Three Essays at the Interface of Operations Management, Accounting and Entrepreneurship

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This dissertation is a study on the role that metrics and measures serve to incentivize actions by stakeholders whose payoffs are related to how these metrics perform relative to a goal. Specifically, stakeholders maximizing individual payoffs by affecting these measures, may lead to actions that jeopardizes the larger system objective. I study this phenomenon (referred as Goodhart's Law) in the areas of Crowdfunding and Supply Chains. In crowdfunding an entrepreneur sets a target amount to raise, through the duration of a live "campaign." Unless the target is reached, the entrepreneur does not get the investments put forth by investors ("backers," in crowdfunding parlance). If the target amount is raised, the entrepreneur is obligated to deliver the physical product to the investors. The intended purpose of having the target as threshold is to incentivize the entrepreneurs to set a target amount that is large enough to cover for the product development cost, so that the entrepreneur does not find itself in a position where the campaign manages to reach the target, and yet does not have enough to start production. In chapter 2 we find that an entrepreneur, responding rationally to a platform's rule of "campaign promotion," sets a target amount that is lower than the product development cost and exposes backers to the risk of non-delivery. In chapter 3, the entrepreneur can choose to not pursue production after observing the subscription level of the crowdfunding campaign. The investors are exposed to the risk of non-delivery when the crowdfunding campaign manages to reach the target, and yet the entrepreneur chooses to not pursue production. To exercise its right to not produce, the entrepreneur pays a premium to the supplier who supplies the parts to the entrepreneur. In chapter 4, I critique the Cash Conversion Cycle, a measure for operational efficiency. Including individual firm differences of sales growth rates, fiscal year endings and seasonality can significantly alter the interpretations. We show that a lower cash conversion cycle can merely be a result of firm specific differences which, if unaccounted, can be mistaken for better operational efficiency.

Table of Contents

Preface . . . xiii

1.0 Introduction . . . 1

2.0 How Does the Rule to Promote Campaigns by a Crowdfunding Platform Affect Target Setting and Sharing of Campaign's Revenues? . . . 4

2.1 Introduction . . . 4

2.2 Literature Review . . . 9

2.3 Model . . . 12

2.4 Equilibrium Analysis for the Fractional Threshold (FT) Rule . . . 15

2.4.1 Case 1: Low fractional threshold . . . 17

2.4.2 Case 2: Intermediate fractional threshold . . . 21

2.4.3 Comparison of FT and Random Selection Promotion Rules for Low and Intermediate Threshold Cases. . . . 23

2.4.4 Case 3: High fractional threshold . . . 24

2.5 Setting the Sharing Rule of Campaign Revenues . . . 28

2.5.1 The platform can customize the sharing rule . . . 29

2.5.2 The platform sets a uniform sharing rule for heterogeneous campaigns 30

2.6 Concluding Remarks and Future Extensions . . . 35

3.0 Effect of Wholesale Price Contract on Target and Pledge amount in a Crowdfunding Campaign . . . 38

3.1 Introduction . . . 38

3.2 Literature Review . . . 42

3.3 Model . . . 45

3.4 Choice of optimal Target, Pledge and Wholesale Price with no price discrimination . . . 51

3.4.1 Effect of Contingent Wholesale price contract *without* "No-Production" penalty (NOP regime) . . . 51

3.4.2 Effect of Contingent Wholesale price contract *with* "No-Production" penalty (WOP regime) 54
3.4.3 Numerical Analysis - Same Price Regime 55
3.5 Price Discrimination when crowdfunding backers and regular buyers have different valuation 61
3.5.1 Numerical Analysis - Payoffs with Price Discrimination 64
3.6 Conclusion 67
4.0 Effect of Seasonality, Sales Growth and Fiscal Year End on the Cash Conversion Cycle 70
4.1 Introduction 70
4.2 Literature Review 74
4.3 Model and Notation 77
4.3.1 Days of Sales Outstanding 78
4.3.2 Days of Inventory Outstanding 79
4.3.3 Days of Payable Outstanding 79
4.4 Development of Hypotheses 80
4.4.1 Effect of Sales Growth Rate and Firm Type on CCC 80
4.4.2 Mediation Effect of Time through Sales on CCC 82
4.4.3 Effect of Fiscal Year End and Seasonality on CCC 83
4.4.3.1 CCC for Demand with Seasonality and Secular Trend . . 86
4.5 Empirical Analysis 90
4.5.1 Model Specification and Analysis 92
4.5.1.1 Aggregate Level Analysis (Model AL) 92
4.5.1.2 Firm Level Analysis (Model FL) 94
4.5.2 Results 95
4.5.2.1 Model AL Results 95
4.5.2.2 Model FL Results 98
4.5.3 Robustness Checks 101
4.6 Conclusion 103
5.0 Conclusions 106

Appendix A. Chapter 2 108
A.1 Tables and Figures 108
A.2 Proofs of Propositions, Lemmas and Corollaries 110
A.2.1 Proof of Proposition 1 110
A.2.2 Proof of Proposition 2 111
A.2.3 Proof of Proposition 3 111
A.2.4 Proof of Corollary 1 111
A.2.5 Proof of Proposition 4 112
A.2.6 Proof of Corollary 2 112
A.2.7 Proof of Proposition 5 113
A.2.8 Proof of Proposition 6 113
A.2.9 Proof of Lemma 2 113
A.2.10 Proof of Proposition 7 114
A.3 Extensions of the model 114
A.3.1 Allowing informed backers to withdraw pledges when few other informed backers participate 114
A.4 General distribution function of the informed backer population 116
A.5 Empirical Analysis for Kickstarter Data 118
Appendix B. Chapter 3 122
B.1 Proofs 122
B.1.1 Proof of Lemma 3.3 123
B.1.2 Proof of Lemma 3.4 123
B.2 Figures - Comparative Statics without Price Discrimination 124
B.3 Figures - Comparative Statics with Price Discrimination 127
Appendix C. Chapter 4 128
C.1 Detailed Results 128
C.2 Method of Firm Classification 134
C.2.1 *CCC* Comparison - Hackett Group 135
C.3 Proofs of Propositions 4.1 and 4.2 136
C.3.1 Proof of Proposition 4.1 136

C.3.2 Development of Hypothesis 4.2 137
C.3.3 Proof of Proposition 4.2 138
C.4 Demand Patterns 139
C.5 Variance-Covariance Table for Model *AL* 140
C.6 Computational Tables 141
C.7 A Note on the Difference between Cash Conversion Cycle and Working Capital 147
C.7.1 Introduction 147
C.7.2 Effect of changing *FYE* on Working Capital and *CCC* for constant demand. 148
C.7.2.1 Effect of *FYE* on Working Capital and *CCC* for seasonal demand. 150
C.7.2.2 Effect of changing *FYE* on Working Capital and *CCC* for demand with trend only. 152
References 154

List of Tables

1.1 Research Area - Map with reference to business maturity and discipline. . . 3
4.1 Sensitivity of *CCC* to change in *SGR* for a linear demand form 81
4.2 Sensitivity of *CCC* to a change in *FYE* location 85
4.3 Change in *CCC* with *Seasonality* and *FYE*. 89
4.4 Results of **Model *AL*** variants with *CCC* as the dependent variable and for Model *S*. 97
4.5 Mediation Effect of *Time* on *CCC* by *FirmType* (95% Confidence Interval) 98
4.6 Model *FL*: Effect of *SGR* on *CCC* (Details in Appendix C.2) 99
4.7 Model *FL*: Firm Level Mediating Effect of *Time* on *CCC* (95% Confidence Interval) 99
4.8 **Model *RC***. The impact of change in *FYE* from Q4 end 101
A.1 Variable and parameter definitions 108
A.2 Results from Data Analysis of Kickstarter Recommended Campaigns 121
C.1 Model *AL*. Sensitivity of *CCC* to *Time* 128
C.2 Model *FL*. Effect of *SGR* on *CCC* 129
C.3 Model *FL*. Effect of *Time* on *CCC* 130
C.4 List of sample quotes (for the first half of 2019) 131
C.5 Summary of Notations 133
C.6 Basis of Firm Type Classification 134
C.7 *CCC* Analysis of Dell 135
C.8 *CCC* Analysis of HP 135
C.9 Model *AL*. Sensitivity of *CCC* to *Time* 136
C.10 12 month Demand for seasonality indices of 0.11 and 0.42 140
C.11 Summary statistics of industries with average *CCC* and *Sales* by *FYE* . . 141
C.12 List of firms used in this study with Ticker Symbols 142
C.13 Summary statistics of *CCC* for Retailers 144

C.14 Model RC. Parameter estimates for Models $RC1$ and $RC2$ 146

List of Figures

3.1 The stages in investment of a project by an entrepreneur and supplier through a crowdfunding campaign. 50

3.2 Effect of change in backer's risk exposure $Pr\left(x^{LT} - \frac{T}{p}\right)$ with increase in Reputation Cost R, Crowdfunding Signal ρ, and the Entrepreneur's Share of the campaign proceeds γ, under the **NOP** regime 56

3.3 Effect of change in backer's risk exposure $\Pr\left(x^{LT} - \frac{T}{p}\right)$ with increase in Reputation Cost R, Crowdfunding Signal ρ, and the Entrepreneur's Share of the campaign proceeds γ, under the **OP** regime 57

3.4 Entrepreneur's Preference for Impatient Backer's as evidenced by the highest payoff with changing Crowdfunding Signal ρ, and the Entrepreneur's Share of the campaign proceeds γ, under Price Discrimination 64

4.1 Timeline for the Zone of Influence (ZoI) relative to a Fiscal Year Ending at τ. 83

4.2 Seasonal Demand form $f(t)$ 87

4.3 Factors Influencing CCC 90

A.1 A snapshot of recommended projects in Kickstarter 109

A.2 Stages of a crowdfunding campaign 110

B.1 Effect of change in Pledge, Wholesale Price and Target with increase in Reputation Cost R, Crowdfunding Signal ρ, and the Entrepreneur's Share of the campaign proceeds γ, under the **NOP** regime 124

B.2 Effect of change in Pledge, Wholesale Price and Target with increase in Reputation Cost R, Crowdfunding Signal ρ, and the Entrepreneur's Share of the campaign proceeds γ, under the **WOP** regime 125

B.3 Effect of change in Total Channel Profit and Entrepreneur's Share in Total Channel Profit, under the **NOP** regime 126

B.4 Effect of change in Total Channel Profit and Entrepreneur's Share in Total Channel Profit, under the **WOP** regime 126

B.5 Effect of change in Pledge, Wholesale Price and Option Premium under Price Discrimination in the **WOP** regime 127
C.1 Demand with seasonality indices of 0.11 and 0.42 139

Preface

In my experience as a supply chain professional, I often had to work with novice entrepreneurs who were suppliers to TATA Hitachi, the firm I worked for before starting my PhD. One of their prime concerns was timely payment and ensuring liquidity. These were individuals who had little or no transactional history with our organization, and therefore no established credibility. It was then that I realized the unique problems a novice entrepreneur faces, specifically in the context of funds availability and liquidity. I realized that the *metric* through which the financial health of these businesses got evaluated was equally critical. This had always inspired me to look at operations management, not as a discipline in silo, but one that is deeply entwined with finance and accounting.

The three chapters of my thesis deal with generation of funds and monitoring liquidity. I look at the role of crowdfunding platforms in matching entrepreneurs in need of money with investors, and interpretation of the Cash Conversion Cycle to measure operational efficiency. Specifically, I study the impact of the "rule" to feature some campaigns in a crowdfunding platform's recommended pages, and "learning" from crowdfunding subscription levels, on an entrepreneur's ability to deliver on its commitments. In showing how crowdfunding platforms can discipline opportunistic entrepreneur behavior, policy makers can incorporate these ideas to improve the entrepreneur's product delivery commitment. In the context of supply chain, I highlight how Cash Conversion Cycle, a purported "scale-free" metric is susceptible to the time of measurement, unique differences of demand seasonality and growth rates.

Throughout this long journey of my pursuit for a PhD, my advisor, Professor Prakash Mirchandani has been a pillar of support, both academically and personally. By gently nudging me into areas that I had been sceptical about, he saw what I didn't when I embarked on these projects. I am also deeply indebted to Professor Esther Gal-Or for introducing me to the beauty of Game Theory in her seminar. The papers on crowdfunding stand a lot better due to her hands on involvement, constant support and encouragement. I am thankful to Professor Mihai Banciu, who provided unconditional support on all matters academic and otherwise. I am also very grateful to my other committee members; Professor Jennifer Shang and Professor Leon Valdes, who were generous in sparing time to provide support and advice in my most challenging moments. I would be remiss if I did not acknowledge the role of the doctoral office, especially Ms. Carrie Woods, without whose support I would have failed to make progress. A huge thank you to past and present inmates of 241 Mervis: Meheli, Mike, Krista, Tiffany and Jing, who made tough moments lighter and therefore bearable. Lastly, my deepest gratitude to the Port Authority of Pittsburgh for letting me commute for free. The passengers and drivers, some of whom I got to know personally, were typical Pittsburghers; friendly and warm. I will miss them!

