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Should subscription-based content creators display their earnings on crowdfunding platforms? Evidence from Patreon

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A B S T R A C T

In January 2017, the subscription-based crowdfunding platform Patreon allowed their users (creators) the ability to hide their earnings from existing and potential subscribers. Prior to this, all monthly earnings were visible. We investigate what effect this policy change had on creators' subscriber numbers over the following six months. Using double-robust and endogenous treatment estimation techniques, we find evidence that creators who removed the visibility of their earnings had more subscribers as a result. This suggests that the provision of social information does not lead to an increase in subscribers.

> *"Imagine if LinkedIn displayed your salary right below your name. Or imagine if doctors were forced to plaster their annual income on their signage outside."* (Jack Conte, Patreon CEO, January 2017)

1. Introduction

Crowdfunding has revolutionised fundraising for all manner of projects. The rise of the digital platform economy, coupled with the development of online crowdfunding platforms, allows for-profit ventures, non-profit projects, and freelance operators to bypass traditional models of financing and connect with individual investors around the world. Alternative finance, which includes crowdfunding, is a rapidly growing sector that facilitated US$304.5 billion in transaction volume in 2018 alone (Cambridge Centre for Alternative Finance, 2020).

Since its inception, a variety of different crowdfunding models have emerged. The most popular of these are equity-, loan-, donation-, and reward-based crowdfunding (Belleflamme et al., 2015; Butticè et al., 2018; Dalla Chiesa and Handke, 2020). To date, academic literature examining crowdfunding has primarily focused on identifying the determinants of successful crowdfunding campaigns, particularly for rewards-based crowdfunding platforms. Recent studies include Agrawal et al. (2015), Belleflamme et al. (2014), Cecere et al. (2017), Chang (2020), Colombo et al. (2015), Jiang et al. (2021) and Mollick (2014).

Recently, subscription-based crowdfunding has emerged as an alternative crowdfunding model for content creators such as writers, musicians, artists, and the like. Subscription-based crowdfunding can be viewed as a subset of the rewards-based model. Instead of a one-off payment, subscription-based crowdfunding allows funders to contribute to creators on an ongoing basis in exchange for a continuing stream of content. Patreon, the largest of the subscription-based crowdfunding platforms, has paid out over US$2 billion to

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creators since it was founded in 2013 (Conte, 2020).

Despite the burgeoning popularity of subscription-based crowdfunding, economic studies that examine the leading indicators of campaign success and the long-term viability of subscription-based income sources are scarce. Regner (2021) examines transaction-level data from Patreon's launch in 2013–2015, concluding that crowdfunding a monthly income offers content creators a viable alternative to advertising-based models. However, investigations concerning optimal platform design are yet to be empirically explored.

This study exploits a natural experiment that occurred on the Patreon platform in January 2017. Until this time, all creators on Patreon were forced to display details about how many backers (subscribers) they had, along with earnings information. After this time, Patreon changed their policy and gave creators the ability to hide their earnings. The move divided the Patreon community. The loss of financial transparency, often a cornerstone of the crowdfunding model, was viewed as potentially damaging. Others noted earnings figures are typically confidential, and that should be no different on Patreon's platform.

Every Patreon creator is faced with the choice of whether to make their earnings visible to the public. From an economic point of view, it is not *a-pirori* obvious if such a decision has an impact on subscribers and, by extension, earnings. Existing research on fundraising and charitable giving suggests that altruism (List, 2011) and empathy (Fisher et al., 2008) are important drivers of successful campaigns. In a subscription-based crowdfunding setting, signals of success (in the form of high levels of monthly earnings) may potentially undermine the altruistic and empathetic motivations of potential subscribers. However, the provision of information about others' contributions has been shown to have a positive effect on campaign success in other fundraising contexts (Croson and Shang, 2008). We provide empirical evidence whether the disclosure of income information helps or hinders content creators on subscription-based crowdfunding platforms.

2. Data

We use monthly Patreon data for the 12-month period July 2016 to June 2017. Data were collected from the Graphtreon website.[1] This window provided six months data either side of the policy change that allowed creators to hide the visibility of their earnings on the platform. The policy change occurred from January 1, 2017. We restrict the sample to the subset of creators who held active accounts for each of the 12 months observed.

We consider two types of creators: 1) those with 'visible' earnings for the entire six month period post policy change (control), and 2) those with 'not visible' earnings for the entire six month period post policy change (treatment). To ensure fair comparison, we exclude creators who changed their earnings visibility status after the initial policy change. That is, creators either had visible earnings for all of the 12 months or *only* six of the 12 months.

