MIS Quarterly

RESEARCH ARTICLE

A POTATO SALAD WITH A LEMON TWIST: USING A SUPPLY-SIDE SHOCK TO STUDY THE IMPACT OF OPPORTUNISTIC BEHAVIOR ON CROWDFUNDING PLATFORMS

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Appendix A

Deriving Quality Measures

We have made an effort and have taken one step further to enrich our variable set to gain a more comprehensive and accurate measurement of campaign quality. In the spirit of prior work, we consider the extent to which the entrepreneur has invested effort and resources in the campaign, and the level of professionalism of the entrepreneur.

Mollick (2013) has suggested that venture capitalists and crowdfunders assess entrepreneurial quality in similar ways. Specifically, both ultimately act to rationally assess project quality, of which the entrepreneur's level of preparation is a key indicator. Thus, Mollick hypothesizes that entrepreneurs who demonstrate more *preparedness* are more likely to be funded. We suggest that, in the domain of crowdfunding, entrepreneurial preparation is manifested in the effort and resources invested by the entrepreneur in preparation for launching a campaign. Additionally, marketing literature suggests that potential consumers take sellers' (perceived) effort and expense into account (Modig et al. 2014). In the context of crowdfunding, we can assume that consumers are literate enough to deduce the levels of expense and effort invested by the seller, and use them to infer whether the product is of better quality.

Thus, to measure potential backers' perceptions of such investment, we focused on the following campaign attributes, which a potential backer can deduce from viewing a campaign's page.

- Money spent by the entrepreneur before launching the campaign (Q4 in Table 2 in the paper).
- Time and effort spent in creating the campaign page (Q1 and Q3 in Table 2, respectively).
- Careful planning of the reward structure (Q6 in Table 2). This may indicate the level of detail in which the product or service was planned, and the consideration that the campaign creator has given to what is feasible to promise.

We further draw from literature showing that potential consumers use website design as a manifestation of the seller's *ability*, and that this assessment in turn impacts their online purchase intentions (Schlosser et al. 2006). Thus, in addition to Q3, which captures the effort invested by the entrepreneur in designing the campaign page, we also asked about:

- The level of professionalism of the design of the campaign page (Q2 in Table 2).
- The use of an additional website outside of Kickstarter domain (Q5 in Table 2).

Human capital is associated with entrepreneurial success and quality (Ahlers et al. 2015; Unger et al. 2011). However, the operationalization of human capital may be challenging within the context of Kickstarter, owing to the diversity of campaign categories, which range from art and food to design and technology. For example, for entrepreneurs in the technology category, an academic degree may provide a strong indication of "high" human capital (Doms et al. 2010; Levie and Gimmon 2008). However, a degree may be less useful as an indication of the quality of a dance act. Hence, in building our quality measurements, we directly asked evaluators to rank the (perceived) professionalism of the entrepreneurs in the field in which they operate (Q7 in Table 2). Again, assuming that the evaluators are not very different from the average Kickstarter backer, the answers will provide insights into the degree to which the campaign page signals professionalism within the context of the specific campaign category.

References

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Appendix B

Additional Supply Shocks

Our paper investigates the effects of a sharp increase in low-quality competition using one media shock that brought about a unique state on the Kickstarter platform. Specifically, following the shock, the supply on the platform (i.e., the number of campaigns offered) grew substantially, whereas the demand did not change significantly. To provide further robustness to our results, we searched for additional situations on Kickstarter in which supply increased sharply with no significant effect on demand. To this end, we identified dates in the platform's history on which spikes in supply occurred. We defined a "spike" as a day on which the number of campaigns launched was two standard deviations higher than the average number of campaigns launched in the days of the preceding two months. When searching for such dates we used data collected about all campaigns that were launched after June 3, 2014, when Kickstarter implemented a policy that lowered the entry barriers for new campaigns, and before May 2015. This dataset contained 75,872 campaigns. We identified eight events (unique days) in which there was a substantial increase in supply. These events took place on the following dates: January 20, 2015; January 21, 2015; January 26, 2015; January 27, 2015; February 2, 2015; February 9, 2015; February 17, 2015; and March 2, 2015. However, none of those events possessed the required characteristics. As can be observed, there was substantial overlap between the dates surrounding the different events. Thus, we could not correctly distinguish the demand in the weeks prior to each shock from the demand in the weeks following each shock, seeing as those weeks were influenced not only by the current shock being evaluated but most likely by other shocks as well.