They say it is not the goal but the pursuit that is important. The people who were most directly affected by my state; academic and emotional, were my parents and wife, Kusum. There are no words that can describe how grateful I feel for their support. Your companionship and encouragement gave me hope in the darkest of times. It is only fitting, therefore, that I dedicate this thesis to you.

1.0 Introduction

Following the financial crisis of 2008, the need to revitalize small businesses was acutely felt worldwide. To make capital more accessible for entrepreneurs, the US Congress signed the JOBS Act on April 5, 2012.[1] Crowdfunding, a product of the JOBS Act, soon became a preferred mode of raising funds for new business startups. Crowdfunding not only offered greater participation by including people with average or low incomes, it also served as a signal to convince investors of a promising future market (Roma et al. 2018). A crowdfunding platform facilitates transactions between an entrepreneur seeking funds from "backers" in exchange for a "pledge" amount. We study reward-based crowdfunding in which entrepreneurs get the money raised, and deliver "rewards" to "backers," only if the total amount raised exceeds a "target" amount the entrepreneur wants to raise (henceforth, a commercially "successful" campaign). If the campaign is "unsuccessful," the pledges are returned to the "backers." The intended use of a "target" threshold is to protect entrepreneurs and "backers" against delivery commitment unless the amount raised is sufficient for production. That is, the stated "target" should be more than the cost of product development. We investigate the role of a profit maximizing crowdfunding platform and supplier in engendering a situation where, although the campaign is successful, the raised amount either falls short of development cost or isn't sufficiently large to justify investment in product quality by the entrepreneur. In such a situation rewards cannot be delivered. The Pebble smart watch[2] and Zano drone[3] are among many instances where immensely "successful" campaigns failed to deliver "rewards" to backers. This thesis sheds light on the role of production, and therefore product delivery, being contingent on raising a minimum product development cost.

In chapter 2, I study how a crowdfunding platform's choice of a specific campaign promotion rule affects delivery risk. In chapter 3, I study the role of a supply chain contract in affecting the probability of delivery failure. The contract is exercised contingent on the

[1] `https://www.sec.gov/spotlight/jobs-act.shtml#:~:text=On%20April%205%2C%202012%2C%20the,%2C%20disclosure%2C%20and%20registration%20requirements.`

[2] `https://www.businessinsider.com/how-smartwatch-pioneer-pebble-lost-everything-2016-12`

[3] `https://www.bbc.com/news/technology-34069150`

subscription levels in crowdfunding being large enough to justify investment in quality by the entrepreneur. By studying the equilibrium conditions in these two chapters we can infer why many campaigns, which are otherwise remarkably successful in raising the target amount, may still fail to deliver the product to the investors. By studying the role of two important stakeholders, the platform and the supplier, I contribute to studies at the confluence of crowdsourcing and operations management (Allon and Babich 2020).

In chapter 4, I look at a metric that represents cash turnaround time of an organization, the Cash Conversion Cycle (CCC). A frequently used metric, CCC is purported to be a boundary spanning metric of operational efficiency. We find that CCC is sensitive to sales growth rate, seasonality and fiscal cycles which are exogenous to the operations of an organization. Benchmarking CCC with industry peers, therefore, is fraught with the risk of wrongfully attributing a lower CCC to good operating policy, when in reality, it maybe due to an advantageous demand seasonality, growth rate, and fiscal cycle. I study the sensitivity of CCC to seasonality, growth rate and fiscal year end by treating existing credit terms to suppliers and customers, and inventory processing time as parameters of an analytical model. Deriving our hypotheses from the model, we validate them empirically by compiling a dataset of firms that offer a rich variety in the sales growth they have experienced, their demand seasonality and fiscal cycle.

My thesis lies at the intersection of supply chain management, entrepreneurship and accounting. I position the thesis along the dimensions of business maturity and the specific discipline(s) it addresses (Table 1.1). Since chapter 2 looks at the role of a crowdfunding platform in affecting the decisions of the entrepreneur, it falls under a larger ambit of Platform Economics as applied to a startup. Chapter 3 looks at the role of a specific supply chain contract on the crowdfunding parameters set by an entrepreneur, and chapter 4 looks at the role a widely used accounting metric plays in conveying efficiency of a supply chain. In effect, the thesis brings caveats to the extant understanding of target and pledge amount as signals of quality in crowdfunding (Chakraborty and Swinney 2019); and of a low CCC to be a result of operational improvements and policy measures.

	Startup	Mature Firm
Platform Economics	Chapter 2	
Supply Chain	Chapter 3	Chapter 4
Accounting		Chapter 4

Table 1.1: Research Area - Map with reference to business maturity and discipline.

In summary, we study a new mechanism for fundraising, crowdfunding, and its vulnerability to fail as a mechanism, by inviting entrepreneurs who have "little to lose." Crowdfunding involves the "crowd" and therefore, anything that increases the crowd's risk of not getting their returns, merits investigation. As businesses grow in size, metrics need to be devised to gauge operating efficiency. However, when these metrics become the basis of compensating managers, people are incentivized to manage the metric rather than the objective it is designed to measure.[4] The cash conversion cycle, which is often treated as a scale free all encompassing measure of operating efficiency, runs the risk of being such a metric if, as we show, differences in sales growth rate, seasonality and fiscal year are not accounted for.

[4] This phenomenon is referred to as "Goodhart's Law" which is captured in the maxim: When a measure becomes a target, it ceases to be a good measure. A more rigorous statement for the same phenomenon from Goodhart (1975) is "Any observed statistical regularity will tend to collapse once pressure is placed upon it for control purposes."

2.0 How Does the Rule to Promote Campaigns by a Crowdfunding Platform Affect Target Setting and Sharing of Campaign's Revenues?

We investigate strategies a reward-based crowdfunding platform employs to align an entrepreneur's choice of pledge and target levels with its own preferences. We consider two instruments the platform can employ: the way it chooses to promote campaigns to potential backers, and its share of the campaign revenues. Kickstarter, for instance, promotes a select set of campaigns by compiling a list of projects on its "recommended list." We find that in choosing its promotion and sharing rule the platform exposes entrepreneurs to the risk of not generating sufficient funds to start production. Only when the damage to the platform's reputation, in case the entrepreneur fails to fulfil her obligations, is sufficiently high, does the platform's promotion and sharing rules strategies ensure that any promoted campaign will have sufficient funds to start production. The strategies utilized by the platform are more likely to ensure production when backers are more altruistic, when the development cost is lower, or when the entrepreneur has minimal liability and reputational cost in case production fails. In such instances, the entrepreneur is motivated to set a low target, which increases the likelihood that the funds raised are insufficient to start production despite raising enough to meet the campaign's target. The platform's choice of promotion and sharing rule is intended to rectify such misalignments on the part of the entrepreneur.

2.1 Introduction

Crowdfunding (CF) platforms have gained prominence as viable channels to raise funds for new projects. Participants on CF platforms consist of entrepreneurs seeking funds and investors (backers) [1] willing to contribute to campaigns. Unlike conventional investments, backers active on reward-based CF platforms do not anticipate growth in value of an un-

[1] For terms prevalent in the crowdfunding community, we refer the reader to https://help.kickstarter.com/hc/en-us/articles/115005028514-What-are-the-basics-

derlying asset. Instead, they expect consumption of a novel product in the future.[2] In a reward-based CF campaign, the entrepreneur chooses a funding target that determines the minimum amount necessary for the campaign to be declared successful, and a pledge amount that backers need to contribute to be entitled to the promised product if completed. If the aggregate pledge amount exceeds the target, the platform deducts its commission and remits the remaining fraction of the amount raised to the entrepreneur. When the entrepreneur receives the campaign funds, backers expect to receive a reward. If the campaign is unsuccessful in reaching the funding target, pledges are returned to backers.[3]

The entrepreneur can deliver the promised product only when her share of the campaign proceeds covers the development cost of the product. Hence, a higher target ensures that whenever the campaign is successful, the entrepreneur is also more likely to deliver the promised product to backers. As a result, a higher target allows the entrepreneur to raise the pledge amount because the expected payoff of the backer increases. Setting a very high funding target, however, reduces the likelihood of reaching the target, in which case neither the entrepreneur nor the platform receives any proceeds from the campaign. When the funding target is set low in comparison to the development cost, backers face greater risk of not receiving the promised product and losing their pledge. With non-delivery, both the entrepreneur and the platform may face legal costs and reputational losses. In fact, recent contractual changes have substantially increased the cost entrepreneurs face upon non-delivery of the promised product (Swanner 2014, Markowitz 2013). Similarly, competition in the CF market forces each CF platform to pay closer attention to preserving its reputation for trustworthiness.

The interests of the entrepreneur and the platform in setting the target level are not always aligned. Whereas the entrepreneur may anticipate sales in the external market (i.e., post-campaign sales) if the product development is successful, the profits of the platform accrue only from its share of the revenues generated in the CF campaign. In addition, in case of product non-delivery, the limited resources of an early-stage entrepreneur cap her liability cost, while the platform's loss is much greater when its trustworthiness is questioned

[2]We use "he" for an investor (backer), "she" for the entrepreneur and "it" for the platform.

[3]Such a rule is popularly known as All-or-Nothing, and is the focus of this paper. In other formats, a campaign keeps the amount even if the raised amount falls short of the target.

and its appeal to new backers and projects is weakened.

In this paper, we investigate strategies a platform can employ to motivate entrepreneurs to choose the pledge and target levels of the campaign that are consistent with its interests. We consider two instruments that the platform can employ: the rule to promote campaigns to potential backers and its share of campaign revenues. The platform plays an important role in providing extra visibility to some campaigns. Reward-based CF platforms promote a select set of campaigns by compiling a list of recommended projects. Because it is difficult for some backers to differentiate among the many campaigns active on a CF platform, being included on the "recommended list" carries great benefits to the entrepreneur.[4] The sharing rule of campaign revenues is also an important instrument at the platform's disposal. When the platform awards a larger share of campaign revenues to the entrepreneur, she is more likely to have sufficient funds to produce the product, thus lowering the likelihood of reputational losses to the parties due to promises being unfulfilled.

Because the platform has very limited verifiable information about the project quality at the time of its launch, it is unclear what its strategy should be for compiling its "recommended list." One rule that seems to be utilized by Kickstarter in choosing its "recommended list" is the success of a campaign, early after its launch, in raising a substantial share of its declared funding target. Figure 1 illustrates that recommended campaigns tend to be those that raised a substantial share of their declared funding target, soon after their launch. Raising a substantial share indicates that many backers are interested in the project. If early backers tend to be those who are better informed about the specifics of the project, a large number of early contributions can serve as a signal of a higher quality project to less informed potential backers.[5] Moreover, using the early success of the campaign in raising funds as a basis for promoting the campaign is also consistent with results reported in the herding and information cascades literature (Banerjee 1992, Bikhchandani et al. 1992, Chamley and Scaglione 2013). This literature has demonstrated that the convergence of beliefs among individuals about an uncertain environmental parameter leads to informa-

[4]Adomavicius et al. (2017) conduct a controlled experiment to show that willingness to pay increases for a highly recommended product, even if it is of poor quality.

[5]Hildebrand et al. (2016) demonstrate this possibility in the context of a peer-to-peer lending platform (Prosper.com), where the early investment of 'group leaders' incentivizes unsophisticated investors to extend loans to borrowers.

tion cascades, where individuals start disregarding their own private signals after observing overwhelming agreement by others.

By setting a high-enough threshold for promoting campaigns, measured by the proportion of the target raised, the platform can guarantee that the promoted campaign raises sufficient funds not only to meet its target but also to cover the development cost to start production. Thus, setting a high threshold reduces the risk of delivery failure by the entrepreneur, minimizing possible loss of reputation for both the platform and the entrepreneur. However, setting a very demanding threshold level for promotion implies that fewer campaigns are eligible for promotion. This reduces visibility of campaigns and size of potential backers, thus adversely affecting the platform's profits.

The sharing rule for campaign revenues introduces similar counteracting effects on the platform's profits. While a bigger share awarded to the entrepreneur increases the odds of successful product delivery, it also reduces the platform's share of the campaign revenues, and thus its expected profits. Our analysis suggests that when backers derive lower consumption or altruistic benefits, when there are fewer informed backers who can evaluate the product characteristics, when entrepreneurs incur significant reputational losses if they cannot deliver the product, and when the product development cost is high, the platform finds it optimal to lower its share of the campaign revenues. As well, if altruism plays a role in the decision of backers to fund the campaign and the platform's reputational cost is low, the revenue sharing rule selected by the platform does not prevent participation of some entrepreneurs who are projected, with certainty, to never deliver the promised product.