Patreon creators are categorised into 14 groups, and further subdivided depending on whether or not they supply adult content. Panel a of Table 1 reports the number of subscribers for each category as of December 2016, i.e. just prior to the policy change. All category-level distributions are right-skewed as most creators attract very few subscribers but a small number attract a very large number. In addition to subscribers, we also observe earnings for all creators prior to the policy change. The average creator had an average (median) of 39 (6) subscribers and earned an average (median) of US$204 (US$33) per month. The correlation between these two variables is 0.87.

In panel b of Table 1 we summarise subscriber numbers and earnings broken down by whether the account holder changed their earnings to become 'not visible' from January 1, 2017. As is clear from the table, only 760 of the 27,760 creators changed their earnings status at this time, although many more changed this in months (and years) after the policy became more widely known and understood. One obvious difference between the creators who kept their earnings visible versus those who did not was that the latter generally had both a higher number of subscribers and higher levels of earnings. This has implications for the empirical strategy that we discuss in detail below.

In addition to information regarding subscribers and earnings, we also have data on each creator's social media metrics for Facebook (likes), Twitter (followers), and YouTube (subscribers). Different creators favour different social media, so in many cases we only observe one or two of these metrics for a given user. Across the 13,312 creators with active Facebook pages, the average number of likes was 18,775. For the 18,562 creators with Twitter accounts, the average number of followers was 5845. Finally, the 13,636 creators with YouTube channels had an average of 71,957 subscribers. These averages are all right skewed, as the medians were 768, 606, and 1,197, respectively.

3. Empirical strategy

To investigate the causal impact of the policy change that allowed creators to hide their earnings, we use the Inverse Probability Weighted Regression Adjustment (IPWRA) method. This estimator has the well-known property of double robustness, which permits causal inference if either the outcome or treatment model is correctly specified. However, even with our control variables in the treatment model, there is still concern that unobserved variables may impact the decision to hide earnings. For this reason, we also consider an endogenous treatment model that utilises a control function to account for unobserved variables. Wooldridge (2010) provides an excellent discussion of both empirical methods.

[1] See https://graphtreon.com/.

Table 1
Summary statistics.

Panel a	Not Adult				Adult			
Category	Obs	Mean	Median	SD	Obs	Mean	Median	SD
Animation	323	30.2	4	144.0	247	88.5	20	335.7
Comics	2187	35.5	7	159.3	1311	46.0	12	115.0
Cosplay	137	11.1	3	24.7	132	69.1	7	288.9
Crafts & DIY	72	16.7	3	44.3				
Dance & Theater	78	15.0	3	53.2				
Drawing & Painting	1580	13.7	3	63.7	1404	23.7	6	62.9
Games	2257	28.7	6	96.5	584	144.2	14	429.1
Magazine	128	77.4	8	356.9				
Music	2191	28.3	4	183.0	115	11.4	3	24.8
Other	1624	13.4	3	38.4	573	23.1	5	69.4
Photography	200	14.3	4	31.6	165	44.2	9	120.9
Podcasts	1836	77.2	11	317.8	175	46.3	6	357.5
Video	7090	47.1	6	266.5	942	37.2	6	187.1
Writing	1894	22.5	5	80.0	515	14.4	4	33.6

Panel b	Subscribers				Earnings			
Earnings	Obs	Mean	Median	SD	Obs	Mean	Median	SD
Not visible	760	128.8	21.0	421.6	760	802.6	146.9	2428.3
Visible	27,000	36.2	5.0	191.1	27,000	186.8	31.9	875.3
Total	27,760	38.7	6.0	201.5	27,760	203.6	33.0	957.3

Notes: Panel a reports mean, median and standard deviation (SD) summary statistics of Patreon subscribers by Patreon user category, including both 'adult' and 'not adult' categories. Panel b reports summary statistics of number of subscribers and (monthly) earnings. These are reported for creators who had 'visible' and 'not visible' earnings after the policy change date.

We formulate the treatment model as a logit model where the (binary) dependent variable is whether or not the creator kept their earnings visible (zero) or not (one) post policy change. Formally, this can be expressed as $t_i = E(t_i|\mathbf{z}_i) + \nu_i$, where t_i is a binary variable for whether individual i received the treatment, $\mathbf{z}_i$ is the vector of determinants of the treatment, and ν_i is the unobserved component. The primary independent variables are (log) number of subscribers and (log) monthly earnings, which are both observed at the month prior to the policy change (December 2016). We also make use of the social media metrics described in Section 2. Because not all creators are active on each social media platform, we estimate additional models for each social media type. In each such model, we include the relevant (log) social media metric as an additional explanatory variable. Finally, we include category fixed effects in all models.

