowed on the platform (Statt, 2017). The situation was then further exacerbated by scandals surrounding two of the platform's most prominent Youtubers (Gillespie, 2018), entailing further scrutiny. In reaction to this ”adpocalypse”, the platform announced more manual curation of Youtubers allowed to the YPP in December 2017 as an effort to ensure that advertisements are only shown alongside unproblematic content (Wojcicki, 2017). In January 2018, the platform went on to reveal new criteria determining the eligibility to apply to the program, which would take effect one month later, in February 2018 (Mohan and Kyncl, 2018).

This rule change contained two important elements: First, it updated the eligibility criteria. Now, to be able to apply for the YPP, Youtubers had to have accumulated a minimum of 1,000 subscribers and 4,000 hours of ”watchtime” over the preceding twelve months. The latter is calculated by multiplying the times videos are viewed with the amount of time each viewer actually spends with the videos. Together, this made access considerably more restrictive compared to the previous requirement of 10,000 lifetime views.[7] Second, those Youtubers who had been part of the YPP, but did not meet the new criteria would be excluded from the

[7] For reference, a view is counted when a video is watched for at least 30 seconds. Accordingly, before the change the requirement of 10,000 views translates to a minimum of 83,33 hours of watchtime ($\frac{10{,}000}{60\times60}$), without any further restriction on the time span across which a Youtuber may attain this goal.

program, effectively making it impossible for them to earn money on the platform. In the blog post announcing these changes, it was also noted that – while affecting a “significant number of channels” – the financial ramifications of this “demonetization” would be mild as ”99 % of those affected were making less than 100 [USD] per year in the last year, with 90 % earning less than 2.50 [USD] in the last month” (Mohan and Kyncl, 2018). In addition, it was announced that those Youtubers who lost access would get the possibility to reapply once they met the new criteria.

Still, YouTube faced negative reactions following this announcement, primarily from Youtubers who were affected by the rule change (Alexander, 2018). Points of criticisms are diverse. Some Youtubers worried about the loss of earnings, while others rather felt treated unfairly. Others were not primarily concerned about the financial ramifications, but rather felt disappointed to lose the platform’s endorsement after having been part of it for a long time. Others still considered it a sign that YouTube generally shifted its focus from smaller Youtubers to larger, more prominent ones, regarding it as an indication that ”the golden age of YouTube is over” (Alexander, 2019).

The rule change presents a well-suited opportunity to study how a platform’s increased use of control mechanisms affects the supply of complements. First, the primary reason for the platform to increase access requirements has been to make more manual curation feasible. In light of the sheer amount of videos that are uploaded to the platform, limiting the number of participating Youtubers has arguably been necessary. Second, the rule change occurred in reaction to advertiser boycotts, which in turn had been sparked by problematic content, such as hate-speech by many small channels, but also controversies surrounding popular Youtubers. However, *all* Youtubers who did not meet the new requirements lost access to the platform. Therefore, the majority did not become demonetized due to their content being problematic, but because they happened to not be meet the new criteria. We therefore study complementors who were not the *cause* of the rule change, but who were very much *affected* by it.

3.3 Complementor Reactions: Expected Effects

We study how the losing access to the partner program affected the supply of complements of demonetized Youtubers. We are interested in two aspects in particular. First, we are interested in how their *activity* or extent of content they create for the platform changes. Second, we investigate if and how demonetized Youtubers change the *type of content* they create, namely its quality and diversity. Both are a question of how the supply incentives are affected by the rule change. Many Youtubers are nonprofessional content creators, and the rule change demonetized smaller ones in particular. They are driven by a mix of financial and non-pecuniary drivers.

3.3.1 Youtuber Activity

We study two outcomes related to how the activity changed for those who lost access to the partnership program. Youtubers can stop supplying content altogether by leaving the platform. Losing access to ad-revenue takes away any financial incentive, at least as long as they do not meet the increased eligibility criteria. However, many (nonprofessional) Youtubers may not have been driven by financial incentives in the first place. Still, we would expect that it also deteriorates non-pecuniary incentives. First, losing access may send the signal (Hukal et al., 2020) that the content they provide is not valued by the platform anymore. Having previously achieved the status as "YouTube Partner" is likely perceived as a sign of appreciation (Ho and Rai, 2017), driving content creations by reinforcing intrinsic and generating reputational sources of motivation. Therefore, the rule change deteriorated financial and non-pecuniary incentives, and we would expect that the likelihood of platform *exit* is higher for Youtubers who lost access to the program, relative to those who did not.

In addition, those Youtubers who did not outright exit the platform may also change the amount of content they supply. In particular, they may change the frequency at which they create and upload videos. Here, expectations are not as straight-forward as losing access likely changed incentives in ways that lead to opposing predictions. On the one hand, deteriorated financial and non-pecuniary motives imply a decreased supply of content. Even if a Youtuber stays on the platform, she may be less willing to put as much effort into video production, leading to less frequent uploads. On the other hand, the platform clearly stated that reentering the partner program is possible if a Youtuber manages to fulfill the new eligibility criteria, setting a goal for them to work towards. Therefore, we may expect an increase in effort to attract subscribers, leading to more frequent uploads and longer videos. This is consistent with motivations from pursuing a goal (Locke and Latham, 2002), which has been previously demonstrated in the context of community badges (Anderson et al., 2013; Goes et al., 2016). In the end, it is an empirical question which of the two forces dominate in our context. If the deteriorating of incentives dominates, we expect a *decrease* in *upload frequency* for Youtubers who lost access to the program relative to those who did not. However, if goal-based motivations dominate, we expect an *increase* in content supply.

3.3.2 Type of Content

Losing access to the partner program may also change characteristics of the generated content. Youtubers changing the effort they put into producing videos may not only manifest in changes in the amount they supply, but also in their quality. Similar to the arguments above, this leads to opposing predictions. On the one hand, deteriorating incentives imply decreased effort provision, and *lower average video quality*. In contrast, efforts to regain access to the program by growing the number of subscribers imply a *higher average video quality*.

In addition, Youtubers may change the their content diversity. On the platform, this is done via keywords that guide viewer searches and help classifying the content by genre (e.g. gaming, beauty, cooking, etc.). Losing access to the partner program can trigger Youtubers to reevaluate their content strategy on the platform. Again, we can form opposing expectations. On the one hand, a greater diversity can mean an effort to cater to a broader audience. As such, it would be indicative efforts to increase the subscriber count to regain access to the program. Moreover, negative performance feedback can trigger "problemistic search" (Posen et al., 2018), i.e. efforts to find ways to reach a certain aspiration level. In other words, a higher level of diversity may be indicative of Youtubers experimenting with different types of contents to evaluate what works well. On the other hand, deteriorating incentives caused by the rule change may have the opposing effect. Youtubers may begin focusing more on certain types of content, which they may personally enjoy more. This would lead to a decrease in content diversity.