We consider an entrepreneur, who has access to only CF as a source of funding, and assume that potential backers of the campaign derive both consumption benefits when the product becomes available and altruistic benefits from helping novice entrepreneurs. Burtch et al. (2013) demonstrate that investors are, indeed, driven by motivation to help creators of new ideas when participating in CF campaigns. There are two types of backers in our model: informed and uninformed. Informed backers know about the campaign when it is launched. The number of informed backers who fund the campaign is a random variable, and the platform may choose to promote a campaign based upon the realization of this random variable. Our supplementary empirical investigation verifies that Kickstarter tends to include campaigns on its "recommended list" based upon their success in raising a substantial share of their declared target during the early period of the campaign.[6] Therefore, in formulating the platform's promotion strategy, we assume that the platform includes campaigns on its "recommended list" that are successful in raising a prespecified share of their declared target. We refer to this promotion rule as the Fractional Threshold (FT) rule. After the platform promotes the campaign, uninformed potential backers become familiar with the campaign and can also observe the level of contributions so far in the campaign. When a larger number of informed backers have already contributed, more uninformed backers are willing to contribute to the campaign. Hence, the uninformed use the number of the informed backers as a signal of the potential success of the project.

When backers are altruistic, we find that the entrepreneur sets a funding target that exposes backers to the risk of not receiving the product because, even though the funding target is reached, the amount raised is insufficient to start product development. We obtain this result despite our assumption that the entrepreneur can expect positive net profits from sale of the completed product in the external market. It seems that altruism causes entrepreneurs to intentionally raise the risk of forgoing future profits in favor of short-term proceeds from the campaign. We also find that the FT level for campaign promotion chosen by the platform may not ensure that the entrepreneur generates sufficient funds to start production. Hence, the platform may choose a threshold that does not eliminate the risk induced by the target setting behaviour of the entrepreneur. Only when the damage to its reputation, in case the entrepreneur is unable to fulfil her promises, is sufficiently high, does the platform choose a threshold level to guarantee that the necessary funds to start production are raised. Also, when the platform's promotion strategy does not ensure sufficient funds for starting production, we show that the platform's profits remain the same even if it switches from using the FT promotion rule to simply choosing campaigns randomly.

To the best of our knowledge, this is the first study that focuses on strategies that a CF platform can use to enhance its profitability. Earlier theoretical work on CF has focused

[6] Because crowdfunding platforms use the "Load More" or "Show More" buttons at the bottom of each page of recommended campaigns to continue displaying additional campaigns from the recommended list, we use improvement in the ranking of a campaign as a measure of the recommendation in our empirical investigation.

on strategies entrepreneurs should adopt to ensure success in raising funds or to facilitate learning about the state of the demand for their products. Belavina et al. (2019) is the only paper with which we are familiar that addresses the role of the platform in operating the CF market. The emphasis of this paper is on designing mechanisms to eliminate deliberate malicious intent and to alleviate the problem of performance opacity of the entrepreneur. We consider an environment where the inability of entrepreneurs to deliver their promised products is not the result of malicious intent. Instead, entrepreneurs fail to fulfill their promises because they are unable to raise sufficient funds or because they encounter technical difficulties. In our setting, the legal costs and reputational losses facing the platform and the entrepreneurs in case of non-delivery of the promised products play the role of disciplining the entrepreneurs against dishonest behavior.

The rest of the paper is organized as follows. In Section 2, we conduct a review of the literature. In Section 3, we describe the assumptions of the model. In Section 4, we derive the equilibrium implied by the FT promotion rule, for a fixed sharing rule of campaign revenues. In Section 5, we derive the optimal sharing rule of revenues chosen by the platform to maximize its profits, and in Section 6, we conclude the paper. We present the technical results related to this paper in two online appendices. Appendix A contains the proofs of our theoretical results, and Appendix B discusses two extensions of our model.

2.2 Literature Review

Although most early studies on CF are empirical (Ordanini et al. 2011, Agarwal et al. 2011, Mollick 2014, Ahlers et al. 2015, Burtch et al. 2013, Colombo et al. 2015, Mollick and Nanda 2016), there is a growing number of theoretical studies of late. These studies address various aspects of CF campaigns, mostly with a focus on the entrepreneur's behavior. One important theme in this stream is how entrepreneurs use CF campaigns as vehicles for learning about future demand of the product. Roma et al. (2018), for instance, demonstrate how demand information gained in the campaign can help entrepreneurs convince venture capitalists (VC) to invest in the company. Babich et al. (2019) study learning via CF campaigns when VC and/or bank financing can supplement funds raised in the campaign. Drawing from the real option literature, Chemla and Tinn (2019) investigate how the outcome of the CF campaign can guide the entrepreneur in her decision on whether to initiate production. This option to abandon production is especially valuable when the demand uncertainty is high. Our study does not address issues related to entrepreneurs using CF as a vehicle for learning. The only aspect of learning that we touch on is that of uninformed backers learning from the pledging behaviour of informed backers in their decision on whether to fund the campaign.

CF is also a price discrimination strategy when consumers have heterogenous product valuations. Hu et al. (2015) examine how a project creator offers a menu of product options in a CF campaign to facilitate price discrimination. Bender et al. (2019) show that allowing consumers to pledge can lead to more successful extraction of consumer surplus when they have different valuations and when the cost of gaining access to external funding is not prohibitive. Because all consumers in our model have the same valuation for the product, price discrimination is not relevant in our study.

The extant literature has also addressed whether signalling can resolve problems related to incomplete information of backers regarding the quality of crowdfunded projects. Chakraborty and Swinney (2019b) and Sayedi and Baghaie (2017), for instance, investigate how an entrepreneur can select instruments of the campaign (funding target and pledge) to signal project quality. While we do not formally model the type of incomplete information facing potential backers, in our model uninformed backers use the behavior of early backers in assessing prospects of the project.

The question of "why investors invest" has received extensive attention. Besides capital appreciation, extant studies show altruistic motives influence investment behaviour. In a controlled experiment, Gneezy et al. (2012) find that people are willing to incur an expense to validate their self-perceived social image. In the CF context, the desire for self-image confirmation, rather than purely utilitarian motives, may drive 'serial backers' to pledge. Andreoni (1989) studied the distinction between altruism and warm-glow in the context of a public good. We use the term altruism in our model broadly, to refer to any non-economic motives that might guide backer behaviour. Burtch et al. (2013) have confirmed the possible altruistic motives of backers in a CF marketplace for online journalism projects. They find evidence of a slowdown in contributions once participants observe that contributions by others have already reached a high level, and interpret this behavior as indication that altruism may guide the decision of backers in CF campaigns. We demonstrate that when backers have such non-economic motives, entrepreneurs may choose a funding target lower than that necessary to accomplish production, and the platform's share of campaign revenues may attract entrepreneurs who, with certainty, will never deliver the product to backers.

All the above studies focus on entrepreneur behaviour and not on platform strategies for governing campaigns. Rietveld et al. (2019) study specific factors that lead to endorsement of complements in the video game industry and find support that games with sales in the top 2.6 - 20th. percentile are more likely to be endorsed by the platform. We find that the percentage of target raised affects promotion in the first pages of a reward-based CF campaign. Belavina et al. (2019) is the only paper, to our knowledge, that addresses the platform's role in eliminating deliberate malicious intent of fund misappropriation by the entrepreneur and in reducing performance opacity of the entrepreneur. We address the platform's role in lowering the risk backers face of product non-delivery. Our model captures the reputational cost that entrepreneurs and platform incur when the entrepreneur reneges on delivering the reward. Wessel et al. (2017) and Gaessler and Pu (2019) study the choice and effect of moving from a manual review of campaigns before listing them in platforms to "open acceptance". By establishing a rule of campaign promotion, the platform attains the objective of providing lower visibility to some campaigns. Although not a binary screening process, we find that when a platform optimizes its revenue share, it may exclude campaigns with high development cost. The literature has also addressed other forms of CF, besides reward-based-campaigns. Belleflamme et al. (2014), for instance, compare reward-based and equity-based campaigns, where in the former funders are consumers who pre-order the product and in the latter funders invest in exchange for a share of future profits. Gal-Or et al. (2019) consider equity-based CF, where the investor and the entrepreneur populations differ by their risk profiles and ask whether competing platforms can appeal to different entrepreneur populations. Our paper focusses exclusively on reward-based CF.

To summarize, our main contribution to the literature stems from our focus on strategies a CF platform can use to enhance its profitability. We address the following questions: Is the target and pledge setting strategy of the entrepreneur fully aligned with the interests of the platform? When deciding which campaigns to promote, should the platform use a promotion strategy to ensure that the campaign cover the development cost? What characteristics of the CF environment determine the platform's share of campaign revenues? And, should the platform choose this rate to minimize the risk of production failure by the entrepreneur?

2.3 Model

There are two types of backers, informed and uninformed. Informed backers know about the campaign when it is launched and can evaluate its characteristics. Unless a campaign is promoted by the platform, the uninformed backers are either unaware of the project's existence or are uninterested in finding out information about it. Thus, uninformed backers back a campaign only if it is promoted. When a platform promotes a campaign in its "recommended list", the uninformed backers consider contributing to the campaign. At that time, the uninformed backers can also observe how many informed backers have funded the campaign. They interpret a larger number of informed backers as a signal of a higher quality project. Hence, the number of uninformed backers who fund the campaign increases with the number of informed backers that the campaign attracted before promotion.

The rule used by the platform to promote a campaign is to tie promotion to the campaign meeting a certain specified fraction α of its declared target.[7] We refer to this rule as the Fractional Threshold (FT) rule.[8] When promoted, the number of uninformed backers attracted to the campaign is determined as a non-negative multiple, δ of the number of informed backers. There is uncertainty regarding the size of the informed backer population. We designate by N the random size of the informed backer population and assume

[7] In a supplementary empirical investigation, we demonstrate that the ability of a campaign to cover a significant share of its declared target soon after its launch guides Kickstarter in its promotion strategy.

[8] Alternately when a campaign is promoted if the aggregate contributions from informed backers exceed a certain threshold level is available from the authors upon request. We refer to this rule as the Aggregate Threshold rule. The expected profits of the platform remain the same under both promotion rules, except when the reputational cost incurred by the entrepreneur in case of non-delivery of the product is relatively high.

this size to be distributed uniformly[9] over the support $\left[0, \bar{N}\right]$. Thus, if n is the realized number of informed backers, conditional on a campaign's promotion, the total size of the backer population becomes $n\left(1+\delta\right)$. Intuitively, uninformed backers use the realization of the number of informed backers as a proxy for the probability of project success. That is, if a total of $\bar{N}$ informed backers are able to evaluate projects in a certain category, and only n of them choose to back the project, uninformed backers infer that the probability of project success is $\frac{n}{\bar{N}}$. If the total size of the uninformed backer population on the platform is Z, then promoting the project will attract $\frac{nZ}{\bar{N}}$ new backers. Hence, defining δ to be $\frac{Z}{\bar{N}}$, we get an expansion of $n\delta$, as we suggest.[10]

The entrepreneur chooses two instruments when she launches a campaign: a target T and a pledge p. The target determines the minimum amount necessary for the campaign to be successful. Only when the campaign revenues reach the selected target, can the entrepreneur collect its share of the revenues. Paying the pledge amount, p entitles the backers to receive the product when successfully developed. We assume that the only source of funding available to the entrepreneur is the CF campaign. This assumption is consistent with the reality that early-stage entrepreneurs have very limited access to conventional funding sources such as banks or equity markets. Therefore, to initiate production, the entrepreneur needs to raise the development cost, M from the campaign. Even if enough funds to cover this cost are raised, technical difficulties may prevent the entrepreneur from delivering the product as promised. We designate the probability of technical success by k. If the entrepreneur raises sufficient funds to reach the target but is unable to deliver the promised product to backers, both the entrepreneur and the platform suffer reputational loss and legal costs of settling lawsuits because backers, in this case, lose their pledges. We designate the reputational cost incurred by the entrepreneur (platform) as R_e (R_p). Given that the entrepreneur has no financial sources, except CF, to cover the development cost, M, it is unlikely that she would be able to compensate disappointed backers by an amount bigger than M. Therefore, we assume $R_e < M$. If the entrepreneur completes and successfully delivers the product,

[9]In Appendix A.4, we show that our results remain qualitatively similar for a general distribution function.

[10]In Appendix A.3, we extend our investigation to allow for the possibility that some informed backers may withdraw their pledge upon observing a low number of other informed backers participating in the campaign.

she can expect additional profits π from selling the product in the external market, where $k\pi - (1-k)\,R_e > M$. Hence, we focus on projects that have a positive expected payoff from the external market.

We assume that informed backers are rational and fully informed of the values of the parameters M, π, R_e, R_p, and of the probability distribution function of the random variable N. They know that they may lose their pledges because the entrepreneur cannot always deliver the product. They incorporate this risk in their decision on whether to submit the required pledge p. All backers have the same willingness to pay for the product if delivered as promised, which we designate by g. This willingness to pay declines to $v \equiv kg$, when backers incorporate the possibility that the product might not be successfully produced even when the development cost is collected from the campaign.