Both the double-robust and endogenous treatment methodologies estimate the outcome model on the 'control' and 'treated' samples. These can be expressed as $y_{i0} = E(y_{i0}|\mathbf{x}_i) + \epsilon_{i0}$ and $y_{i1} = E(y_{i1}|\mathbf{x}_i) + \epsilon_{i1}$, respectively. In these specifications y_{ij}, for $j = \{0, 1\}$, is the potential outcome and $\mathbf{x}_i$ is the vector of explanatory variables. The error term, ϵ_{ij}, is assumed independent of both $\mathbf{x}_i$ and $\mathbf{z}_i$. That is, $E(\epsilon_{ij}|\mathbf{x}_i, \mathbf{z}_i) = E(\epsilon_{ij}|\mathbf{x}_i) = E(\epsilon_{ij}|\mathbf{z}_i) = 0$ for $j = \{0, 1\}$. The outcome model is estimated as a linear model, where the dependent variable is (log) number of subscribers observed at the end of the sample period (July 2017). The only independent variable is (log) number of subscribers observed immediately prior to the policy change (December 2016).

As mentioned above, there is concern that the treatment itself might be endogenous if there are unobserved variables that simultaneously affect the number of subscribers and the treatment status. If this is the case, $E(\epsilon_{ij}|t_i) \neq 0$. Given the assumption of independence between ϵ_{ij} and $\mathbf{z}_i$, the correlation between t_i and the unobserved components can be stated as $E(\epsilon_{ij}|t_i) = E(\epsilon_{ij}|E(t_i|\mathbf{z}_i) + \nu_i) = E(\epsilon_{ij}|\nu_i) = \nu_i\beta_{2j}$. This is the basis for the control function approach, which can be expressed as $E(y_{ij}|\mathbf{x}_i, \nu_i, t_i = j) = \mathbf{x}_i\beta_{1j} + \nu_i\beta_{2j}$ for $j = \{0, 1\}$.[2] However, by controlling for endogeneity in this way, the double robust property no longer holds, so both the treatment model and outcome model are implicitly correctly specified.

4. Results

Table 2 provides results from the IPWRA and endogenous regression adjustment estimations. In all instances, we report the Average Treatment Effect on the Treated (ATET), as we are interested to know the (unobserved) potential outcome of the group who opted to hide their earnings. In models 1–4, we report the double robust IPWRA estimates, where endogeneity is not addressed. The estimated ATETs suggest creators who hid their earnings realised more subscribers than they would have had they not done so.

In addition to the ATET estimates, we report parameter estimates from the underlying treatment and outcome models. With respect to the treatment model, the positive relationship observed with (log) earnings conforms with *a-priori* intuition, given its likely relevance to the user's decision about whether or not to keep earnings visible. The (log) number of subscribers and/or respective (log)

[2] The control function approach has the benefit that identification comes from the non-linearity of the inverse Mills ratio, not through an exclusion restriction assumed in instrumental variable estimation.

Table 2
Double robust and endogenous treatment results.

Estimation	Double Robust Regression Adjustment				Endogenous Regression Adjustment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATET	0.051***	0.069***	0.050**	0.043	0.741***	0.354*	0.415**	0.611**
	(0.018)	(0.026)	(0.020)	(0.027)	(0.195)	(0.194)	(0.176)	(0.273)
PO mean	3.243***	3.325***	3.295***	3.361***	2.552***	3.041***	2.929***	2.793***
	(0.065)	(0.093)	(0.078)	(0.093)	(0.199)	(0.199)	(0.177)	(0.279)
Outcome model 0								
log(subscribers)	1.028***	1.025***	1.027***	1.024***	1.006***	1.007***	1.009***	1.007***
	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
const.	−0.009	0.005	−0.012	0.010	0.018***	0.038***	0.023***	0.034***
	(0.009)	(0.015)	(0.012)	(0.012)	(0.004)	(0.007)	(0.006)	(0.007)
Outcome model 1								
log(subscribers)	1.022***	1.014***	1.015***	1.008***	1.015***	1.007***	1.010***	1.004***
	(0.009)	(0.013)	(0.010)	(0.013)	(0.011)	(0.016)	(0.013)	(0.015)
const.	0.060	0.110**	0.077**	0.106**	0.336*	0.360	0.269	0.251
	(0.038)	(0.054)	(0.043)	(0.056)	(0.194)	(0.286)	(0.214)	(0.255)
Treatment model								
log(earnings)	0.301***	0.362***	0.143***	0.268***	0.113***	0.136***	0.143***	0.096***
	(0.050)	(0.074)	(0.027)	(0.075)	(0.021)	(0.032)	(0.027)	(0.031)
log(subscribers)	0.128***	−0.001	0.015**	0.181**	0.074***	0.025	0.015**	0.101***
	(0.050)	(0.074)	(0.028)	(0.076)	(0.022)	(0.033)	(0.028)	(0.033)
log(social media)		0.091***	0.026***	−0.032		0.036***	0.026***	−0.013
		(0.027)	(0.011)	(0.020)		(0.012)	(0.011)	(0.009)
Category FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endog. Test					14.130	2.930	5.210	4.520
(p-value)					(0.001)	(0.231)	(0.074)	(0.104)
Social media	None	Facebook	Twitter	YouTube	None	Facebook	Twitter	YouTube
Observations	27,760	12,312	18,562	13,636	27,760	12,312	18,562	13,636