3.3.3 Mainstream vs. Niche Creators

We expect the rule change to have altered incentives in ways that lead to several opposing expectations about complementor reactions, and which dominate is ultimately an empirical question. In addition, the relevance of some mechanisms may differ between different types of Youtubers, namely those who provided mainstream or niche content before the rule change. Their ex-ante positioning on the platform is indicative of which type of incentives – financial or non-pecuniary – is more relevant for them, hence their reaction to the rule change may differ.

Mainstream Youtubers are more likely to be driven by financial incentives. All else equal, providing content that is popular on the platform shows an effort to maximize views (Wilbur, 2008). If financial incentives are relatively more important than non-pecuniary ones, we would expect a reaction that is consistent with regaining access to the program. Driven by goal-based motivations, mainstream creators should therefore increase their supply of videos, as well as their quality, to grow their subscribers. In addition, given that their positioning is informed by what is popular on the platform, it is unlikely that losing access to the platform is perceived as a signal that their content is not desirable. Therefore, if mainstream Youtubers adjust their positioning, we would expect them to increase their focus on this type, rather than trying to diversify their videos.

In contrast, niche Youtubers are more likely to be driven by non-pecuniary motivations. They deliberately position themselves outside the mainstream, where they face limited demand (Zhu and Zhang, 2010). Therefore, the benefits they had gained from participating in the program are perceived as an personal achievement, which reinforces and rewards intrinsic motivations. As a result, losing access to the program is likely perceived as a strong signal that their relatively narrow-appeal content is no longer desirable on the platform. Hence, we would not expect them to increase their efforts to regain access to the program, as – to them – it would no longer create non-pecuniary benefits. Instead, we would expect a decrease in the amount of content they supply to the platform. In addition, given their focus on a niche, they would likely experience disutility from deviating from their preferred, narrower segment (Sun and Zhu, 2013). While we expect financial incentives to play a limited role for them, their presence may still have led them to also produce content outside their particular niche. As a result, without these incentives, we would expect them to adjust their content strategy towards a greater focus on that niche.

4 Data and Methods

4.1 The Data

To analyze how the supply of videos changed for Youtubers who lost access to the YPP after the rule change, we combine information from two waves of data collection via the YouTube Data API. First, we use the same snapshot as Kerkhof (2020) who has obtained information about all active German YouTube channels as of December 2017 – i.e. just before the rule change –, including whether or not they have participated in the YPP at that point in time. This piece of information is unique and crucial to our analysis, as it is impossible to assess historic information on a Youtuber's program participation otherwise. From that snapshot we select all Youtubers who were part of the YPP and had between 500 and 5,000 subscribers by the end of 2017[8], i.e. whom we consider at risk of losing access to the program.

For the second wave, we again accessed the YouTube Data API from September to November 2020 to obtain a snapshot containing updated information for the selected sample of Youtubers, which lets us track their upload history since January 2018. Combining the two snapshots provides us with crucial information for the construction of our regression samples and key variables. We obtained cross-sectional information at the Youtuber level, such as their subscriber count in December 2017 (first snapshot) and November 2020 (second snapshot) and their total number of videos. In addition, we collected information at the video-level, such as the number of views, likes, dislikes, duration, date of upload, used keywords, and the video category. This lets us track each Youtuber's video uploads over time, and provides us with information about the extent of their activity (e.g. upload frequency), as well as if and how their content strategy has changed over time. One shortcoming is that a Youtuber's watchtime is not directly provided via the API. However, this measure is crucial for our analysis as it is part of the new eligibility criteria instituted by the rule change under study. Broadly speaking, a Youtuber's watchtime corresponds to the absolute time that viewers spend watching her videos. As the measure is not publicly available, we compute it ourselves using the length of her videos and the number of views they have accumulated. In addition, we have to make an assumption how long each video is actually being watched. Maggi et al. (2018) find that even the least popular videos are watched to about 50%, on average; the most popular ones are watched to about 75%, on average. Since our sample consists of relatively unknown Youtubers with small channels, we assume that 50% of each video is watched for our main analyses. We then simply multiply each video's duration by 0.5 and subsequently take the sum over all videos in the twelve months before

[8] The distribution of subscribers over Youtubers is heavily skewed; in other words, there are many more Youtubers with few than Youtubers with many subscribers (the median number of subscribers in Kerkhof (2020) is around 1,000). Thus, to ensure that we have a sufficient number of observations in our main analysis, we decided to use a relatively large initial bandwidth regarding the upper subscriber bound.

demonetization in February 2018 for our computation of Youtubers' watchtime just before the rule change. Finally, note that not all selected Youtubers appear in the second snapshot. This is the case if they exited the platform between December 2017 and November 2020.

4.2 Empirical Framework

4.2.1 Identification Strategy

We want to estimate the causal effect of losing access to the partner program on subsequent Youtuber activity. As this is determined by their watchtime and subscriber counts at the time of the rule change, we face the challenge of separating the effect from unobserved Youtuber characteristics that may otherwise drive our estimates. Specifically, those who are better able to produce engaging content will have more subscribers (hence they do not lose access to the program), and they may be less inclined to change their video supply. At the same time, the clearly defined subscriber and watchtime thresholds provide us with a quasi-experimental setting to implement a regression discontinuity design to estimate the causal effect: For Youtubers very close to these thresholds the treatment of being demonetized can be considered as good as random. In other words, those of similar quality likely still exhibit small subscriber count and watchtime differences, and we can attribute differences in behavior after the rule change to losing or retaining access to the partner program.