In addition, backers are altruistic and derive additional utility from backing new entrepreneurs. We designate this altruistic utility by s, and assume that $s < v$. The parameter s measures the amount backers are willing to pledge even in absence of any promise of receiving a reward. The existence of altruism among contributors to CF campaigns has been discussed in Burtch et al. (2013). We assume that the informed backer population is not large enough to ensure that the development cost can be raised in the campaign. Recall that promoting the campaign has the potential to expand the population of backers by attracting more backers who were not initially interested in the project. Table A.1 summarizes our notation.

The game proceeds in the following stages. In the first stage, the platform chooses which fractional threshold level α to use in implementing the FT promotion rule and the fraction γ for sharing funds raised with the entrepreneur. In the second stage, the entrepreneur chooses the target level, T and pledge amount, p, while being aware of the platform's stage-one decisions. In the third stage, informed backers submit their pledges after observing the selection of the entrepreneur. In the fourth stage, the platform chooses whether to promote the campaign using the FT rule. If the campaign is promoted by the platform, the uninformed backers become aware of and invest in the project in the fifth stage. When the combined revenue from informed and uninformed backers exceeds the target, T, the campaign is declared successful. In this case, the platform collects a fraction $1-\gamma$ of the proceeds from the campaign and the entrepreneur retains the residual share γ. In the sixth and final stage, production takes place if the entrepreneur's share of revenues covers the development cost M. If the production stage is technically successful (with probability k), the entrepreneur delivers the promised product to the backers and receives the additional profit π from selling the product in the external market. If the entrepreneur is unable to deliver the product to backers either because of insufficient funds to cover development cost or because of technical difficulties, backers lose their investment, and both the entrepreneur and platform incur the reputational and legal costs R_e and R_p, respectively. Note that for production to occur in stage six, the total revenues raised in the campaign should exceed M/γ. We refer to a campaign as a commercial success if the revenues raised are at least as high as the target T set by the entrepreneur, and as a production success if the revenues raised in the campaign suffice to start production, that is, revenues exceed M/γ. In order for the campaign to be viable we assume that $\gamma p\,(1+\delta)\,\overline{N} > M$, namely in the best state, when the number of informed backers is realized at its highest value $\overline{N}$, the funds the entrepreneur receives from the campaign are sufficient to cover the development cost. Recall that if the campaign is not promoted, the funds raised do not cover the development costs, namely $\gamma p\overline{N} \leq M$. Figure A.1 depicts the stages of the game.

2.4 Equilibrium Analysis for the Fractional Threshold (FT) Rule

When using the FT rule, the platform promotes a campaign if the amount raised in the first round by informed backers exceeds a fraction α of the target T, namely if $pn \geq \alpha T$. An appropriate selection of the threshold α can guarantee commercial success of the campaign and/or that sufficient funds to start production become available. For instance, if $\alpha \geq \frac{1}{1+\delta}$, the commercial success of the campaign is assured. Promotion implies that $np \geq \alpha T$ and the commercial success of the campaign implies that $(1+\delta)\,np \geq T$. The former inequality imposes a more demanding constraint on the realization of the random variable N when $\alpha \geq \frac{1}{1+\delta}$, implying that when the campaign is promoted, it will definitely raise enough funds to meet the target. Similarly, when $\alpha \geq \frac{M}{\gamma T(1+\delta)}$, it is guaranteed that the aggregate funds raised in the campaign are sufficient to start production. Promotion implies that $np \geq \alpha T$ and the production success of the campaign implies that $(1+\delta)\, np \geq \frac{M}{\gamma}$.The former inequality imposes a more demanding constraint on n when $\alpha \geq \frac{M}{\gamma T(1+\delta)}$.

It is never optimal for the entrepreneur to set a target level higher than the amount of pledges required to start production.[11] Thus, we restrict attention to the case $T \leq \frac{M}{\gamma}$, and consider three cases depending on the FT value. We say that the FT value is:

- *low* if $\alpha < \frac{1}{1+\delta}$. In this case, neither the commercial nor the production success of the campaign can be guaranteed,

- *intermediate* if $\frac{1}{1+\delta} \leq \alpha < \frac{M}{\gamma T(1+\delta)}$. In this case, commercial success can be guaranteed but not production success, and

- *high* if $\alpha \geq \frac{M}{\gamma T(1+\delta)}$. In this case, both commercial and production success can be guaranteed.

We denote the low, intermediate, and high cases by L, I, and H respectively. In all the three cases we consider, we will assume that the entrepreneur sets the instruments of the campaign to ensure that informed backers are not exposed to the risk of losing their pledges when the campaign is not selected for promotion. Specifically, she does not set the target so low that she can collect the pledges of the informed backers when $pn < \alpha T$. We will later impose conditions on the parameters that guarantee that to be the case at the equilibrium. If $\alpha \leq 1$, the additional risk is definitely removed because when a campaign is not promoted $pn < \alpha T \leq T$, and the aggregate pledges of the informed backers are insufficient to meet the target when a campaign is not promoted.

[11] We show that when $T = \frac{M}{\gamma}$, the entrepreneur can set the pledge level at the highest willingness to pay of informed backers $v + s$. Hence, raising the target level further cannot increase the pledge level. As well, setting a higher target than $\frac{M}{\gamma}$ does not reduce the risk of the entrepreneur not delivering the product. The only effect of raising the target beyond $\frac{M}{\gamma}$ is to lower the likelihood that the campaign is commercially successful, thus reducing the expected profits of the entrepreneur.

2.4.1 Case 1: Low fractional threshold

Because promotion of the campaign cannot guarantee either commercial success or start of production in this case, the expected payoff of the informed backer can be expressed as

$$\mathbb{E}\left(\Pi_b^L\right) = s + \left[v\left[1 - \frac{M}{\gamma\left(1+\delta\right)p\overline{N}}\right] - p\left[1 - \frac{T}{\left(1+\delta\right)p\overline{N}}\right]\right] \tag{2.1}$$

where $\mathbb{E}\left(\Pi_b^L\right)$ denotes the expected payoff of an informed backer for the low fractional threshold case. Despite his ability to evaluate the project quality at the time of submitting his pledge, an informed backer faces several uncertainties. He is uncertain whether the platform will promote the campaign. He is also uncertain of how many other informed backers will back the project, and whether production will materialize even if the platform promotes the campaign. If the platform does not promote the project, the payoff of informed backers is s given our assumption that the entrepreneur does not set the target so low that the informed backers face the risk of losing their pledges when the campaign is not promoted. If the platform promotes the project, informed backers derive the expected benefit[12] v from consuming the product if production is successful, namely if the proceeds of the campaign are sufficient to cover the development cost (if $\gamma p\left(1+\delta\right)n \geq M$). They must pay the pledge whenever the campaign is commercially successful (when $p\left(1+\delta\right)n \geq T$). Note that in all cases informed backers derive the additional altruistic benefit s from supporting new entrepreneurs. This benefit is added to the payoff regardless of whether backers get to consume the product. [13]

Since for Case 1, the conditions $\gamma p\left(1+\delta\right)n \geq \frac{M}{\gamma}$ and $p\left(1+\delta\right)n \geq T$ are more binding than the condition necessary for promotion, $pn \geq \alpha T$, the prior probabilities of production and commercial success do not depend on the threshold level α selected by the platform. Recall that informed backers are concerned about prior probabilities because at the time of their submitting the pledge they are uncertain of whether the campaign will be promoted and whether there are sufficiently many informed backers to support commercial success or the start of production. The instruments selected by the entrepreneur must ensure that

[12] Recall that $v = kg$, thus the informed backers incorporate the likelihood of the technical success of the entrepreneur in forming their expected benefit.

[13] We implicitly assume that capital markets are perfect, implying that backers don't face a budget constraint. Specifically, they can procure funds to invest in any project that they perceive to be profitable. The fact that many backers, especially those who are better informed, may be venture capital funds justifies this assumption.

informed backers derive non-negative expected utility. From 2.1, therefore, we can solve for the highest pledge level that the entrepreneur can choose as a function of the target level. We express this highest level, $p^L(T)$ as follows:

$$p^L\left(T\right) = \begin{cases} \frac{\left[(1+\delta)(v+s)\bar{N}+T\right]+\sqrt{\left[(v+s)\left((1+\delta)\bar{N}\right)-T\right]^2-4\left[(1+\delta)\bar{N}\right]\left[v\frac{M}{\gamma}-(v+s)T\right]}}{2\left[(1+\delta)\bar{N}\right]} & \text{if } T < \frac{Mv}{\gamma(v+s)} \\ v+s & \text{if } T \geq \frac{Mv}{\gamma(v+s)} \end{cases} \tag{2.2}$$

From the expression 2.2, we observe that the pledge level is strictly increasing with the target for $T < \frac{Mv}{\gamma(v+s)}$. Moreover, the entrepreneur can extract the entire willingness to pay of backers, $v+s$, when setting a target at least at $\frac{Mv}{\gamma(v+s)}$. Interestingly, when $s > 0$, the last expression is strictly smaller than the campaign revenues of $\frac{M}{\gamma}$ needed to start production. Hence, when backers derive some altruistic benefits from participating in the campaign, the entrepreneur can expose them to the risk of production failure and still extract their full willingness to pay for participating in the campaign.

It also follows from 2.2 that the pledge level increases when the consumption or altruistic benefits (v or s) are higher, when the entrepreneur's share (γ) of the campaign revenues is larger, and when the development cost (M) is lower. While the effect of changes in v and s on the pledge level are to be expected, the effect of changes in the other variables require additional explanation. To understand the effect of the target level, note that when the entrepreneur sets a higher target, she reduces the likelihood that the campaign is commercially successful, but the product is never delivered to backers. This is also the case when γ is higher or when M is lower.

Next, we express the expected profits of the entrepreneur for the low fractional threshold case, $\mathbb{E}\left(\Pi_e^L\right)$ as a function of the pledge and target levels, as follows:

$$\begin{aligned} \mathbb{E}\left(\Pi_e^L\right) = \frac{\gamma p\left(1+\delta\right)\bar{N}}{2}\left[1-\left(\frac{T}{\left(1+\delta\right)p\bar{N}}\right)^2\right] \\ + \left[k\pi-\left(1-k\right)R_e-M\right]\left[1-\frac{M}{\gamma\left(1+\delta\right)p\overline{\bar{N}}}\right]-R_e\left[\frac{\frac{M}{\gamma}-T}{\left(1+\delta\right)p\overline{\bar{N}}}\right] \end{aligned} \tag{2.3}$$

when $T \leq \frac{M}{\gamma}$ and p is expressed in terms of T as in 2.2. The first term in 2.3 is the entrepreneur's expected revenues from the campaign. The second term measures the expected profits of the entrepreneur from external sale of the completed product if she collects sufficient funds to start production, and the last term corresponds to the entrepreneur's reputational cost if the campaign is a commercial but not a production success. When $T > \frac{M}{\gamma}$, the last term of 2.3 vanishes because production success is guaranteed. As well, in this region of target levels, it follows from 2.2 that the pledge level is equal to the backers' willingness to pay, $v + s$. As a result, the entrepreneur's expected payoff is a strictly decreasing function of the target level when $T > \frac{M}{\gamma}$, implying that the entrepreneur will never set his target level in this region. We summarize this result in Lemma 2.1.

Lemma 2.1. *The entrepreneur never sets the target at a level higher than M/γ, that is, she sets the target so that the amount she receives from the campaign does not exceed the development cost, M. Optimizing the entrepreneur's expected profits, $\mathbb{E}\left(\Pi_e^L\right)$ with respect to the target level yields the optimal target level, $T_e^{L^*}$ reported in Proposition 2.1.*

Proposition 2.1 (Optimal Target set by Entrepreneur for Low Threshold)**.**

$$\begin{aligned} \textit{If } R_e < \frac{Mv}{v+s},\ T_e^{L^*} &= \frac{Mv}{\gamma\,(v+s)}, \textit{ and} \\ \textit{If } R_e \geq \frac{Mv}{v+s},\ T_e^{L^*} &= \frac{R_e}{\gamma}. \end{aligned}$$

If the reputational cost incurred by the entrepreneur is relatively high (i.e., $R_e \geq \frac{Mv}{v+s}$), the optimal target level is set at $\frac{R_e}{\gamma}$. This level is higher the greater the reputational cost and the lower the share of campaign revenues awarded to the entrepreneur. When the reputational cost is not as high (i.e., $R_e < \frac{Mv}{v+s}$), the entrepreneur evaluates the effect of the target on both the expected revenues raised in the campaign and on her long-term profitability. A higher target level may introduce two counteracting effects on the profits of the entrepreneur. On one hand, a higher target reduces the likelihood that the campaign is commercially successful, thus reducing expected profits. On the other hand, it also leads to a higher pledge level and to improved long-term profits because the entrepreneur is less likely to incur reputational cost and more likely to raise sufficient funds to cover the development cost. It turns out that the latter effect dominates and the entrepreneur chooses the highest target level consistent with the region $T \leq \frac{Mv}{\gamma(v+s)}$, namely $T_e^{L^*} = \frac{Mv}{\gamma(v+s)}$ if $R_e \leq \frac{Mv}{v+s}$. In this case, the target level is lower the more altruistic backers are (i.e., the bigger s is) and the bigger the share of campaign revenues awarded to the entrepreneur (the bigger γ is). Note that regardless of the optimal target level chosen by the entrepreneur, it follows from 2.2 that she can set the pledge level equal to the maximum willingness to pay of backers, equal to $v+s$.