Appendix C

Illustration of Time Proximity Identification Method

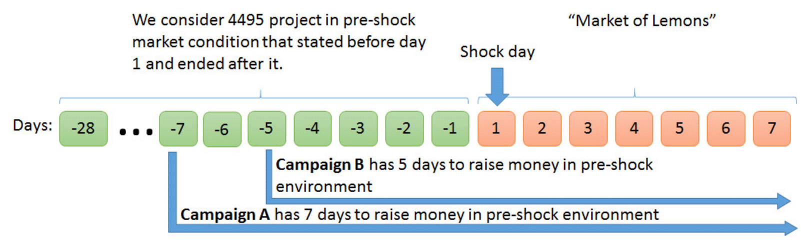

Figure C1. Illustration of Time Proximity Identification Method

Appendix D

PSM Identification: Balancing Tests for H2

Our matching was not performed on the variable *QualityPca*, but rather on the individual variables attributed to quality, as well as additional campaign characteristics. Thus we had to make sure that, for each low- and high-quality subsample (created by *QualityBinary*), *QualityPca* was balanced between the "before" and "after" groups. We tested this using both the Mann-Whitney rank test and the Wilcoxon rank-sum test. The results in Table D1 show that *QualityPca* was balanced for both the low-quality subsample and the high-quality subsample.

Table D1. Balancing Test of *QualityPca* Between "Before" and "After" Campaigns

	Mann-Whitney Rank Test	Wilcoxon Rank-Sum Test
Low quality	Statistic = 115996 ; p = 0.79	Statistic = 0.25 ; p = 0.79
High quality	Statistic = 114845 ; p = 0.99	Statistic = -0.01; p = 0.99

Appendix E

Interpretation of Coefficients and Economic Effects

In this appendix, we provide details about the calculation of the economic impacts reported in the paper. We first provide the calculations for all regression analyses in which a campaign's likelihood of success (*IsSuccessful*) was the dependent variable. Then we provide calculations for all regression analyses in which the amount pledged (*lnAmountPledged*) was the dependent variable. For each performance variable, we first present the regressions estimated using the time proximity identification, and then those estimated using the PSM identification.

For convenience of presentation, in what follows, the variable notation *DaysFromShockDay* has been shortened to *days*, *IsSuccessful* has been shortened to *success*, and *AmountPledged* has been changed to *pledged*.

Logistic Regressions Focusing on the Success Rate

Time Proximity Identification:

(a) Effect of ln(*days*) on success, no interaction term

Let **success** be the binary outcome variable indicating failure/success with 0/1, and let p be the probability of success to be 1, p = prob(success=1). Let $\ln(days)$, and $X_2 \ldots X_k$ be a set of predictor variables. Then the logistic regression of success on $\ln(days)$ and $X_2 \ldots X_k$ estimates parameter values for β0, β1, …, βk using the following equation.

logit(p) = log(p/(1-p))= $\beta_0 + \beta_1 * \ln(days) + \ldots + \beta_k * X_k$

$$\frac{p}{1-p} = e^{\beta_0 + \beta_1 \ln(days) + \beta_{2:k}\boldsymbol{X}} = e^{\beta_0}(days)^{\beta_1} e^{\beta_{2:k}\boldsymbol{X}}$$

All else being held equal, if *days* increases by 10%, that is, by a factor of 1.1, then:

$$\frac{p}{1-p} = e^{\beta_0}(1.1days)^{\beta_1} e^{\beta_{2:k}\boldsymbol{X}} = e^{\beta_0}(days)^{\beta_1} e^{\beta_{2:k}\boldsymbol{X}} (\mathbf{1.1})^{\boldsymbol{\beta_1}}$$

That is, all else being held equal, for a 10% increase in *days* the odds of being successful change by a factor of $(\mathbf{1.1})^{\boldsymbol{\beta_1}}$
For our data this means that for a 10% increase in *days*, the odds of being successful increase by a factor of $(1.1)^{0.155}$ = **1.0149** when controlling for QualityPca and by a factor of $(1.1)^{0.16}$ = **1.0154** when controlling for QualityBinary.