In principle, there are two running variables determining treatment status, subsribers and watchtime. The latter, however, we can only approximate and it is measured with noise. For our analysis we therefore use the subscriber count as the only running variable determining the treatment status, but include watchtime as a control (Papay et al., 2010). Therefore, we compare Youtubers just above the subscriber count threshold to those just below. Our key identifying assumption is that the two groups are comparable within a reasonably narrow bandwidth, and that subsequent differences in behavior can be attributed to the rule change (Lee and Lemieux, 2010; Imbens and Lemieux, 2008). Specifically, for our main analysis, we select Youtubers who have at least 900, but no more than 1,200 subscribers.[9] As there are more Youtubers just below the 1,000 subscriber threshold than above, this selection ensures that we analyze comparable Youtubers that are sufficiently close to the threshold, while also maintaining a reasonable sample size that is balanced between treatment and control groups. We can then obtain an unbiased estimate for the effect of losing access by estimating the following equation:

$$Y_i = \alpha + f(Subscribers_i) + \beta \cdot LostAccess_i + \gamma \cdot Watchtime_i + \epsilon_i, \tag{1}$$

where Y_i is the outcome of interest, $LostAccess_i$ is a dummy variable indicating whether Youtuber i got demonetized, and $Subscribers_i$ is our running variable, the subscriber count. The function $f(\cdot)$ captures the underlying relationship between the subscriber count and our outcomes of interest. We let the slopes of our fitted lines differ on each side of the Subscriber threshold by interacting $f(\cdot)$ with $LostAccess_i$ to control for differential trends in $Subscribers_i$. We include a control for $Watchtime_i$ as this also determines treatment status similar to (Papay et al., 2010). The term ϵ_i represents the error term. The coefficient of interest, β, gives us the local average treatment effect (LATE) for each regression. We implement a local linear regression approach by letting $f(\cdot)$ be a linear function of subscribers.[10]

Following (Calonico et al., 2020) we use a triangular Kernel function which assigns zero weight to all observations outside of our specified bandwidth, and positive weights to all observations within our bandwidth. The weight is maximized at the threshold, and declines symmetrically and linearly going away from the threshold. Standard errors are clustered on the Youtuber level to account for serial correlation. Due to our non-parametric approach, we also report robust standard errors that account for the misspecification error (Calonico et al., 2020). Finally, a potential threat to identification is that Youtubers very close to the threshold may manipulate their subscriber count to remain in the YPP, known as bunching. Therefore, we implement a

[9] We provide robustness checks using both a narrower and wider bandwidth in section 5.2.2.

[10] We provide robustness checks using quadratic and cubic model fits in section 5.2.1

“donut” by excluding Youtubers with subscribers between 990 and 1010 or watchtime between 3950 and 4050. In addition, we perform a test for continuity in the subscriber count distribution around the threshold in section 4.4.1.

We use the specification described in equation (1) for the entirety of our analysis, but use different outcomes of interests to investigate different aspects of Youtuber behavior. For each, we perform the analysis both before and after the rule change. Differences in behavior between treated and untreated should only exist after the rule change, but not before. Hence, if the coefficient of interest β is insignificant in the before period, but significant after, we can attribute it to the rule change.

4.2.2 Outcome variables

Youtuber Activity We have two measures for the amount of content Youtubers supply to the platform. First, we consider the probability of *exit*. To that end, we check if a Youtuber who appeared in the first wave of data collection is also present in the second wave. If this is not the case, the Youtuber has closed down her channel in the meantime. Hence, for each Youtuber we generate an dummy variable to indicate this. Second, we investigate if and to what extent Youtubers' *upload frequency* differs between those who lost access and those who did not. This is measured as the average number of videos she has uploaded per month over the six months after the rule change.

Type of Content First, we measure the the average *quality* of videos a Youtuber uploads using information about viewer engagement, who can leave ”likes” or ”dislikes”. In particular, this is calculated as share of likes over all viewer reactions, $\frac{\text{Likes}}{\text{Likes+Dislikes}}$. Second, we study if and to what extent Youtubers who lost access change the diversity of their content compared to those who did not. Each video is given illustrative keywords by its Youtuber – for instance, a funny cat video would be equipped with the keywords “funny” and “cat” – to indicate this. To measure this, we first count the number of unique keywords attached to the each video uploaded in the six months after the rule change. We then calculate this monthly average number of unique keywords a YouTuber uses over that period. A smaller number then indicates a greater focus in a Youtubers horizontal positioning on the platform. In contrast, a greater number indicates increased experimentation with different content types, or attempts to appeal to a broader audience that exhibits a wider range of tastes for horizontal content attributes. Table 1 includes an overview of the four outcome variables we use in our analysis.

=== Table 1 here ===

4.2.3 Mainstream and Niche Youtubers

We again use keywords to classify Youtubers as either mainstream or niche and adopt the same approach as (Kerkhof, 2020). For each month and video category, keywords are ranked by how many views videos they are attached to attract, i.e. by their popularity. The upper one percent of the keywords in this distribution is then classified as "mainstream". In a next step, we further classify videos who exhibit at least one such keyword as "mainstream" as well. Finally, we calculate the share of a Youtuber's "mainstream videos". In fact, the vast majority exclusively uploads such videos. Hence, we classify a Youtuber as "niche" if her share of mainstream videos is smaller than one. We use this distinction in our analysis of heterogeneous effects.

4.3 Summary Statistics

Table 2 contains summary statistics for our main estimation samples. A total of 902 Youtubers fall within within the subscriber count bandwidth we use (900 to 1200). The majority (78 %) are below the threshold and lost access to the program. This is case despite our asynchronous bandwidth selection and shows the "long tail" distribution in subscriber count – as it is the case in most media markets, most content creators are relatively unsuccessful (Anderson, 2004). Still, the average Youtuber had 1059.42 subscribers at the time of the rule change and an watchtime of 5841.23 hours. Moreover, with 82 % most Youtubers are classified as mainstream in our sample. This is not surprising, as – by definition – this is the most popular and prevalent type of content on the platform.

Out of the total number of Youtubers that appeared in the first wave of data collection 46 % had exited the platform by the time of the second wave. Hence, the sample size is reduced to 428 for our analysis of their behavior after the rule change (aside from exit). Within the subsequent six months, the average YouTuber uploaded an average of 4.58 videos per months, using a monthly average of 24.63 unique tags, and received an average monthly like share of 91 %. The high share of likes is likely due to rating inflation, which is common on digital platforms (Zervas et al., 2021).

=== Table 2 here ===

4.4 Tests for Quasi-Randomized Assignment

The main identifying assumption of our empirical approach is that losing access to the partnership program is as good as random within the specified subscriber count bandwidth (see e.g. Flammer, 2015). We perform two tests for the validity of this assumption.

4.4.1 Continuity at the threshold

We show that the distribution of subscriber counts is continuous around the threshold. If we would detect a discontinuity at the threshold, this would indicate that assignment to the treatment is in fact not as good as random. For instance, it may be that Youtubers who had been below the threshold before the rule change show efforts to increase their subscriber count to not lose access to the partner program by the time of the rule change. Following Cattaneo et al. (2017), we conduct an automatic manipulation test which does not reject the null of continuity around the threshold ($p = 0.99$). Figure 1 shows a visualization of the test. Together, this shows that the continuity assumption is not violated in our sample.