It is noteworthy that whenever backers derive some altruistic benefit from participating in the campaign, namely if $s>0$, the target level set by the entrepreneur is lower than the amount of funds necessary to start production. Both $\frac{Mv}{v+s}$ and $\frac{R_e}{\gamma}$ are smaller than $\frac{M}{\gamma}$ in this case. By setting the target at a level lower than $\frac{M}{\gamma}$, the entrepreneur exposes the backers to higher risk of not receiving the promised product despite a commercially successful campaign. We obtain this result despite our assumption that the entrepreneur can expect positive net profits from sale of the completed product in the external market. It seems that altruism causes the entrepreneur to intentionally raise the risk of foregoing future profits in favor of short-term proceeds from the campaign.

In order to support our assumption that informed backers are not exposed to the risk that they lose their pledges even when the campaign is not promoted, one of two scenarios are necessary. Either $\alpha<1$, or if $\alpha\geq 1$ then $T>\overline{N}p$. Given the result reported in Proposition 2.1, the last inequality imposes an additional condition on the parameters of the model when $\alpha\geq 1$, namely that $\max\left\{\frac{Mv}{\gamma(v+s)},\frac{R_e}{\gamma}\right\}>\overline{N}\left(v+s\right)$. The latter condition does not violate the requirement that the campaign is viable, namely that $(1+\delta)\,\overline{N}\left(v+s\right)>\frac{M}{\gamma}$, if δ is sufficiently big. Hence, when the expansion factor that is facilitated by promotion is sufficiently big, we are assured that there are parameter values that support the assumption we make regarding the reduced risk to backers.[14]

Given the optimal pledge and target setting of the entrepreneur we can now express the expected profits of the platform, $\mathbb{E}\left(\Pi_p\right)$ as follows:

$$\mathbb{E}\left(\Pi_p^L\right)=\frac{(1-\gamma)(1+\delta)(v+s)\bar{N}}{2}\left[1-\left(\frac{T}{(1+\delta)(v+s)\bar{N}}\right)^2\right]-(1-k)\,R_p\left[1-\frac{M}{\gamma(1+\delta)(v+s)\bar{N}}\right]-\frac{R_p(M\gamma-T)}{(1+\delta)(v+s)\bar{N}} \tag{2.4}$$

where $T=\frac{Mv}{\gamma(v+s)}$ if $R_e<\frac{Mv}{(v+s)}$ and $T=\frac{R_e}{\gamma}$ if $R_e\geq\frac{Mv}{(v+s)}$.

[14]Our model can be easily extended to allow for the possibility that informed backers are exposed to the additional risk of losing their pledge even when the campaign is not promoted. Our qualitative results remain the same with such an extension.

The first term of equation 2.4 measures the platform's expected revenues from the campaign and the last two terms measure the expected reputational cost the platform incurs when sufficient funds are raised in the campaign but the product is not delivered to backers, either because of technical difficulties arising in production (second term) or because of insufficient funds to start production (third term.)

It is noteworthy that the platform may be interested in a different target level than that selected by the entrepreneur. Consider, for instance, the environment where the entrepreneur chooses her target as $T_e^{L^*} = \frac{R_e}{\gamma}$. In this case, from 2.2, the pledge is a constant equal to $v+s$. The optimal target level from the platform's perspective, $T_p^{L^*}$, can be derived by optimizing its payoff function 2.4 with respect to T. This optimization yields that $T_p^{L^*} = \frac{R_p}{1-\gamma}$, which may be lower or higher than the level most preferred by the entrepreneur. Specifically, if $R_p > \left(\frac{1-\gamma}{\gamma}\right) R_e$ the platform would have preferred the entrepreneur to set a higher target level and the opposite is the case if $R_p < \left(\frac{1-\gamma}{\gamma}\right) R_e$. It is interesting that even when the liability borne by the platform for non-delivery of the product by the entrepreneur is lower than that borne by the entrepreneur (i.e., even when $R_p < R_e$) the platform may still sometimes prefer a higher target level than that chosen by the entrepreneur. This happens for relatively large values of the sharing rule γ chosen by the platform. Because in most CF campaigns $\gamma > 0.9$, the platform may indeed prefer a higher target level if its reputational cost is at least as high as 1/9th of the reputational cost borne by the entrepreneur.

2.4.2 Case 2: Intermediate fractional threshold

In this case, a promoted campaign will be definitely commercially successful but may not result in sufficient funds to start production. The expected payoff of the informed backer in this case, $\mathbb{E}\left(\Pi_b^I\right)$ is:

$$\mathbb{E}\left(\Pi_b^I\right) = s + \left[v\left(1 - \frac{M}{\gamma\left(1+\delta\right)p\overline{N}}\right) - p\left(1 - \frac{\alpha T}{p\bar{N}}\right)\right] \tag{2.5}$$

Setting $\mathbb{E}\left(\Pi_b^I\right) = 0$ yields the highest pledge level that the entrepreneur can set as a function of the target level, as follows:

$$p\left(T\right) = \begin{cases} \frac{\left[(v+s)\bar{N}+\alpha T\right]+\sqrt{\left[(v+s)\bar{N}-\alpha T\right]^2-4\bar{N}\left[\frac{v\left(\frac{M}{\gamma}\right)}{(1+\delta)}-(v+s)\alpha T\right]}}{2\bar{N}} & \text{if} < \frac{v\left(\frac{M}{\gamma(v+s)}\right)}{\alpha(1+\delta)} \\ v+s & \text{if} \quad \geq \frac{v\left(\frac{M}{\gamma(v+s)}\right)}{\alpha(1+\delta)} \end{cases} \tag{2.6}$$

The effect of changes in the parameters on the pledge level remains as in 2.4.1. In particular, a higher target level leads to a higher pledge. Next, we express the expected payoff of the entrepreneur $\mathbb{E}\left(\Pi_e^I\right)$:

$$\begin{aligned} \mathbb{E}\left(\Pi_e^I\right) = \Bigg\{ & \frac{\gamma\left(1+\delta\right)p\bar{N}}{2}\left[1-\left(\frac{\alpha T}{p\bar{N}}\right)^2\right] \\ & + \left(k\pi-\left(1-k\right)R_e-M\right)\left[1-\frac{M}{\gamma\left(1+\delta\right)p\bar{N}}\right]-R_e\left[\frac{M}{\gamma\left(1+\delta\right)p\bar{N}}-\frac{\alpha T}{p\bar{N}}\right] \end{aligned} \tag{2.7}$$

where $T \leq \frac{M}{\gamma}$ and p is given in 2.6.

The explanation for the terms in (2.7) is very similar to that discussed for the entrepreneur's expected profits in Case 1. The only difference is that the commercial success of the campaign is now tied to meeting the threshold target required for promotion, αT, instead of meeting the target. As discussed in Lemma 2.1 for Case 1, here as well, the entrepreneur will never set the target higher than $M\gamma$. In this region, the last term of (2.7) vanishes and the pledge according to (2.6) is equal to $v+s$. As a result, the entrepreneur's payoff is a strictly decreasing function of the target level when $T > M\gamma$.

The entrepreneur chooses the target level to maximize (2.7) subject to the expression derived for the pledge level in terms of the target level in (2.6). We report in Proposition 2.2 the optimal target levels, $T_e^{I^*}$ from the entrepreneur's perspective for the intermediate fractional threshold case.

Proposition 2.2 (Optimal Target set by Entrepreneur for Intermediate Threshold)**.**

$$\begin{aligned} &\textit{If } R_e < \frac{Mv}{v+s},\ T_e^{I^*} = \frac{vM}{\gamma\left(v+s\right)\alpha\left(1+\delta\right)},\ \textit{and} \\ &\textit{If } R_e \geq \frac{Mv}{v+s},\ T_e^{I^*} = \frac{R_e}{\gamma\alpha\left(1+\delta\right)}. \end{aligned}$$

As in the low fractional threshold case, in both regions of the reputational cost R_e included in Proposition 2.2, the entrepreneur is able to extract the entire surplus of backers by setting the pledge at the backers' maximum willingness to pay, $v + s$. Note that the target level in Case 2 is unambiguously lower than in Case 1. When the platform sets a more demanding threshold level α (recall that in Case 2, $\alpha \geq \frac{1}{1+\delta}$), it incentivizes the entrepreneur to lower the target in order to meet the more demanding threshold level for promotion. However, by comparing (2.3) and (2.7) at the optimal target values, we note that the likelihood of non-delivery of the product does not depend on the chosen value of α and is the same for both Cases 1 and 2.

Substituting the optimal values of the pledge and target selected by the entrepreneur into the expected profits of the platform, yields:

$$\mathbb{E}\left(\Pi_p^I\right) = \frac{(1-\gamma)(1+\delta)(v+s)\bar{N}}{2}\left[1-\left(\frac{\alpha T}{p\bar{N}}\right)^2\right] - (1-k)\,R_p\left(1-\frac{M}{\gamma(1+\delta)(v+s)\bar{N}}\right) - R_p\left[\frac{M}{\gamma(1+\delta)(v+s)\bar{N}} - \frac{\alpha T}{(v+s)\bar{N}}\right] \tag{2.8}$$

where $T = \frac{vM}{\gamma(v+s)\alpha(1+\delta)}$ if $R_e < \frac{vM}{v+s}$ and $T = \frac{R_e}{\gamma\alpha(1+\delta)}$ if $R_e \geq \frac{vM}{v+s}$.

Observe that (by substituting the value of T for either of the two cases of the entrepreneur's reputational cost), the expected profit of the platform does not depend on the threshold level the platform selects for promoting projects. In Proposition 2.3, we use expressions (2.4) and (2.8) to compare the expected profits of the platform in Cases 1 and 2.

Proposition 2.3. *When the threshold level α selected by the platform does not guarantee the production success of the campaign (i.e., $\alpha < \frac{M}{\gamma T(1+\delta)}$), the expected profit of the platform is the same irrespective of whether or not the selected threshold value, α ensures the commercial success of the campaign. Moreover, the expected profit is independent of the value of the selected threshold level α.*

2.4.3 Comparison of FT and Random Selection Promotion Rules for Low and Intermediate Threshold Cases.

In view of the result reported in Proposition 2.3, we now investigate whether the platform benefits from using the FT promotion rule if α is either low or intermediate. Specifically, we investigate whether by using a simpler promotion rule, called random selection (RS), that identifies campaigns for promotion randomly after informed backers have submitted their pledges, the platform can earn the same expected profits as with the FT approach. To facilitate this comparison, we keep γ the same for both the FT and RS approaches. Corollary 2.1 shows that, under these conditions, the platform is indifferent between the FT and RS rules.

Corollary 2.1. *If by utilizing the FT promotional rule, the platform does not attempt to ensure that sufficient funds to start production become available (i.e., $\alpha < \frac{M}{\gamma T(1+\delta)}$) and γ is the same, the platform is indifferent between using the RS and the FT promotional rules.*

The intuition behind this finding is as follows. Under Cases 1 and 2, the FT rule does not provide any additional favorable information about the campaign beyond the information regarding the realized number of informed backers. It is only this number that carries meaningful information about the quality of the project to uninformed backers. The promotion rule has some meaningful informational content only if it can reduce the likelihood of non-delivery of the product despite a commercially successful campaign. In Cases 1 and 2, the risk of product non-delivery is the same under both the RS and FT approaches. Therefore, the information observable by the backers at the time of promotion is the same regardless of the rule utilized by the platform, as is the total expected campaign revenue. Under both approaches, the platform receives the same expected revenues and is at the same risk of incurring reputational cost, thus making it indifferent between the two approaches.

From another perspective, when the FT rule utilizes a relatively low threshold level, backers still face the same risk of production failure in Cases 1 and 2 (despite guaranteed commercial success in Case 2), as they do with a random selection rule. The FT rule provides risk mitigating information only when it guarantees production success.