(b) Effect of ln(*days*) on success, with binary interaction term

Continuing with the logic above, we examine the following equation:

logit(p) = log(p/(1-p))= $\beta_0 + \beta_1 \ln(days) + \beta_2 quality_{binary} + \beta_3 \ln(days)\, quality_{binary} + \beta_{4:k}\boldsymbol{X}$

$$\frac{p}{1-p} = e^{\beta_0 + \beta_1 \ln(days) + \beta_2 quality\_binary + \beta_3 \ln(days) quality\_binary + \beta_{4:k}\boldsymbol{X}}$$
$$= e^{\beta_0}(days)^{\beta_1} e^{\beta_2 quality\_binary} e^{\beta_3 \ln(days) quality\_binary} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when QualityBinary = 0** then:

$$[\frac{p}{1-p} | quality\_binary = 0] = e^{\beta_0}(\boldsymbol{days})^{\boldsymbol{\beta_1}} e^{\beta_{4:k}\boldsymbol{X}}$$

That is, all else being held equal, when considering **low-quality** campaigns, a 10% increase (that is an increase by a factor of 1.1) in *days* changes the odds of being successful by a factor of $(\mathbf{1.1})^{\boldsymbol{\beta_1}}$**.**

All else being held equal, **when *QualityBinary* = 1** then:

$$[\frac{p}{1-p} | qualityBinary = 1] = e^{\beta_0}(days)^{\beta_1} e^{\beta_2} e^{\beta_3 \ln(days)} e^{\beta_{4:k}\boldsymbol{X}} = e^{\beta_0 + \beta_2}(days)^{\beta_1}(days)^{\beta_3} e^{\beta_{4:k}\boldsymbol{X}} = e^{\beta_0 + \beta_2}(\boldsymbol{days})^{\boldsymbol{\beta_1 + \beta_3}} e^{\beta_{4:k}\boldsymbol{X}}$$

That is, all else being held equal, when considering high-quality campaigns, a 10% increase in *days* changes the odds of being successful by a factor of $(\mathbf{1.1})^{\boldsymbol{\beta_1 + \beta_3}}$

For our data this means that for low-quality campaigns, the odds of being successful increase by a factor of $(\mathbf{1.1})^{\mathbf{0.305}}$ = 1.03 for a 10% increase in the distance from the shock. In contrast, for high-quality campaigns the odds increase by a factor of $(\mathbf{1.1})^{\mathbf{0.305-0.244}}$ =1.006.

Matching:

(a) Effect of *before* on success, no interaction term

$$\text{logit(p)} = \log(\text{p}/(1-\text{p})) = \beta_0 + \beta_1 before + \beta_{2:k}\boldsymbol{X}$$

$$\frac{p}{1-p} = e^{\beta_0 + \beta_1 before + \beta_{2:k}\boldsymbol{X}}$$

$$\frac{p}{1-p} = e^{\beta_0 + \beta_1 before + \beta_{2:k}\boldsymbol{X}} = e^{\beta_0} e^{\beta_1 before} e^{\beta_{2:k}\boldsymbol{X}}$$

All else being held equal, **when QualityBinary = 0** then:

$$[\frac{p}{1-p}|Before = 0] = e^{\beta_0} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when QualityBinary = 1** then:

$$[\frac{p}{1-p}|Before = 1] = e^{\beta_0} e^{\beta_1} e^{\beta_{4:k}\boldsymbol{X}}$$

$$\frac{\frac{p}{1-p}|Before = 1}{\frac{p}{1-p}|Before = 0} = \frac{e^{\beta_0} e^{\beta_1} e^{\beta_{4:k}\boldsymbol{X}}}{e^{\beta_0} e^{\beta_{4:k}\boldsymbol{X}}} = e^{\beta_1} \rightarrow [\frac{p}{1-p}\Big|Before = 1] = [\frac{p}{1-p}\Big| Before = 0] * \boldsymbol{e^{\beta_1}}$$

This means that, all else being held equal, launching a campaign before the shock changes the odds of being successful by a factor of $\boldsymbol{e^{\beta_1}}$.