=== Figure 1 here ===

4.4.2 Differences before the rule change

We analyze differences in behavior between Youtubers who lost access to the program and those who did not in the period after the rule change. However, it is possible that such differences already existed before the change. This would threaten the validity of our empirical approach because it would indicate that even differences within our narrow subscriber count bandwidth may be the result of this. As a consequence, the treatment assignment could not be regarded as good as random. To test this, we perform a regression analysis using our outcomes of interests measured based on Youtuber behavior in the six months before the rule change. The exception is the analysis of the exit probability, which is based on appearances in both waves of data collection. Results from the RDD regressions are shown in Table 3. We do not find significant differences in behavior between treated and control before the rule change. Hence, if we find differences afterwards, we can attribute this to losing access to the partner program.

=== Table 3 here ===

5 Results

5.1 Main Analysis

5.1.1 Complementor Activity

Table 4 contains the results of our analysis of contributor activity. Model 1 uses Youtubers' probability of exit as outcome of interest. We find that those who lost access to the partner program left the platform at higher rates compared to those who did not ($\beta = 0.156$, $p < 0.05$).[11] Specifically, the exit probability is 15.6 percentage points higher for the treated. Figure 2a

[11] Note that the dummy we actually estimate indicates observations above the threshold, i.e. those Youtubers who did not lose access. For the sake of discussion we therefore multiplied the coefficient by -1 and report this as "Lost Access" in all regression tables instead.

contains the accompanying RDD plot showing the linear model fit. As expected, this provides evidence for a deterioration of incentives, which led affected Youtubers to close down their channel and cease all activity on the platform at higher rates. To provide evidence on the relevance of different motivational sources, we split the sample between mainstream and niche Youtubers in models 2 and 3, respectively. Recall that we assume financial incentives to be more relevant for the former, and non-pecuniary incentives (e.g. reputation and intrinsic motivation) for the latter type. We do not find a significant effect of the rule change on the exit probability of mainstream Youtubers ($\beta = 0.005$, $p > 0.1$). In contrast, we find a strong and highly statistically significant effect for niche Youtubers ($\beta = 0.393$, $p < 0.001$). Together, this suggests that a deterioration of financial incentives is not likely to be the predominant driver of exit. Instead, the rule change appears to have been perceived as a signal for a lack of (continued) support for niche content. This in line both with Youtube officials noting that affected Youtubers did not earn much money to begin with (Mohan and Kyncl, 2018), and with media reports documenting a shift in focus towards more mainstream and professional content on the platform (Alexander, 2018). In addition, it shows that closing off part of the platform's functions can have an adverse affect on Youtuber motivation even if tangible, financial incentives do not seem to be an important determinant of activity.

=== Table 4 here ===

Next, model 4 uses Youtubers' upload frequency in the six months following the rule change as outcome of interest. Recall that we use a sample of Youtubers who did not exit the platform here. We find that, each month, Youtubers who lost access to the partner program uploaded significantly fewer videos to the platform compared to those that did not lose access ($\beta = -3.548$, $p < 0.05$). Specifically, they uploaded 3.548 fewer videos, which – considering the sample mean of 4.58 – is a sizable effect. Again, figure 2b shows the accompanying RDD plot. This provides further evidence that Youtubers were less motivated to provide content to the platform due to losing access to the program. We again split the sample between mainstream and niche Youtubers in models 5 and 6. The coefficient of interest is statistically insignificant for both, which is due to the reduced sample sizes as a result of the split. Still, we find that the estimated coefficients are of similar magnitude compared to the full sample (but with larger standard errors). In addition, the effect sizes are similar for both Youtuber types. Together, even though the estimates ares imprecise, we still take this as an indication that he change in upload frequency does not differ meaningfully between the two types.

=== Figure 2 here ===

5.1.2 Complement Quality and Diversity

Table 5 contains the the results of our analysis of the type of content Youtubers create after the rule change. In model 1, we investigate the content quality, which is measured as the share of likes uploaded videos receive from viewers. Youtubers who lost access to the partner program upload significantly less well-received content compared to those who remain ($\beta = -0.048$, $p < 0.01$). Figure 2c shows the accompanying RDD plot. Specifically, the average like share is 4.8 percentage points lower for the treated. We again split the sample between mainstream and niche Youtubers in models 2 and 3. The effect is entirely driven by mainstream Youtubers who exhibit a 6.1 percentage points lower like share ($p < 0.01$). While we do not find that eroding financial incentives drives platform exit for this type, this results suggests that it does drive the supply of lower-quality content to the platform. Further, niche Youtubers not being affected shows that they are indeed driven by non-pecuniary sources of motivation. Those who do not leave the platform also do not produce lower-quality content, with speaks to the notion that they are driven by intrinsic motivation. Even when other sources of motivation are removed, they still put in efforts to create content of high quality.

=== Table 5 here ===

We next analyze if and to what extent Youtubers change the diversity of content they supply to the platform. Specifically, we investigate if their content becomes more or less diverse. Results for the full sample are presented in model 4. We find that Youtubers who lost access to the partner program exhibit a lower degree of content diversity compared to those who remain ($\beta = -25.380$, $p < 0.01$). Again, we show the RDD plot in figure 2d. Specifically, the treated attache an average 25.38 fewer unique keywords per month to their uploaded videos. Considering the sample mean of 24.63 this is a considerable effect size. Models 5 and 6 show the results for the sample split between mainstream and niche. We find reduced content diversity for both types. However, it is more pronounced for niche than mainstream Youtubers. Evidently, losing access did not spark experimentation with different types of content or efforts to appeal to a broader range of tastes. Instead, both types rather "honed into" specific types of content. In addition, the greater effect for niche Youtubers speaks to the notion that they experience a higher level of disutility from deviating from their preferred segment.

5.2 Robustness Checks

5.2.1 Higher order polynomials

Following recent recommendations (Gelman and Imbens, 2019), we use local linear regressions in our main analysis. Here, we test the robustness of our results to using higher order polynomials. For each outcome, we run regressions using both quadratic and cubic model fits. Results are shown in table 6. When using a quadratic fit (models 1, 3, 5, and 7) the estimated coefficients are consistent with our main analysis, but generally larger. However, they are also estimated with less precision. Hence, with the exception of our analysis of the upload frequency, they become statistically insignificant. We show the RDD plots for the quadratic model fits in figure 3 and the graphical evidence is also consistent with our main analysis shown in figure 2. Together, we therefore do not attribute the reduced statistical significance to the modeling choice, but rather the insufficient statistical power when attempting to estimate models with higher order polynomials with a relatively small sample size (see e.g. Gelman, 2018).