2.4.4 Case 3: High fractional threshold

In this case, both the commercial and the production success of the campaign are guaranteed if the campaign is promoted. As a result, we can set the pledge at the maximum level of $v+s$, and express the expected profits of the entrepreneur, $\mathbb{E}\left(\Pi_e^H\right)$ as follows:

$$\mathbb{E}\left(\Pi_e^H\right) = \frac{\gamma(1+\delta)(v+s)\bar{N}}{2}\left[1-\left(\frac{\alpha T}{(v+s)\bar{N}}\right)^2\right] + \left(k\pi - (1-k)\,R_e - M\right)\left[1-\frac{\alpha T}{(v+s)\bar{N}}\right]$$

Notice that the entrepreneur incurs the reputational cost in this case only because of technical failure and not because of lack of funds to start production. Because this objective is a decreasing function of the target level, the entrepreneur sets the lowest target consistent with this case, namely $T_e^{H*} = \frac{M}{\alpha\gamma(1+\delta)}$. The expected payoff of the platform, $\mathbb{E}\left(\Pi_p^H\right)$, can be expressed as:

$$\mathbb{E}\left(\Pi_p^H\right) = \frac{(1-\gamma)(1+\delta)(v+s)\bar{N}}{2}\left[1-\left(\frac{M}{\gamma(1+\delta)(v+s)\bar{N}}\right)^2\right] - (1-k)\,R_p\left(1-\frac{M}{\gamma(1+\delta)(v+s)\bar{N}}\right) \tag{2.9}$$

The first term of (2.9) is the expected revenue the platform collects from the campaign and the second term is the reputational loss it incurs when technical difficulties prevent the entrepreneur from delivering the product. It is noteworthy that even when ensuring the production success of the campaign, the platform does not eliminate completely the risk of non-delivery of the promised product by the entrepreneur. Unexpected technical difficulties may prevent, the entrepreneur from completing production successfully, even when raising sufficient funds to start production. However, by setting the fractional threshold for promotion sufficiently high, the platform eliminates the additional risk backers may face, that the entrepreneur will not have sufficient funds to start production despite a commercially successful campaign. As well, observe that the actual threshold level α for promotion does not affect the platform's expected profit. Any value of α that ensures production success generates the same expected profits for the platform. When the platform chooses a higher value of α, it incentivizes the entrepreneur to lower the target level T without changing the value of αT, which equals $\frac{M}{\gamma(1+\delta)}$ in all instances that ensure production success.[15] Importantly, the platform faces a tradeoff in its decision of whether to ensure the production success of the campaign. While the platform reduces its liability for product non-delivery, it reduces also its expected revenues from any given campaign. Because the requirement for

[15] For instance, when $\alpha = (1+\delta)$, $T = \frac{M}{\gamma(1+\delta)^2}$. This implies that when $n > \alpha T$ implies $n > \frac{M}{\gamma(1+\delta)}$, and any project that qualifies for promotion will definitely lead to the start of production.

promotion is more demanding, any given campaign is less likely to meet it, and therefore, less likely to deliver revenues for the platform.

In Proposition 2.4, we use the results obtained in Proposition 2.3 and the expression of the platform's profits in (2.9), to report how the platform chooses the promotional threshold level α.

Proposition 2.4 (Platform's choice of promotion threshold to ensure production success)**.** *For a fixed value of γ,*

- *If $R_e < \frac{vM}{(v+s)}$ and*
  - *a. If $R_p < \frac{(1-\gamma)M(2v+s)}{2\gamma(v+s)}$, the platform chooses α in a manner that does not guarantee production success (Low or Intermediate Threshold).*
  - *b. If $R_p \geq \frac{(1-\gamma)M(2v+s)}{2\gamma(v+s)}$ the platform chooses α to ensure production success (High Threshold).*
- *If $R_e \geq \frac{vM}{(v+s)}$ and*
  - *a. If $R_p < \frac{(1-\gamma)(M+R_e)}{2\gamma}$, the platform chooses α in a manner that does not guarantee production success (Low or Intermediate Threshold).*
  - *b. If $R_p \geq \frac{(1-\gamma)(M+R_e)}{2\gamma}$, the platform chooses α to ensure production success (High Threshold).*

According to Proposition 2.4, the platform does not always have an interest in ensuring the commencement of production unless the harm to its reputation upon non-delivery of the product is sufficiently high. The fact that CF platforms specifically absolve themselves of any responsibility[16] for either non-delivery of rewards or for poor quality of the product delivered implies, therefore, that the backers are exposed to the risk of non-delivery even when the campaign is successful as it may not lead to the start of production. Note that the platform is more likely to ensure the start of production if backers are more altruistic (higher s), development cost (M) is lower, expected valuation of the product (v) is lower, and the reputational cost incurred by the entrepreneur (R_e) is lower. In all of these instances, the

[16]Refer "Can Kickstarter refund the money if a project is unable to fulfill?" in the link `https://www.kickstarter.com/blog/accountability-on-kickstarter` . Indiegogo, a competing crowdfunding platform, lists similar disclaimers at `https://www.indiegogo.com/about/terms?utm_source=learn&utm_medium=referral&utm_campaign=ent-trustandsafety&utm_content=bodylink#/backingacampaign`.

minimum level of the platform's reputational cost that incentivizes the platform to ensure production success, specified in the Proposition 2.4 as $\frac{(1-\gamma)M(2v+s)}{2\gamma(v+s)}$ or $\frac{(1-\gamma)(M+R_e)}{2\gamma}$ are smaller, thus making it more likely that the reputational cost of the platform exceeds these minimum levels. We summarize these results in the next Corollary.

Corollary 2.2. *The platform is more likely to choose its FT rule of promotion to ensure production if the reputational cost incurred by the platform, R_p is higher, backers are more altruistic (i.e., higher value of s), the share of campaign revenue, γ awarded to the entrepreneur is higher and if product valuation (v), development cost (M), and the reputational cost borne by the entrepreneur (R_e) are lower.*

To provide some intuition for the results in Corollary 2.2, note that when s is higher or when v and R_e are smaller, the entrepreneur sets a lower target level if the threshold for promotion chosen by the platform does not guarantee production success. The lower target raises the odds that a commercially successful campaign is not a production success. Thus, the reduction of the target level raises the likelihood that the platform suffers reputational losses. The platform is more inclined, therefore, to raise the threshold level α to ensure that sufficient funds for the start of production are available. The comparative statics results with respect to R_p and M are quite intuitive. Higher R_p incentivizes the platform to ensure production success to prevent disgruntled backers from eroding the platform's reputation. A lower M implies that it is easier to generate sufficient campaign revenues to cover the development cost, thus making the FT rule to support production success easier to achieve. It is noteworthy that choosing campaigns randomly for promotion instead of selecting a campaign using the FT rule, cannot ensure that the campaign generates sufficient funds to start production. Hence, given Proposition 2.4 and Corollary 2.1, the advantage of using the FT rule over a random selection rule for promotion depends upon the extent to which the platform worries about the damage to its reputation when the entrepreneur cannot deliver the product to backers. We summarize the comparison of the FT and random rules of selection in the next Proposition.

Proposition 2.5 (Choice of Fractional Threshold and Random Selection promotion rules)**.** *(i) For low levels of reputational cost incurred by the platform, as defined in Proposition 2.4,* *the platform is indifferent between using the random selection and the FT promotion rules. (ii) For high levels of reputational cost incurred by the platform, as defined in Proposition 2.4, the platform strictly prefers using the FT rule. The actual level of this threshold does not matter as long as it ensures the production success of the campaign.*

When the reputational cost incurred by the platform is relatively high compared to the reputational cost incurred by the entrepreneur (part (ii) of Proposition 2.5) the platform's objective is to eliminate the risk to backers that a commercially successful campaign is not a production success. It can accomplish this objective by utilizing the FT rule with a sufficiently high threshold level α. It cannot accomplish this objective when randomly selecting campaigns for promotion. However, when the platform's reputational cost is low, using the FT rule does not add any benefit over the random selection rule because the platform has no interest in eliminating the risk facing backers.

2.5 Setting the Sharing Rule of Campaign Revenues

In this section we explore ways in which the platform chooses the parameter γ which determines the share of campaign revenues to the entrepreneur. We distinguish between two environments: (i) when the platform can tailor the sharing rule to the individual characteristics of different campaigns, and (ii) when the platform sets the same sharing rule to heterogenous campaigns. While the former case is not common on CF platforms, we consider it in order to illustrate how changes in the parameters of the model affect the tradeoff between the promotion and sharing rules in disciplining the target setting strategy of the entrepreneur. From our earlier derivation, this strategy can be summarized as:

$$T_e^{j^*} = \begin{cases} \max\left\{\frac{Mv}{\gamma(v+s)},\ \frac{R_e}{\gamma}\right\} & \text{if } j\text{=}L,I \text{ i.e., the platform does not ensure production success.} \\ \frac{M}{\gamma\alpha(1+\delta)} & \text{if } j\text{=}H \text{ i.e., if the platform ensures production success).} \end{cases} \tag{2.10}$$

The pledge in either case is equal to the maximum willingness to pay of backers, i.e., $p = v + s$.

2.5.1 The platform can customize the sharing rule

To obtain the optimal sharing rule, we differentiate the expected profits of the platform with respect to γ. When the platform does not choose the threshold level, α to guarantee production success (i.e., α is sufficiently small), we differentiate (2.4) with respect to γ (recall that the platform's profits do not depend on α for Cases 1 and 2), and when the platform chooses α to ensure production success (i.e., α is sufficiently big), we differentiate (2.9) with respect to γ. The differentiation yields: When production success is not guaranteed, i.e., j is L or I in expression (2.11) below,

$$\frac{\partial \mathbb{E}\left(\Pi_p^j\right)}{\partial \gamma} = \begin{cases} \left(\frac{vM}{(v+s)^2(1+\delta)\bar{N}}\right)^2 \left[\frac{2-\gamma}{\gamma^3}\right] + \frac{2kR_pM}{\left[\gamma(v+s)(1+\delta)\bar{N}\right]^2} - 1 = 0 & \text{if } R_e < \frac{vM}{(v+s)} \\ \left(\frac{R_e}{(1+\delta)(v+s)\bar{N}}\right)^2 \left[\frac{2-\gamma}{\gamma^3}\right] + \frac{2kR_pM}{\left[\gamma(v+s)(1+\delta)\bar{N}\right]^2} - 1 = 0 & \text{if } R_e \geq \frac{vM}{(v+s)} \end{cases} \tag{2.11}$$

When production success is guaranteed,

$$\frac{\partial \mathbb{E}\left(\Pi_p^H\right)}{\partial \gamma} = \left(\frac{M}{(v+s)\left(1+\delta\right)\bar{N}}\right)^2 \left[\frac{2-\gamma}{\gamma^3}\right] - \frac{2\left(1-k\right)R_pM}{\left[\gamma\left(v+s\right)\left(1+\delta\right)\bar{N}\right]^2} - 1 = 0 \tag{2.12}$$

Note that the expected profit of the platform is a concave function of γ, implying that the first order conditions (2.11) and (2.12) are both necessary and sufficient. In Proposition 2.6, we conduct a sensitivity analysis to investigate how changes in the parameters affect the sharing rule chosen by the platform.

Proposition 2.6 (Comparative Statics - Platform Commission)**.**

1. *When the platform's choice of threshold for promotion does not ensure production success of the campaign (i.e., α is sufficiently small):* $\frac{\partial \gamma}{\partial v}, \frac{\partial \gamma}{\partial s} < 0$, $\frac{\partial \gamma}{\partial M}, \frac{\partial \gamma}{\partial k}, \frac{\partial \gamma}{\partial R_p} > 0$, $\frac{\partial \gamma}{\partial R_e} \geq 0$. *The sharing rule is independent of the value of $\bar{N}$ and δ.*
2. *When the platform's choice of threshold for promotion ensures production success of the campaign (i.e., α is sufficiently big):* $\frac{\partial \gamma}{\partial M}, \frac{\partial \gamma}{\partial k} > 0$, $\frac{\partial \gamma}{\partial R_p} < 0$. *The sharing rule is independent of the parameters $R_e, v, s, \bar{N}$ and δ.*

It is interesting that changes in the reputational cost incurred by the platform have a different effect on the share of the revenues awarded to the entrepreneur, contingent upon whether the platform's choice of the promotion threshold, α guarantees production success. If this threshold does not guarantee production success (part (i) of the Proposition), a higher R_p leads to a higher share of revenues awarded to the entrepreneur. A higher share raises the odds that the entrepreneur will have enough funds to deliver the product to backers, thus reducing the likelihood that the platform incurs the higher reputational cost due to non-delivery of the product. In contrast, when promotion of the campaign guarantees the start of production (part (ii) of the Proposition), higher reputational costs lead to a lower share of campaign revenues awarded to the entrepreneur. Because the FT level α guarantees that sufficient funds to start production are available, the platform is more inclined to lower the share of campaign revenue awarded to the entrepreneur, given that its expected payoff is lower if it does incur higher reputational costs. The reduction of the entrepreneur's share does not change the odds of the entrepreneur's ability to deliver the product. The entrepreneur may still renege on her promises, but only because of technical difficulties unrelated to the revenue sharing rule chosen by platform. The comparative statics with respect to R_p illustrate the tradeoff facing the platform when choosing how to utilize the two instruments at its disposal. When the promotion rule is ineffective (part (i)) in ensuring production, the platform relies on the sharing rule in guiding the behaviour of the entrepreneur. When the promotion rule guarantees production success (part ii), the platform relies more heavily on this rule rather than on the sharing rule in guiding the entrepreneur's behaviour. The comparative statics imply that the entrepreneur's share of revenues is highest at the boundary between the regions of enforcing and not enforcing production success by the platform (i.e., when $R_e < \frac{vM}{(v+s)}$ this boundary is $R_p = \frac{(1-\gamma)M(2v+s)}{2\gamma(v+s)}$).