For our data, this means, that that the odds that a campaign launched before the shock will succeed are greater by a factor of $\boldsymbol{e}^{0.276}$ =1.3 compared with the odds that a (similar) campaign launched after the shock will succeed.

(b) Effect of *before* on success, with binary interaction term

$$\text{logit(p)} = \log(\text{p}/(1-\text{p})) = \beta_0 + \beta_1 before + \beta_2 quality\_binary + \beta_3 before * quality\_binary + \beta_{2:k}\boldsymbol{X}$$

$$\frac{p}{1-p} = e^{\beta_0 + \beta_1 before + \beta_2 quality\_binary + \beta_3 before * quality\_binary + \beta_{4:k}\boldsymbol{X}}$$

$$= e^{\beta_0} e^{\beta_1 before} e^{\beta_2 qualityBinary} e^{\beta_3 before * qualityBinary} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when before = 0 and QualityBinary = 0** then:

$$[\frac{p}{1-p}|Before = 0; qualityBinary = 0] = e^{\beta_0} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when before = 1 and QualityBinary = 0** then:

$$[\frac{p}{1-p}|Before = 1; quality\_binary = 0] = e^{\beta_0} e^{\beta_1} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when before = 0 and QualityBinary = 1** then:

$$[\frac{p}{1-p}|Before = 0; quality\_binary = 1] = e^{\beta_0} e^{\beta_2} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when before = 1 and QualityBinary = 1** then:

$$[\frac{p}{1-p}|Before = 1; quality\_binary = 1] = e^{\beta_0} e^{\beta_1} e^{\beta_2} e^{\beta_3} e^{\beta_{4:k}\boldsymbol{X}}$$

When considering **low-quality** campaigns (QualityBinary = 0):

$$\frac{\frac{p}{1-p}|Before = 1; quality\_binary = 0}{\frac{p}{1-p}|Before = 0; quality\_binary = 0} = \frac{e^{\beta_0}e^{\beta_1}e^{\beta_{4:k}\boldsymbol{X}}}{e^{\beta_0}e^{\beta_{4:k}\boldsymbol{X}}} = e^{\beta_1}$$

That is, when considering low-quality campaigns, being a "before" campaign changes the odds of being successful by a factor of $\boldsymbol{e^{\beta_1}}$.

When considering high-quality campaigns (QualityBinary = 1):

$$\frac{\frac{p}{1-p}|Before = 1; quality\_binary = 1}{\frac{p}{1-p}|Before = 0; quality\_binary = 1} = \frac{e^{\beta_0}e^{\beta_1}e^{\beta_2}e^{\beta_3}e^{\beta_{4:k}\boldsymbol{X}}}{e^{\beta_0}e^{\beta_2}e^{\beta_{4:k}\boldsymbol{X}}} = e^{\beta_1}\boldsymbol{e^{\beta_3}}$$

That is, when considering high-quality campaigns, launching a campaign before the shock changes the odds of being successful by a factor of $\boldsymbol{e^{\beta_1+\beta_3}}$. Additionally, this means that compared to the change in low-quality campaigns, the effect of *before* on the odds to succeed differs by a factor of $\boldsymbol{e^{\beta_3}}$.

For our data this means that for a low-quality campaign, the odds of being successful increase by a factor of $\boldsymbol{e}^{0.511} = 1.67$ if the campaign is launched before the shock, whereas for a high-quality campaign the odds increase only by a factor of $e^{\mathbf{0.511-0.403}} = 1.11$.