For the sake of completeness, we also report results using a cubic fit (models 2, 4, 6, and 8). In line with our previous observation, we mostly find estimated coefficients that are consistent with our main analysis, but estimated with even lower reduced precision. We again attribute this to a lack of statistical power. However, our analysis of the exit probability is the exception here (model 2): the estimated coefficient shows the opposite sign in addition to being statistically insignificant.

Together, most estimated coefficients are consistent with our main analysis, but estimated with less precision. The only exception is the analysis of the exit probability when using a cubic model fit. In all, we therefore do not believe that our main results emerge purely as a result of choosing a local linear regression approach.

=== Table 6 here ===

=== Figure 3 here ===

5.2.2 Different bandwidths

In our main analysis, we use a subscriber count bandwidth from 900 to 1200. We believe this to be the best solution for the trade-off between only having comparable Youtubers in our sample (*identification*) while maintaining a sufficiently large sample size for our local linear regressions (*statistical power*). Here, we provide robustness checks using both wider (800 to 1400 subscribers) and narrower (950 to 1100 subscribers) bandwidths. Results are presented in table 7.

We start by discussing the results using a narrower bandwidth (models 2, 4, 6, and 8). The coefficients are qualitatively consistent with our main analysis, but estimated with less precision due to the reduced sample sizes. Only the coefficient of interest when analyzing unique keywords remains statistically significant ($p < 0.05$). In addition, when analyzing the exit probability the coefficient is also considerably smaller ($\beta = 0.039$) compared to our main analysis ($\beta = 0.156$).

Next, results when using a wider bandwidth are reported in models 1, 3, 5, and 7. Here, sample sizes are larger, but they include Youtubers who are further away from the subscriber threshold. Results for upload frequency and unique keywords are qualitatively consistent, statistically significant (at the one and five percent level, respectively), but effect sizes are smaller than in our main analysis. The results for like share show the same sign, but are smaller and statistically insignificant ($\beta = -0.01$, $p > 0.1$). Finally, we see the most pronounced difference to our main results for the exit probability (model 1). Here, we find a negative effect of losing access to the partner program, i.e. those Youtubers left a *lower* rates compared to those who remained. In addition, the estimated coefficient is larger than in our main results and highly statistically significant ($\beta = -0.256$, $p < 0.01$). Clearly, this result is sensitive to the choice of bandwidth. In addition, the negative effect goes against our expectations. A potential reason for the sign flip is the inclusion of Youtubers who are further away from the threshold. A graphical analysis provides some evidence for this conjecture. Figure 4 shows the RDD plots for the wider bandwidth and using a linear (4a) and quadratic (4b) model fit. The area between the two red references lines contains observations also in our main sample. At the low end of the subscriber count range, the wider bandwidth now includes additional observations with relatively high exit rates, resulting in a downward-sloping linear fit (figure 4a) below the threshold. Hence, the possible explanation here is that the wider bandwidth includes Youtubers that have been relatively unsuccessful to begin with, and would likely have left the platform regardless of the rule change. The pattern is similar when we use a quadratic fit (figure 4b) to account for the exit rate pattern above the threshold. Hence, the sign-flip may be the result of exit patterns that are unrelated to the rule change.

Together, again most estimated coefficient are qualitatively consistent – if not always statistically significant – with our main results. The exception here is the analysis of the exit probability, which is more sensitive to the choice of bandwidth.

=== Table 7 here ===

=== Figure 4 here ===

6 Discussion and Conclusion

We study how an increase in platform control affected the subsequent supply of videos on Youtube. After receiving widespread criticism and advertiser boycotts, the platform significantly increased the criteria for its complementors – Youtubers who create videos – to be eligible for its partner program, which allows them to monetize their content via advertising. Not only did this make it harder for new Youtubers to achieve the status of "Youtube partner", but it also removed those who already participated in the program if they did not meet the increased criteria. This constituted an increase in platform control because it enabled YouTube to apply and enforce stricter rules via more manual content curation. In this paper, we empirically analyze the reaction to this rule change of those Youtubers who originally participated in the program, but then lost access to it. Specifically, we investigate how they changed the amount and type of content they create on the platform. To a large degree, the platform relies on user-generated content, which is supplied by nonprofessionals and hobbyists. Earning money may not be the only (or even most important) motivational source for them (Ma and Agarwal, 2007). Instead, many are likely intrinsically driven or thrive to build an online reputation among their peers. We therefore also study how the reaction to the rule change differs between mainstream and niche Youtubers to learn about the role of financial and non-pecuniary incentives.

We use a regression discontinuity design to estimate the causal effect of losing access to the program on subsequent Youtuber behavior. The new criteria provide us with a clear threshold in their subscriber count at the time of the rule change. Hence, we compare the supply of videos between those who were just below that threshold to those just above. In our empirical analysis of German Youtubers we find that those who lost access to the partner program exited the platform at higher rates compared to those who did not. In addition, among those who did not exit the platform, we find that affected Youtubers decreased the frequency of which they upload videos to the platform. Together, this speaks to a deterioration of incentives due to the rule change, which led affected Youtubers to either leave the platform completely, or to decrease the amount of content they supply to it. Further, we find that the effect on platform exit is completely driven by niche Youtubers (we do not find differences in upload frequency), whom we believe to be more driven by non-pecuniary than financial incentives. We take this as evidence for the notion that this Youtuber type perceived the rule change as a withdrawal of platform support for their rather narrow-appeal content.

Affected Youtubers also created content of lower quality after the rule change. Here, the effect is completely driven by mainstream Youtubers whom we believe to be relatively more driven by financial than non-pecuniary incentives. While not leading to increased exit rates, deteriorating financial incentives led to decreased efforts to provide content of high quality. Moreover, the fact that niche Youtubers do not reduce their content quality speaks to the notion that they are intrinsically motivated – while this type left the platform at higher rates, those who remained are evidently not ready to compromise the integrity of their content.

Finally, we find that affected Youtubers reduced the diversity of content they create. Both mainstream and niche Youtubers displayed an increased focus in their content strategy. Evidently, the loss of financial incentives reduced the need to appeal to a broader audience that exhibits a wider range of tastes. In addition, the effect is considerably stronger for niche Youtubers. Again, this speaks to their unwillingness to compromise on the type of content they supply, or to move outside their narrow segment.