2.5.2 The platform sets a uniform sharing rule for heterogeneous campaigns

Campaigns active on the platform may differ along many dimensions including development costs, consumption and altruistic benefits derived by consumers, and the reputation costs incurred by the entrepreneur and platform when the product cannot be delivered to backers. Despite such heterogeneity, platforms usually set a uniform sharing rule to all campaigns. We now investigate how the platform sets its uniform sharing rule for a heterogeneous population of campaigns.

To simplify the analysis, we assume that campaigns differ along one dimension.[17] Specifically, all campaigns have the same characteristics except their development cost. We assume that development costs in the population are distributed uniformly on the support $\left[\underline{M}, \overline{M}\right]$. We consider the case that for all campaigns, the reputational cost incurred by the entrepreneurs is relatively low, so that $R_e < \frac{v\underline{M}}{(v+s)}$.

To illustrate how a uniform sharing rule affects the composition of campaigns active on the platform, we restrict attention to the case when the platform uses a low FT level (Case 1)[18] because its reputational cost is relatively low. From (2.4), therefore, the platform's expected profits decrease with a campaign's development cost. It is reasonable, therefore, that the platform may choose the sharing rule γ to discourage campaigns characterized by relatively high development costs from participating on the platform, so that only campaigns in the interval $[\underline{M}, M^*]$, where $\underline{M} < M^* \leq \overline{M}$, are active. The threshold campaign, with development cost M^*, is indifferent between participating and not participating in the campaign. Specializing the general expression for expected profit (2.3) to an entrepreneur whose development cost is M^*, and setting this profit, $W(M^*)$ to zero gives:

$$W(M^*) \equiv \begin{array}{r} \frac{\gamma(1+\delta)(v+s)\bar{N}}{2}\left[1-\left(\frac{vM^*}{\gamma(v+s)^2(1+\delta)\bar{N}}\right)^2\right] + \left[k\pi - (1-k)\, R_e - M^*\right]\left[1-\frac{M^*}{\gamma(1+\delta)(v+s)\bar{N}}\right] - \\ R_e\left[\frac{sM^*}{\gamma(1+\delta)(v+s)^2\bar{N}}\right] = 0 \end{array}$$

Define $\mu \equiv \gamma\,(1+\delta)\,(v+s)\,\bar{N}$, and $\lambda \equiv k\pi - (1-k)\, R_e$, where μ measures the highest possible level of funds the entrepreneur can generate from the campaign when the number of informed backers assumes the highest value possible $\bar{N}$, and λ measures the entrepreneur's expected payoff (excluding the funds raised in the campaign) when she is able to start

[17] It is possible to extend the analysis to consider heterogeneity along multiple dimensions without changing the qualitative results of our investigation.

[18] The authors can provide upon request the derivations for the case that the platform chooses the threshold for promotion to ensure commercial and production success of some campaigns.

production. If a real solution to the above quadratic equation in M^* exists, it can be expressed as follows:[19]

$$M^* = \left[\frac{v+s}{v^2+4vs+2s^2}\left\{\left[(\mu+\lambda)(v+s)+R_e s\right]-\sqrt{\left[\lambda(v+s)+R_e s\right]^2 - s\mu\left[(\mu+2\lambda)(2v+s)-2R_e(v+s)\right]}\right\} \tag{2.13}$$

Note, from, (2.13) that M^* increases with μ. In turn, since μ increases with γ, it follows that $\frac{\partial M^*}{\partial \gamma} > 0$. Hence, when the platform awards a larger share of the revenues to entrepreneurs, campaigns facing higher development costs join the platform. If for any value $\gamma \in (0,1)$ there is no real solution to the equation $W(M^*) = 0$, $W(M^*) > 0$ for all values of γ, and the entire population of entrepreneurs is active on the platform. We characterize further the solution for M^* in the next Lemma.

Lemma 2.2. *For a given share of campaign revenues γ awarded to the entrepreneurs:*

- *As the share increases, more entrepreneurs choose to run a CF campaign.*
- *If this share is sufficiently big, the solution for M^* in (13) may exceed the value of $\overline{M}$. In this case, the entire population of entrepreneurs will join the platform.*
- *If this share is sufficiently small, the solution for M^* in (13) can fall short of the value of $\underline{M}$. In this case, none of the entrepreneurs will be interested in joining the platform.*
- *When $s = 0$, $M^* = \mu$, and if $\underline{M} < \mu < \overline{M}$, only a portion of the population of entrepreneurs, having relatively low development costs, participates in the campaign. For $s > 0$, $M^* > \mu$, and a larger number of entrepreneurs join the platform.*

According to Lemma 2.2, the revenue sharing rule determines how many entrepreneurs join the platform: A larger share awarded to the entrepreneur attracting more entrepreneurs. Part (iv) of the Lemma states that the threshold development cost M^* is equal to $\mu \equiv \gamma(1+\delta)(v+s)\bar{N}$, when backers do not derive any altruistic benefit, implying that all the campaigns that do participate satisfy the inequality $M \leq \gamma(1+\delta)(v+s)\bar{N}$. As pointed out earlier, unless this inequality holds, it is certain that campaign proceeds will not cover the developmental costs and the product will not be produced. When backers derive positive

[19] The solution exists if the term inside the radical in (13) is positive. Namely, if $\left[\lambda(v+s)+R_e s\right]^2 - s\mu\left[(\mu+2\lambda)(2v+s)-2R_e(v+s)\right] > 0$.

altruistic benefits, part (iv) states that the threshold M^* is greater than μ. Because $M^* > \mu$ when $s > 0$, altruism of backers attracts some entrepreneurs that will never be able to deliver their products. Entrepreneurs facing development cost M in the interval $\mu < M \leq M^*$ can expect to receive positive funds from the campaign in spite of never being able to deliver the product. Note that the existence of heterogeneity in the types of campaigns active on the platform exposes backers to different degrees of risk of losing their pledges. Specifically, backers of campaigns that face higher development cost are more at risk of non-delivery of the product. However, these backers are also submitting lower pledges to compensate for this higher risk. We also find that when participation provides altruistic benefits to backers, they definitely lose their pledges if they contribute to campaigns facing development cost in the interval, $\mu < M \leq M^*$. These backers are willing to contribute, nevertheless, because of their altruism and the low pledges that such campaigns require.

Using the results reported in Lemma 2.2, we now investigate how the platform chooses its uniform sharing rule. We first express the objective function of the platform using the results reported in (2.4). Because we assume that $R_e < \frac{vM}{(v+s)}$, the platform's payoff as a function of $M^*, \mathbb{E}\left(\Pi_p^L(M^*)\right)$ equals

$$\begin{cases} \frac{1}{(\overline{M}-\underline{M})} \int_{\underline{M}}^{M^*} \left\{ \frac{(1-\gamma)(1+\delta)(v+s)\bar{N}}{2} \left[1 - \left(\frac{vM}{\gamma(v+s)^2(1+\delta)\bar{N}} \right)^2 \right] - R_p \left[1 - k + \frac{\frac{Mk}{\gamma} - \frac{vM}{(v+s)}}{(v+s)(1+\delta)\bar{N}} \right] \right\} dM & \text{if } M^* < \overline{M}. \\ \frac{1}{(\overline{M}-\underline{M})} \int_{\underline{M}}^{\overline{M}} \left\{ \frac{(1-\gamma)(1+\delta)(v+s)\bar{N}}{2} \left[1 - \left(\frac{vM}{\gamma(v+s)^2(1+\delta)\bar{N}} \right)^2 \right] - R_p \left[1 - k + \frac{\frac{Mk}{\gamma} - \frac{vM}{(v+s)}}{(v+s)(1+\delta)\bar{N}} \right] \right\} dM & \text{if } M^* \geq \overline{M}. \end{cases}$$

where M^* is given in (2.13).

The platform chooses the sharing rule to maximize the above payoff function. Differentiating $\mathbb{E}\left(\Pi_p^L(M^*)\right)$ with respect to γ, yields the following first order conditions:

$$\partial \mathbb{E}\left(\Pi_p^L(M^*)\right) \partial \gamma = \left[\left(\frac{v}{(v+s)^2(1+\delta)\bar{N}} \right)^2 \left(\frac{2-\gamma}{\gamma^3} \right) \frac{\left(M^{*2} + M^* \underline{M} + \underline{M}^2 \right)}{3} - 1 + \frac{R_p k (M^* + \underline{M})}{\left[\gamma (v+s)(1+\delta)\bar{N} \right]^2} \right] (M^* - \underline{M}) + (1-\gamma) \left[1 - \left(\frac{vM^*}{\gamma(v+s)^2(1+\delta)\bar{N}} \right)^2 - \frac{2R_p}{\left[(v+s)(1+\delta)\bar{N} \right]} \left\{ 1 - k + \frac{M^* \left(\frac{k}{\gamma} - \frac{v}{(v+s)} \right)}{(v+s)(1+\delta)\bar{N}} \right\} \right] \frac{\partial M^*}{\partial \gamma} = 0 \text{ if } \underline{M} < M^* < \overline{M} \tag{2.14}$$

$$\partial \mathbb{E}\left(\Pi_p^L(M^*)\right) \partial \gamma = \left[\left(\frac{v}{(v+s)^2(1+\delta)\bar{N}} \right)^2 \left[\frac{2-\gamma}{\gamma^3} \right] \frac{\left(\overline{M}^2 + \overline{M}\underline{M} + \underline{M}^2 \right)}{3} - 1 + \frac{R_p k \left(\underline{M} + \overline{M} \right)}{\left[\gamma (v+s)(1+\delta)\bar{N} \right]^2} \right] = 0 \; if \; \overline{M} \leq \; M^* \tag{2.15}$$

While the first order condition above appears rather cumbersome, it simplifies significantly when $s = 0$, namely when backers do not derive any altruistic benefits. From (2.13), when $s = 0$, $M^* = \mu = \gamma v (1+\delta) \bar{N}$, and therefore, $\partial M^* \partial \gamma = v (1+\delta) \bar{N}$ when $\underline{M} < \mu < \overline{M}$. Hence, the optimal sharing rule solves the following expression:

$$\frac{\partial \mathbb{E}\left(\Pi_p^L(M^*)\right)}{\partial \gamma} = \begin{cases} \frac{1}{3}\left[\frac{2-\gamma}{\gamma}\right]\left[1 + \frac{\underline{M}}{\mu} + \left(\frac{\underline{M}}{\mu}\right)^2\right] - 1 + \frac{R_p k(\underline{M}+\mu)}{\mu^2} - (1-\gamma)^2 R_p = 0 & \text{if } \mu < \overline{M} \\ \frac{1}{3}\left[\frac{2-\gamma}{\gamma}\right]\left[\left(\frac{\overline{M}}{\mu}\right)^2 + \frac{\overline{M}\underline{M}}{\mu^2} + \left(\frac{\underline{M}}{\mu}\right)^2\right] - 1 + \frac{R_p k\left(\underline{M}+\overline{M}\right)}{\mu^2} = 0 & \text{if } \mu \geq \overline{M} \end{cases} \tag{2.16}$$

Notice that the platform payoff is a concave function of γ, implying that the first order condition is necessary and sufficient. In Proposition 2.7, we summarize the properties of the uniform sharing rule.

Proposition 2.7 (Equilibrium Commission rate under the Uniform Sharing Rule)**.**

- *When backers derive only consumption benefit and no altruistic benefit, and the platform selects the low fractional threshold for promotion:*
  a. *If $\underline{M} < \gamma (1+\delta)(v+s)\bar{N} < \overline{M}$, the optimal share awarded to the entrepreneur by the platform is larger when $\underline{M}$, and k are bigger, and $(1+\delta)(v+s)\bar{N}$ is smaller.*
  b. *If $\overline{M} \leq \gamma (1+\delta)(v+s)\bar{N}$, the optimal share awarded to the entrepreneur by the platform is larger when $\underline{M}$, $\overline{M}$,k, and R_p are bigger, and $(1+\delta)(v+s)\bar{N}$ is smaller.*
- *When backers derive both consumption and altruistic benefits in the campaign and $\underline{M} < M^* < \overline{M}$, the platform attracts some entrepreneurs who will never be able to deliver the product because their development costs, M lie in the interval $\left(\gamma (1+\delta)(v+s)\bar{N}, M^*\right]$.*

Section 2.4 shows that when platforms incur relatively low reputational costs they set an FT level for promoting campaigns that does not guarantee production success (Proposition 2.4). When backers derive some altruistic benefits by merely supporting a campaign, the entrepreneur sets a target level lower than the amount necessary to cover the development cost. As a result, backers face a positive probability that following a commercially successful campaign the entrepreneur will not be able to start production. Part (ii) of Proposition 2.7 states the stronger result: With altruistic backers and relatively low reputational cost incurred by the platform for non-delivery of the promised product by the entrepreneur, there are some entrepreneurs active on the platform that, with certainty, will not deliver the product. These are campaigns facing a development cost in the region $\left(\gamma\left(1+\delta\right)\left(v+s\right)\bar{N}, M^*\right]$. As M^* increases, the risk of delivery failure from entrepreneurs whose development costs lie in this interval increases. When γ can vary by campaign (Section 5.1), platforms can fully mitigate this risk by setting γ based on a campaign's development cost. When γ is fixed across campaigns, as is currently the practice, platforms attempt to lower their reputational costs by explicitly explaining to backers the inherent risks associated with crowdfunding a startup, and by permitting easy refunds (see the discussion following Proposition 2.4). When we restrict attention to the case where the platform incurs relatively low reputational cost, the platform can use only the sharing rule and not the promotion rule to guide the entrepreneur's target and pledge setting behaviour. To lower the risk of non-delivery noted in Part (ii) of Proposition 2.7, the platform can increase γ. Doing so, however, decreases its payoff. On the other hand, when the platform's reputational cost is relatively high, it can raise the threshold level for promotion when using the FT rule to ensure production success by all funded campaigns, thus eliminating the risk reported in Part (ii) of Proposition 2.7.