(c) Effect of *before* on success, with continuous interaction term

$$\text{logit(p)} = \log(\text{p}/(1-\text{p})) = \beta_0 + \beta_1 before + \beta_2 quality + \beta_3 before * qualityPca + \beta_{2:k}\boldsymbol{X}$$
$$\frac{p}{1-p} = e^{\beta_0 + \beta_1 before + \beta_2 quality + \beta_3 before * qualityPca + \beta_{4:k}\boldsymbol{X}}$$
$$= e^{\beta_0}e^{\beta_1 before}e^{\beta_2 quality}e^{\beta_3 before * qualityPca}e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when before = 0** then:

$$[\frac{p}{1-p}|Before = 0] = e^{\beta_0}e^{\beta_2 qualityPca}e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when before = 1** then:

$$[\frac{p}{1-p}|Before = 1] = e^{\beta_0}e^{\beta_1}e^{\beta_2 qualityPca}e^{\beta_3 qualityPca}e^{\beta_{4:k}\boldsymbol{X}}$$

$$\frac{\frac{p}{1-p}|Before = 1}{\frac{p}{1-p}|Before = 0} = \frac{e^{\beta_0}e^{\beta_1}e^{\beta_2 qualityPca}e^{\beta_3 qualityPca}e^{\beta_{4:k}\boldsymbol{X}}}{e^{\beta_0}e^{\beta_2 qualityPca}e^{\beta_{4:k}\boldsymbol{X}}} = e^{\beta_1}e^{\beta_3 qualityPca}$$

That is, for a 1-unit increase in quality, the ratio between the odds of being successful before and after equals:

$$\frac{\frac{p}{1-p}|Before = 1}{\frac{p}{1-p}|Before = 0} = \frac{e^{\beta_0}e^{\beta_1}e^{\beta_2 qualityPca+1}e^{\beta_3 qualityPca+1}e^{\beta_{4:k}\boldsymbol{X}}}{e^{\beta_0}e^{\beta_2 quality}e^{\beta_{4:k}\boldsymbol{X}}} = e^{\beta_1}e^{\beta_3(qualityPca+1)} = e^{\beta_1}e^{\beta_3 qualityPca+\beta_3}$$
$$= e^{\beta_1}e^{\beta_3 qualityPca}\boldsymbol{e^{\beta_3}}$$

This means that for a 1-unit increase in the quality, the ratio between the odds of being successful before and after changes by a factor of $\boldsymbol{e^{\beta_3}}$.

For our data, this means that when observing the effect on the odds to succeed, a 1-unit increase in QualityPca decreases the effect of being before the shock by a factor of $\boldsymbol{e}^{-0.120} = \mathbf{0.887}$. That is, as the quality increases the effect of being before the shock decreases. That is, high quality campaigns are less affected.

OLS Regressions Focusing on the Amount of Money Pledged

Time Proximity Identification:

(a) **Effect of ln(*days*) on ln(*pledged*), no interaction term**

$$\ln(pledged) = \beta_0 + \beta_1 \ln(days) + \beta_{2:k}\boldsymbol{X}$$
$$e^{\ln(pledged)} = e^{\beta_0 + \beta_1 \ln(days) + \beta_{2:k}\boldsymbol{X}}$$
$$pledged = e^{\beta_0 + \beta_1 \ln(days) + \beta_{2:k}\boldsymbol{X}} = e^{\beta_0} e^{\beta_1 \ln(days)} e^{\beta_{2:k}\boldsymbol{X}} = e^{\beta_0} (e^{(\ln(days))})^{\beta_1} e^{\beta_{2:k}\boldsymbol{X}} = e^{\beta_0} (days)^{\beta_1} e^{\beta_{2:k}\boldsymbol{X}}$$

All else being held equal, if *days* increases by 10%, that is, by 1.1, then:

$$pledged = e^{\beta_0} (1.1days)^{\beta_1} e^{\beta_{2:k}\boldsymbol{X}} = e^{\beta_0} (\mathbf{1.1})^{\boldsymbol{\beta_1}} (days)^{\beta_1} e^{\beta_{2:k}\boldsymbol{X}}$$

That is, all else being held equal, for a 10% increase in *days*, the amount of money pledged increases by $(\mathbf{1.1})^{\boldsymbol{\beta_1}}$.