Together, these findings show how an increase in platform control can have consequences for the subsequent behavior of even those complementors who it is not directed at. The increased criteria have been put into place to enable manual content curation, which had been impossible due to the sheer number of participants in the program. In addition, our findings suggest that the rule change did not only affect financial incentives on the platform even though that is the primary purpose of the partner program. First, those who lost access to it did not earn a lot of money on the platform to begin with (Mohan and Kyncl, 2018). Second, our analysis of niche Youtubers shows that even those who are unlikely to be primarily driven by financial motives show some of the strongest reactions to the change. Hence, intrinsic and non-pecuniary motivations play an important role in eliciting the supply of complements, and they should not be disregarded when designing or changing platform governance practices.

Our findings contain contributions to two streams of literature: First, we provide novel insights about changes to a platform's governance strategy, and shifts towards more control in particular. Prior studies show that exerting control is necessary to secure a set of high-quality and innovative complements (Boudreau, 2012; Parker and Van Alstyne, 2018) or to avoid uncontrolled creativity (Geva et al., 2019) and threats to a platform's integrity (Eaton et al., 2015). We add to this discussion by demonstrating how an increase in control can have a detrimental effect on the motivation of those complementors who actually are not a cause of concern. This highlights an important issue in large platform ecosystems: The sheer number of participants makes arm's length relationships necessary (Ghazawneh and Henfridsson, 2013; Hukal et al., 2020) – it is impossible to tailor rules towards individual complementors. Still, the indiscriminate creation and enforcement of rules is then likely to have unintended and potentially detrimental consequences for at least a subset of those who are affected by it. Further, recent studies note that it is hard to predict complementor reactions to rule changes more generally (e.g. Boudreau and Hagiu, 2009; Jhaver et al., 2018; Koo and Eesley, 2020). Our results confirm this notion by demonstrating heterogeneous effects from different complementor types, who are likely drawing on different sources of motivation.

Second, we contribute to the stream of literature on supply incentives in the context of user-generated content. Prior studies on financial incentives provide nuanced findings, pointing to limited effectiveness that is often conditional on other factors (e.g. Burtch et al., 2018; Cabral and Li, 2015; Khern-am nuai et al., 2018; Sun et al., 2017). In addition, while most studies on ad-based revenue models point towards content strategies to maximize engagement (Anderson and Gabszewicz, 2006; Kerkhof, 2020; Sun and Zhu, 2013), the exact nature of these strategies seems to be context-specific. Our findings suggest that financial incentives in the context of an ad-based model play a limited role which is likely of relevance to certain complementor types. Non-pecuniary and intrinsic sources of motivations also play an important role in eliciting content supply that is diverse and of high quality. Hence, our contribution lies in providing causal evidence for heterogeneity in reactions to deteriorating incentives along multiple dimensions of activity and the type of content.

Finally, our study contains several limitations and point towards future research opportunities. First, we study a small subset of complementors in a large platform ecosystem. To identify causal effects of losing access to the Youtube partner program we focus on those who fall within a narrow range of subscriber counts. In addition, these complementors are relatively small and unlikely to (individually) contribute a lot of value to the platform. Therefore, they may not be representative of the entire ecosystem. For instance, larger, highly successful complementors may enjoy a stronger bargaining position vis-à-vis the platform, eliciting a different reaction to a rule change similar to the one we study. Therefore, future research could look at heterogeneity along the dimension of complementor size or success. Second, we are unable to clearly separate financial and non-pecuniary incentives in our study. Instead, we approximate this distinction by investigating heterogeneous reactions between different complementor types. Hence, future research could make this distinction explicitly, perhaps in the form of an experiment. Lastly, Youtube consists of both professional and user-generated content. Hence, reactions to increased control may be different in settings with only professional complementors, such as app stores, video game consoles, or e-commerce platforms.