Notes: Table report Average Treatment Effect on the Treated (ATET) estimates using Inverse Probability Weighted Regression Adjustment (IPWRA) and Endogenous Regression Adjustment. ATE measured as difference in subscribers of Patreon creators with 'not visible' earnings relative to creators with 'visible' earnings. ATET is compared to Potential Outcome mean (PO mean) of creators with visible earnings. 'Subscribers', 'earnings' and 'social media' metrics measured in month before policy change. Category fixed effects (FEs) include categories reported in Table 1. Standard errors in parentheses; $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

social media metrics also have relevance in this decision. With respect to the outcome model, (log) number of subscribers prior to the policy change are clearly an important determinant of (log) subscribers at the end of the sample window.

With respect to the endogenous treatment models 5–8, we also find statistically significant and positive ATETs in all models. While there is some difference with the size of the estimated coefficient, the sign and significance supports the main result. As far as the question of whether endogeneity requires remedial attention, in model 5 the null hypothesis test of no endogeneity is clearly rejected, suggesting remedial measures are appropriate. However, in models 6–8 (where social media metrics are included) the evidence is less clear. It is possible the included social media metrics help to mitigate the unobserved variables correlated with the treatment, in which case the IPWRA results could be taken as correct. However, as this is not universal across all three models, we prefer the endogenous results overall.

Exponentiating the ATET estimates, implies an increase of 110% in subscribers for model 5 and 42–84% for models 6–8. All of these are clearly well above the IPWRA estimates, which range 5–7%. Finally, we also provide treatment effect balance summary statistics in Table 3 for the IPWRA results reported in models 1–4 of Table 2. The standardised (mean) differences are all close to zero and the variance ratios are all close to one. Insofar as the double robust results are instead taken to be correct, the samples appear well balanced. Although, as we stress above, these are not our preferred results.

5. Concluding remarks

We exploit a natural experiment from Patreon's 2017 policy change that gave creators the ability to hide their earnings. Using double robust and endogenous treatment analysis, we find that creators who changed their earnings to *not* be visible had, on average, more subscribers than if they had continued to keep their earnings visible. Our findings suggest that subscribers are less likely to offer money to creators when provided with social information that displays earnings. Instead, it appears that subscribers are more inclined to support creators when signals of existing campaign success are unknown. This finding suggests that underlying altruistic and empathetic motivations may be a key driver of subscription-based crowdfunding subscriptions. Future work might consider these motivations in more detail.

CRediT author statement

Paul Crosby: Conceptualization, Methodology, Data Curation, Investigation, Writing - Original Draft, Writing - Review & Editing.

Table 3
Treatment effects balance statistics (models 1–4).

	Model 1		Model 2		Model 3		Model 4	
	Raw	Weighted	Raw	Weighted	Raw	Weighted	Raw	Weighted
Observations								
Total	27,760	27,760.0	12,312	12,312.0	18,562	18,562.0	13,636	13,636.0
Treated	760	13,942.1	413	6197.9	560	9329.4	387	6858.9
Control	27,000	13,817.9	11,899	6114.1	18,002	9232.6	13,249	6777.1
Standardised differences								
log(earnings)	0.783	0.019	0.765	0.026	0.750	0.023	0.763	0.025
log(subscribers)	0.746	0.010	0.692	0.014	0.677	0.013	0.745	0.016
log(social media)			0.535	0.026	0.396	0.019	0.173	0.004
Variance ratio								
log(earnings)	1.110	1.072	1.230	1.189	1.165	1.145	1.178	1.132
log(subscribers)	1.245	0.892	1.360	0.988	1.300	0.972	1.271	0.891
log(social media)			1.336	1.106	1.122	1.056	0.933	0.876

Notes: Table reports Treatment Effect balance summary statistics from unweighted (raw) and weighted samples for models 1, 2, 3 and 4 reported in Table 2. 'Standardised differences' reports standardised mean differences between respective samples. 'Variance ratio' reports the ratio of variances between respective samples.

Jordi McKenzie: Conceptualization, Methodology, Formal analysis, Investigation, Writing - Original Draft, Writing - Review & Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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