For our data this means that for a 10% increase in distance from the shock, we see an increase by a factor of $(1.1)^{0.143} = 1.014$ when controlling for QualityPca and by a factor of $(1.1)^{0.18} = 1.017$ when controlling for QualityBinary. In other words, we see an increase of 1.4-1.7% in the average amount pledged.

If we consider a 50% increase in distance from the shock, we see an increase by a factor of $(1.5)^{0.143} = 1.06$ - $(1.5)^{0.18} = 1.076$, that is, an increase of 6-7.6% in the average amount pledged.

(b) **Effect of ln(*days*) on ln($\boldsymbol{pledged}$) with interaction term**

$$\ln(pledged) = \beta_0 + \beta_1 \ln(days) + \beta_2 quality\_binary + \beta_3 \ln(days)\, quality\_binary + \beta_{4:k}\boldsymbol{X}$$
$$e^{\ln(pledged)} = e^{\beta_0 + \beta_1 \ln(days) + \beta_2 quality\_binary + \beta_3 \ln(days) quality\_binary + \beta_{4:k}\boldsymbol{X}}$$
$$pledged = e^{\beta_0 + \beta_1 \ln(days) + \beta_2 quality\_binary + \beta_3 \ln(days) quality\_binary + \beta_{4:k}\boldsymbol{X}}$$
$$= e^{\beta_0} e^{\beta_1 \ln(days)} e^{\beta_2 quality\_binary} e^{\beta_3 \ln(days) * quality\_binary} e^{\beta_{4:k}\boldsymbol{X}}$$
$$= e^{\beta_0} (e^{(\ln(days))})^{\beta_1} e^{\beta_2 quality\_binary} e^{\beta_3 \ln(days) quality\_binary} e^{\beta_{4:k}\boldsymbol{X}}$$
$$= e^{\beta_0} (days)^{\beta_1} e^{\beta_2 quality\_binary} e^{\beta_3 \ln(days) quality\_binary} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when QualityBinary = 0** then:

$$pledged | quality\_binary = 0 = e^{\beta_0} (days)^{\beta_1} e^{\beta_{4:k}\boldsymbol{X}}$$

That is, all else being held equal, for a 10% increase in *days*, the amount of money pledged to low-quality campaigns increases by a factor of $(\mathbf{1.1})^{\boldsymbol{\beta_1}}$.

All else being held equal, **when QualityBinary = 1** then:

$$pledged | quality\_binary = 1 = e^{\beta_0} (days)^{\beta_1} e^{\beta_2} e^{\beta_3 \ln(days)} e^{\beta_{4:k}\boldsymbol{X}} = e^{\beta_0 + \beta_2} (days)^{\beta_1} (days)^{\beta_3} e^{\beta_{4:k}\boldsymbol{X}} = e^{\beta_0 + \beta_2} (\boldsymbol{days})^{\boldsymbol{\beta_1 + \beta_3}} e^{\beta_{4:k}\boldsymbol{X}}$$

That is, all else being held equal, for a 10% increase in *days*, the amount of money pledged to high-quality campaigns increases by a factor of $(\mathbf{1.1})^{\boldsymbol{\beta_1 + \beta_3}}$.

For our data this means that for low-quality campaigns a 10% increase in distance from the shock is expected to yield an increase by a factor of $(1.1)^{0.265} = \mathbf{1.026}$ (2.6%), whereas for high-quality campaigns a 10% increase in distance is expected to yield only a $(1.1)^{0.265-0.192} = \mathbf{1.007}$ (0.7%) increase in the amount pledged.