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Figures

Figure 1 Test for continuity at the threshold

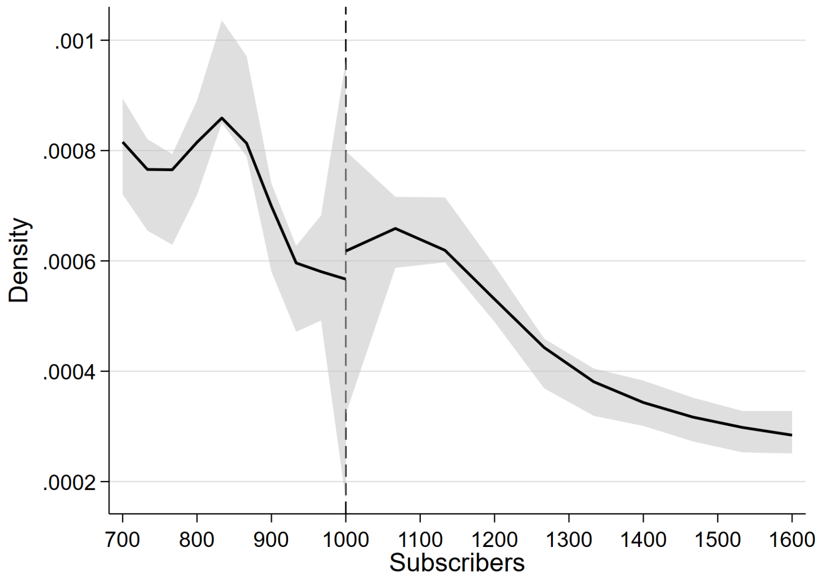
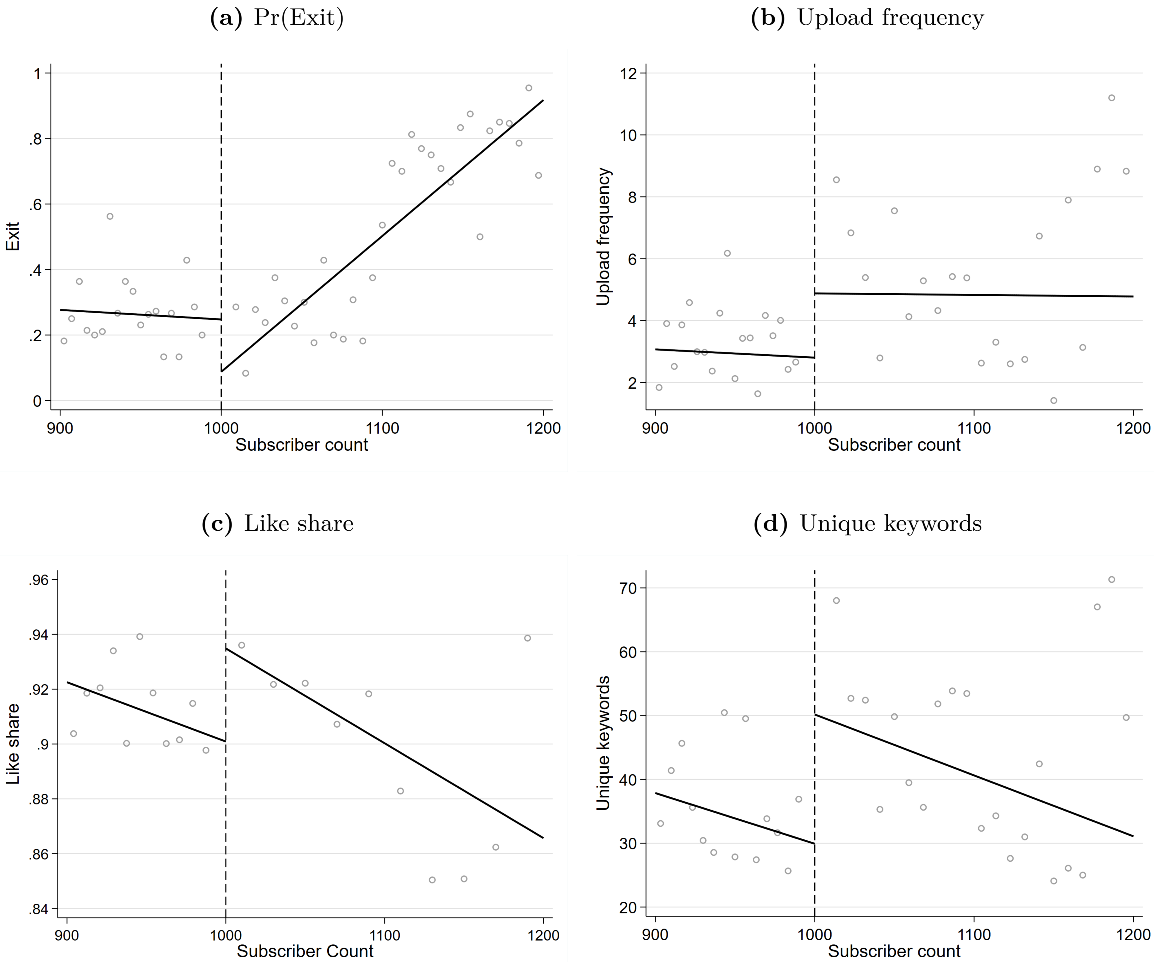


Figure 2 RDD plots: Main results



(a) Pr(Exit)

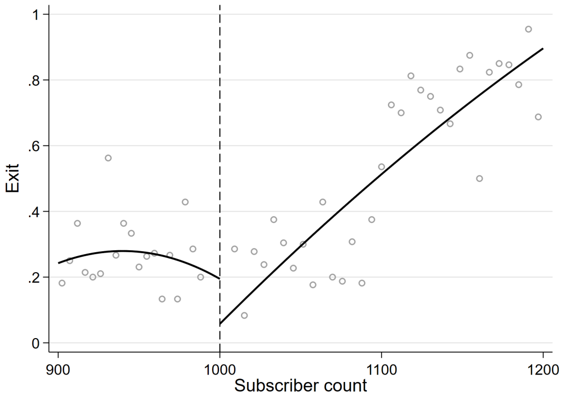
(b) Upload frequency

(c) Like share

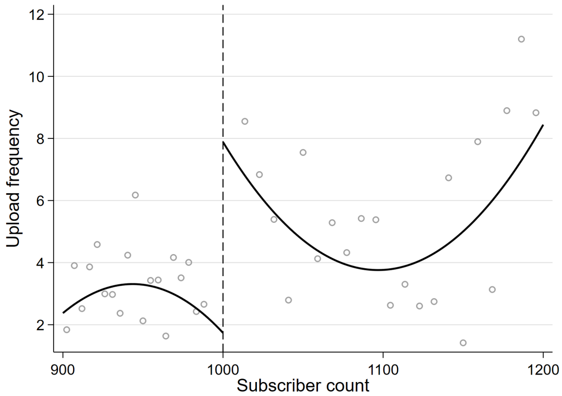
(d) Unique keywords

Figure 3 RDD plots: Quadratic model fit

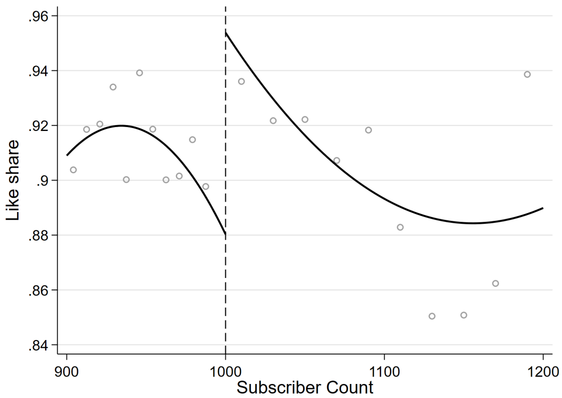
(a) Pr(Exit)



(b) Upload frequency



(c) Like share



(d) Unique keywords

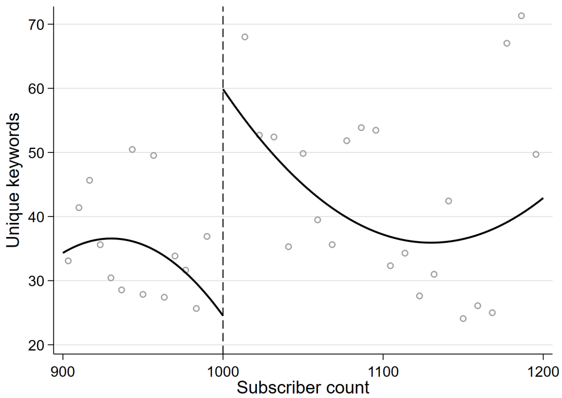
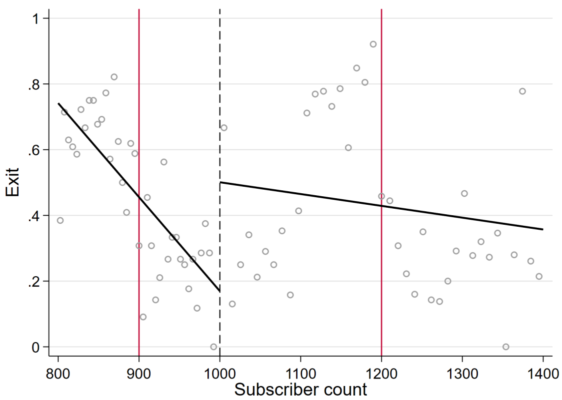
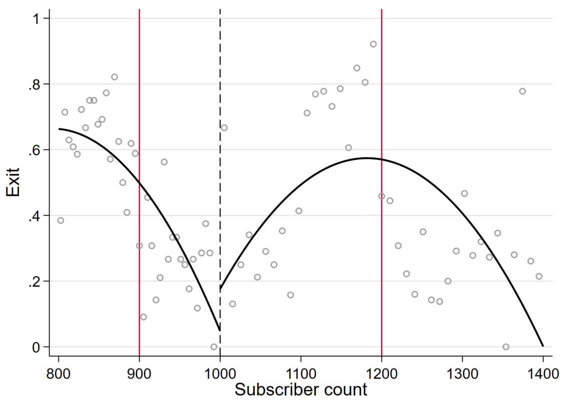


Figure 4 RDD plots: Pr(Exit), wider bandwidth

(a) Linear model fit



(b) Quadratic model fit



Tables

Table 1 Outcome variable descriptions

Variable	Description
Exit	Dummy that equals one if a Youtuber who appeared in the first wave of data collection does not reappear in the second wave
Upload frequency	The average number of videos uploaded by a Youtuber per month in the six months after the rule change
Like share	The average share of likes ($\frac{Likes}{Likes+Dislikes}$) of videos uploaded by a Youtuber per month in the six months after the rule change
Unique tags	The average number of unique keywords a Youtuber attaches to videos per month in the six months after the rule change

Table 2 Summary Statistics

Variable	N	Mean	Std. Dev.	Min.	Max.
Lost Access	902	0.78	0.41	0	1.00
Subscriber count	902	1059.42	86.49	901	1198.00
Watchtime	902	5841.23	16246.51	0	243711.73
Mainstream	902	0.82	0.30	0	1.00
Exit	902	0.46	0.50	0	1.00
Upload frequency	428	4.58	7.22	1	75.00
Like share	425	0.91	0.11	0	1.00
Unique tags	428	24.63	17.02	1	72.37

Table 3 RDD results: Before the rule change

	Upload Frequency (1)	Like Share (2)	Unique Tags (3)
Lost Access	–1.754	–0.035	–4.668
	(1.246)	(0.023)	(6.531)
Bandwidth	[900,1200]	[900,1200]	[900,1200]
Observations	428	425	428

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1. Robust standard errors in parentheses are clustered at the Youtuber level. All models use local linear regressions and control for watchtime. The sample consists of Youtubers who did not exit the platform before the first and second waves of data collection. The outcome variables are calculated based on activity in the six months before the rule change.

Table 4 RDD results: Activity

	Pr(Exit)			Upload frequency		
	Full	Mainstream	Niche	Full	Mainstream	Niche
	(1)	(2)	(3)	(4)	(5)	(6)
Lost Access	0.156*	–0.005	0.393***	–3.548*	–3.510	–3.402
	(0.082)	(0.096)	(0.140)	(1.396)	(2.143)	(3.538)
Bandwidth	[900,1200]	[900,1200]	[900,1200]	[900,1200]	[900,1200]	[900,1200]
Observations	902	512	390	428	253	175

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1. Robust standard errors in parentheses are clustered at the Youtuber level. All models use local linear regressions and control for watchtime. Models 1–3 are estimated on the full sample of Youtubers who had been active before the rule change. Models 4–6 use a sample of Youtubers who did no exit the platform between the first and second waves of data collection.

Table 5 RDD results: Type of content

	Like share			Unique keywords		
	Full	Mainstream	Niche	Full	Mainstream	Niche
	(1)	(2)	(3)	(4)	(5)	(6)
Lost Access	–0.048**	–0.061**	–0.034	–25.380**	–19.803*	–33.294*
	(0.024)	(0.029)	(0.041)	(6.531)	(10.164)	(20.145)
Bandwidth	[900,1200]	[900,1200]	[900,1200]	[900,1200]	[900,1200]	[900,1200]
Observations	425	251	174	428	253	175

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1. Robust standard errors in parentheses are clustered at the Youtuber level. All models use local linear regressions and control for watchtime. All models are estimated on the sample of Youtubers who did no exit the platform between the first and second waves of data collection.

Table 6 Robustness: Higher order polynomials

	Pr(Exit)		Upload frequency		Like share		Unique keywords	
	quadratic	cubic	quadratic	cubic	quadratic	cubic	quadratic	cubic
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lost Access	0.070	–0.057	–5.988*	–6.042	–0.048	–0.021	–32.774	–38.769
	(0.151)	(0.263)	(3.593)	(6.099)	(0.044)	(0.087)	(20.347)	(34.971)
Bandwidth	[900,1200]	[900,1200]	[900,1200]	[900,1200]	[900,1200]	[900,1200]	[900,1200]	[900,1200]
Polynomials	2	3	2	3	2	3	2	3
Observations	902	902	428	428	425	425	428	428

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1. Robust standard errors in parentheses are clustered at the Youtuber level. All models control for watchtime. Models 1–2 are estimated on the full sample of Youtubers who had been active before the rule change. Models 3–8 use a sample of Youtubers who did no exit the platform between the first and second waves of data collection.

Table 7 Robustness: Bandwidth

	Pr(Exit)		Upload frequency		Like share		Unique keywords	
	wide	narrow	wide	narrow	wide	narrow	wide	narrow
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lost Access	–0.256***	0.039	–2.074**	–4.955	–0.010	–0.039	–11.503*	–30.236*
	(0.053)	(0.138)	(1.030)	(3.213)	(0.016)	(0.042)	(6.106)	(18.087)
Bandwidth	[800,1400]	[950,1100]	[800,1400]	[950,1100]	[800,1400]	[950,1100]	[800,1400]	[950,1100]
Observations	1765	408	827	263	819	261	827	263

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1. Robust standard errors in parentheses are clustered at the Youtuber level. All models use local linear regressions and control for watchtime. Models 1–2 are estimated on the full sample of Youtubers who had been active before the rule change. Models 3–8 use a sample of Youtubers who did no exit the platform between the first and second waves of data collection.