<u>Matching:</u>

(a) **Effect of *before* on ln($\boldsymbol{pledged}$), no interaction term**

$$\ln(pledged) = \beta_0 + \beta_1 before + \beta_{2:k}\boldsymbol{X}$$
$$e^{\ln(pledged)} = e^{\beta_0 + \beta_1 before + \beta_{2:k}\boldsymbol{X}}$$
$$pledged = e^{\beta_0 + \beta_1 before + \beta_{2:k}\boldsymbol{X}} = e^{\beta_0} e^{\beta_1 before} e^{\beta_{2:k}\boldsymbol{X}}$$

All else being held equal, **when QualityBinary = 0** then:

$$pledged|Before = 0 = e^{\beta_0} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when QualityBinary = 1 t**hen:

$$pledged|Before = 1 = e^{\beta_0} e^{\beta_1} e^{\beta_{4:k}\boldsymbol{X}}$$

$$\frac{pledged|Before = 1}{pledged|Before = 0} = \frac{e^{\beta_0} e^{\beta_1} e^{\beta_{4:k}\boldsymbol{X}}}{e^{\beta_0} e^{\beta_{4:k}\boldsymbol{X}}} = e^{\beta_1} \rightarrow [pledged|Before = 1] = [pledged|Before = 0] * e^{\beta_1}$$

These results mean that, all else being held equal, being a "before" campaign increases the amount of money pledged by a factor of $\boldsymbol{e^{\beta_1}}$.

For our data, this means that the odds of a "before" campaign succeeding are greater by a factor of $\boldsymbol{e}^{0.310}$ =1.36 (when controlling for QualityPca) compared with those of (similar) campaigns launched after the shock (when controlling for QualityBinary we see an increase by a factor of $\boldsymbol{e}^{0.360}$ =1.43).

(b) **Effect of *before* on ln($\boldsymbol{pledged}$), with binary interaction term**

$$\ln(pledged) = \beta_0 + \beta_1 before + \beta_2 quality\_binary + \beta_3 before * quality\_binary + \beta_{2:k}\boldsymbol{X}$$
$$e^{\ln(pledged)} = e^{\beta_0 + \beta_1 before + \beta_2 quality\_binary + \beta_3 before * quality\_binary + \beta_{4:k}\boldsymbol{X}}$$
$$pledged = e^{\beta_0 + \beta_1 before + \beta_2 quality\_binary + \beta_3 before * quality\_binary + \beta_{4:k}\boldsymbol{X}}$$
$$= e^{\beta_0} e^{\beta_1 before} e^{\beta_2 quality\_binary} e^{\beta_3 before * quality\_binary} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when *before* = 0 and QualityBinary = 0** then:

$$[pledged|Before = 0; quality\_binary = 0] = e^{\beta_0} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when *before* = 1 and QualityBinary = 0** then:

$$[pledged|Before = 1; quality\_binary = 0] = e^{\beta_0} e^{\beta_1} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when *before* = 0 and QualityBinary = 1** then:

$$[pledged|Before = 0; qualityBinary = 1] = e^{\beta_0} e^{\beta_2} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when *before* = 1 and QualityBinary = 1** then:

$$[pledged|Before = 1; quality\_binary = 1] = e^{\beta_0} e^{\beta_1} e^{\beta_2} e^{\beta_3} e^{\beta_{4:k}\boldsymbol{X}}$$

When considering **low-quality** campaigns (QualityBinary = 0):

$$\frac{pledged|Before = 1; qualitybinary = 0}{pledged|Before = 0; qualityBinary = 0} = \frac{e^{\beta_0} e^{\beta_1} e^{\beta_{4:k}\boldsymbol{X}}}{e^{\beta_0} e^{\beta_{4:k}\boldsymbol{X}}} = e^{\beta_1}$$

That is, for low-quality campaigns, being a "before" campaign increases the average amount pledged by a factor of $\boldsymbol{e^{\beta_1}}$.

When considering **high-quality** campaigns (QualityBinary=1):

$$\frac{pledged|Before = 1; quality\_binary = 1}{pledged|Before = 0; quality\_binary = 1} = \frac{e^{\beta_0} e^{\beta_1} e^{\beta_2} e^{\beta_3} e^{\beta_{4:k}\boldsymbol{X}}}{e^{\beta_0} e^{\beta_2} e^{\beta_{4:k}\boldsymbol{X}}} = e^{\beta_1} e^{\beta_3}$$

That is, for high-quality campaigns, being a "before" campaign increases the average amount pledged by a factor of $\boldsymbol{e^{\beta_1+\beta_3}}$. Additionally, this means that when compared to the increase in low quality campaigns, the effect of *before* on the amount pledged to high-quality campaigns is greater by a factor of $\boldsymbol{e^{\beta_3}}$.

For our data this means that for low-quality campaigns, being a "before" campaign increases the amount of money pledged by a factor of $\boldsymbol{e}^{0.621} = 1.86$, whereas for high-quality campaigns, being a "before" campaign increases the amount of money pledged by a factor of only $e^{\mathbf{0.621-0.528}}$ =1.10.

(c) **Effect of *before* on ln($\boldsymbol{pledged}$), with a continuous interaction term**

$$\ln(pledged) = \beta_0 + \beta_1 before + \beta_2 quality + \beta_3 before * quality\_pca + \beta_{2:k}\boldsymbol{X}$$
$$e^{\ln(pledged)} = e^{\beta_0 + \beta_1 before + \beta_2 quality\_pca + \beta_3 before * quality\_pca + \beta_{4:k}\boldsymbol{X}}$$
$$pledged = e^{\beta_0 + \beta_1 before + \beta_2 quality\_pca + \beta_3 before * quality\_pca + \beta_{4:k}\boldsymbol{X}} = e^{\beta_0} e^{\beta_1 before} e^{\beta_2 quality\_pca} e^{\beta_3 before * quality\_pca} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when *before* = 0** then:

$$[pledged|Before = 0] = e^{\beta_0} e^{\beta_2 quality\_pca} e^{\beta_{4:k}\boldsymbol{X}}$$

All else being held equal, **when *before* = 1** then:

$$[pledged|Before = 1] = e^{\beta_0} e^{\beta_1} e^{\beta_2 quality\_pca} e^{\beta_3 quality\_pca} e^{\beta_{4:k}\boldsymbol{X}}$$

$$\frac{pledged|Before = 1}{pledged|Before = 0} = \frac{e^{\beta_0} e^{\beta_1} e^{\beta_2 quality\_pca} e^{\beta_3 quality\_pca} e^{\beta_{4:k}\boldsymbol{X}}}{e^{\beta_0} e^{\beta_2 quality\_pca} e^{\beta_{4:k}\boldsymbol{X}}} = e^{\beta_1} e^{\beta_3 quality\_pca}$$

That is, for a 1-unit increase in quality, the ratio between money pledged before and money pledged after equals:

$$\frac{pledged|Before = 1}{pledged|Before = 0} = \frac{e^{\beta_0} e^{\beta_1} e^{\beta_2 quality\_pca} e^{\beta_3 quality\_pca} e^{\beta_{4:k}\boldsymbol{X}}}{e^{\beta_0} e^{\beta_2 quality\_pca} e^{\beta_{4:k}\boldsymbol{X}}} = e^{\beta_1} e^{\beta_3 (quality\_pca + 1)} = e^{\beta_1} e^{\beta_3 quality\_pca + \beta_3}$$
$$= e^{\beta_1} e^{\beta_3 quality\_pca} \boldsymbol{e^{\beta_3}}$$

This means that for a 1-unit increase in quality, the ratio between the amount pledged before the shock and the amount pledged after the shock changes by a factor of $\boldsymbol{e^{\beta_3}}$.

For our data, this means that when observing the effect on the amount pledged, a 1-unit increase in *QualityPca* decreases the effect of being a "before" campaign by a factor of $\boldsymbol{e}^{-0.116} = \mathbf{0.89}$. That is, as the quality increases, the effect of being a "before" campaign decreases, such that higher-quality campaigns are less affected.