2.6 Concluding Remarks and Future Extensions

In this paper, we consider a reward-based CF platform and investigate how campaign characteristics affect the entrepreneur's optimal target and pledge levels. We find that when backers derive some altruistic benefits from participating in the campaign, the target level set by the entrepreneur is lower than the funds needed for successful production. By setting this lower target, the entrepreneur increases the risk backers face of not receiving the promised product when the campaign is commercially successful. We obtain this result despite our assumption that the entrepreneur can expect positive net profits from the sale of the completed product in the external market. This result implies that altruism causes the entrepreneur to intentionally raise the risk of forgoing future profits in favor of short-term proceeds from the campaign. We also find that the target setting strategy of the entrepreneur may be inconsistent with the interests of the platform.

We investigate how the platform can utilize two instruments to better align the behaviour of the entrepreneur with its interests. These instruments are (i) the share of campaign revenues that the platform charges, and (ii) the promotion rule it uses to raise awareness of selected campaigns among uninformed backers. In setting its revenue share fraction, the platform faces two counteracting effects. On the positive side, keeping a higher share of revenue implies that the platform receives a larger portion of the campaign revenues. Conversely, keeping a higher share of the revenue implies that the entrepreneur is less likely to raise sufficient funds to cover the development cost necessary to start production. Therefore, the entrepreneur is more likely to renege on her promise to backers, damaging the platform's reputation as a trustworthy environment to attract projects and backers. Factoring this trade-off, the platform has to lower its revenue share when the campaign faces higher development cost, when there are fewer informed backers who are able to assess the quality of the product, and when the willingness to pay of the informed backers is lower. We also find that with altruistic backers, the share of revenue set by the platform may not prevent some campaigns from participating even when it is certain that they will not be able to deliver their promised products.

As far as the promotion rule utilized by the platform, we find that tying the promotion to the campaign's ability to reach a certain threshold of the declared target is more profitable than randomly selecting projects for promotion only when the platform has an interest to ensure that sufficient funds become available for the entrepreneur to start production. The platform has such an interest when it is more concerned about damage to its reputation resulting from backers losing their pledges without receiving the promised product from the entrepreneur in return.

Relaxing the assumptions in this paper can lead to several fruitful research directions. First, we assume that entrepreneurs do not have any source of funding other than CF. We make this assumption to highlight the possibility that even in this case the entrepreneur may not set a target level to ensure that the development cost is covered. Allowing for the possibility that entrepreneurs do have access either to loans or venture capital investment is likely to lead to an even lower target set by the entrepreneur because she can access her outside funding source for any shortfall of funds not raised in the campaign. The risk imposed on backers declines in this case despite the lower funding target set by the entrepreneur because funds can be secured externally. However, the external funding can be contingent on how successful the campaign is. It might be useful to investigate this relationship and see how the target level changes with external funding. Second, in our model, all backers derive the same benefit from consuming the finished product, and we do not explicitly model the valuation of the product by consumers in the external market. If backers and consumers in the external market have different valuations or if the population of backers has heterogeneous valuations, the entrepreneur may use the CF campaign as a vehicle for price discrimination.

Third, in our model, informed backers know their valuation of the product with certainty. Moreover, the backer population increases by a known expansion factor when the campaign gets promoted. Earlier literature has investigated environments where there is uncertainty regarding the customer valuation and the overall product demand. Hence, a secondary reason for running the campaign is to learn about the product demand. With learning as a secondary objective, the entrepreneur may abandon the project if the campaign disappoints by attracting only a few backers. Introducing the possibility of learning by the entrepreneur in our model would make it even more likely for backers to lose their pledges, because entrepreneurs may abandon the project despite a commercially successful campaign. Finally, we do not introduce information asymmetry in our model, where the entrepreneur knows more about the product quality than potential backers. With such asymmetry, the entrepreneur may use her choice of target and pledge as a vehicle to signal the quality of her project. We leave it for future researchers to introduce such signaling considerations to the model.

3.0 Effect of Wholesale Price Contract on Target and Pledge amount in a Crowdfunding Campaign

We study how a backer's risk of not getting delivery of a product, even after a "successful" crowdfunding campaign, is affected by an entrepreneur's incentive to set a funding goal that is lower than the amount needed to start product development. The entrepreneur estimates the size of a positively correlated secondary market conditional on the subscription levels in a crowdfunding campaign. Unless the total market size is sufficiently large, the entrepreneur does not produce, incurs a cost to its reputation and pays a penalty to a supplier who is contracted prior to starting the crowdfunding campaign. We call this penalty the "option premium" paid by the entrepreneur to exercise the option to *not* produce. In a contract where a supplier decides on the wholesale price and the option premium endogenously, we study the effect of these parameters on the risk of delivery failure. We find that unlike conventional wisdom, with a supplier involved, a more informative crowdfunding signal can increase a backer's risk of delivery failure. In an environment where the entrepreneur price discriminates between backers and retail consumers in the post-campaign market, we find that there is a greater risk of delivery failure to those who are "impatient". Together, we shed light on the operational issues of why some crowdfunding campaigns fail to deliver to backers even when the campaigns themselves are very successful.

3.1 Introduction

Two central aspects of starting a new business are ensuring there is sufficient demand for the product and having the ability to scale production if indeed sales gathers traction. Both aspects require a healthy cash flow to start and continue operations. Most entrepreneurs start seeking funds for product development very early in the life cycle, for example when either the prototype is not fully developed, or when prototypes are developed which then get tested for functionalities and market acceptability. The need for engaging a supplier is also felt early as both the core competence in developing the specific component, and the ability to scale may not be compatible with a fully in-house production strategy. Early Supplier Involvement (ESI) has received attention in the Operations Management literature (Petersen et al. 2005), although most studies assume that manufacturers and retailers have an established supply chain. In a fledgling business, the channels of supply are not yet streamlined or even initiated. The suppliers need to be convinced about the prospect of future return from the entrepreneur. Although contract manufacturing has become quite popular with new businesses, the question of who bears the risk of investing money to ensure quality (for making tooling, jigs, fixtures, inspection mechanisms, etc.) is critical. This is primarily because, with a new business entity, 'the product' does not exist yet. Unless investment is made to ensure quality the product may not come to fruition.

Clearly the entrepreneur is in a weaker position of bargain, because there is no past sales history of the product. In such a situation a signal for future market demand can be as valuable as the sales itself. One such effective signalling device is crowdfunding. A crowdfunding campaign can assess a prospective customer's willingness to pay, as well as estimate the potential size of a future market. It is likely that the size of a post-campaign market is positively correlated with the subscription levels in the campaign. However, the strength of the signal (the correlation between the subscription levels in the crowdfunding campaign and the demand in the post-campaign market) as a predictor of future market size affects the wholesale price contract extended by the supplier, as well as the crowdfunding parameters set by the entrepreneur in the crowdfunding campaign. This eventually has an impact on the delivery risk faced by investors (backers) in crowdfunding. If the subscription levels in a crowdfunding campaign are not large enough, the entrepreneur may refrain from making the required investment for product development exposing backers to the risk of delivery failure. Since the size of the future market is an estimate that depends on the strength of the crowdfunding signal,[1] the signal itself becomes a crucial parameter in affecting the degree of risk exposure.

We find that as the strength of the crowdfunding signal increases, investors (backers)

[1] We will use the phrase "crowdfunding signal" to imply the signal from the subscription levels in the crowdfunding campaign.

are exposed to a greater risk of losing their investments (pledge amounts) and yet not get possession of the product. This runs contrary to the notion that a more informative signal reduces risk. Among the parameters set in a crowdfunding campaign is the target amount that an entrepreneur wants to raise, and pledge levels through which investors can commit support to the campaign. For the pledge amounts to be actually deducted from the investors account, the aggregate pledge levels committed must exceed the target amount. That is, unless the target is reached the investor is protected from losing her pledge amount. The target, therefore, acts to protect backers from the risk of losing their pledge amounts unless a "sufficiently large" amount is raised to start production and therefore ensure delivery. However a rational entrepreneur may select a target and pledge combination such that success in crowdfunding does not necessarily ensure investment for product development. A "better" crowdfunding signal increases the post-campaign market size, thereby offering the entrepreneur a buffer to absorb the cost of reputation and any penalty to the supplier for "no production." Hence, the entrepreneur sets a low target threshold increasing the backer's risk of non-delivery. On the other hand a "poor" quality signal increases the entrepreneur's reliance on crowdfunding to generate demand (or, by the same token generate funds) as the size of the post-campaign market shrinks. Therefore, an entrepreneur sets a high target threshold, reducing the backer's risk exposure.

When backers in a crowdfunding campaign have a different valuation than consumers in a post-campaign market, an entrepreneur earns a higher payoff by price discrimination. The relative concentration of backer "types," based on the cost of waiting, affects the probability of delivery failure. The possibility of getting a higher surplus from waiting until the product reaches the market limits the pledge amount that may be charged to the backers. If backers do not lose significant value from waiting, then an entrepreneur cannot charge a pledge amount that diminishes backer surplus any more than what they could earn if they waited. As we show, when the backer population consists of either patient or impatient backers, it is only the impatient backers that are exposed to the risk of delivery failure. A larger patient backer population limits an entrepreneur's incentive to keep a lower threshold than needed to break even. The degree of consumer patience is, however, relative to any potential gains in quality from implementing feedback from delivering to the backers in the campaign. This helps explain the proliferation of agencies (Arrow for Kickstarter and Indiegogo)[2] that can attest to the quality of campaigns in crowdfunding platforms where promising campaigns get the aid of product design, supply chain and logistics support. By conveying that there is limited gains in quality from waiting, the proportion of patient backers increase. Thus, getting an endorsement from these agencies besides conveying quality also reduces any opportunistic target setting incentive by the entrepreneurs, thereby reducing the backer's risk exposure.

The role of an effective supply chain in ensuring timely delivery to backers can be understood from the infamous failures of the Pebble SmartWatch and Zano Drone which, although a huge crowdfunding success, failed to deliver the products as promised to its backers because of supply chain issues.[3] We explain the potential causes of these failures by including a supplier's incentives as well. In crowdfunding platforms such as Indiegogo, the entrepreneur can continue to receive orders even after the campaign ends by placing it under a separate 'InDemand' campaign. By modelling the pre and post-campaign demand as two discrete phases, where the entrepreneur places a firm order with the supplier only after the campaign ends, and may not invest unless a threshold number of backers pledge in the crowdfunding campaign, we study the impact of delivery failure on the supplier as well. When an entrepreneur approaches the supplier as a potential future supply source, the supplier offers a wholesale price contract that is contingent on reaching this threshold. We use the term "contingent wholesale price" to refer to the contingency that the entrepreneur may not give the orders to the supplier if the subscription levels are not large enough. In the event this happens, the entrepreneur has to pay the exercise price of not producing. The exact level of this penalty is determined by the supplier endogenously. The crowdfunding target and pledge is kept by weighing the benefits of an easily reached low target threshold against the cost of reputation and the supplier penalty. In the special case where the target and pledge is kept such that the critical number of backers that must pledge for crowdfunding success equals the necessary threshold for the supplier to invest in fixed cost for production (no risk of delivery failure), we find that the optimal target increases with increase in the fixed development cost, variable cost of manufacturing, mean backer population in the

[2]https://www.ema-eda.com/about/blog/arrow-partners-indiegogo

[3]https://medium.com/kickstarter/how-zano-raised-millions-on-kickstarter-and-left-backers-with-nearly-nothing-85c0abe4a6cb

crowdfunding market and correlation in the crowdfunding and post-crowdfunding demand. The target decreases as the mean demand in post-crowdfunding increases. Also, the target increases with uncertainty in the crowdfunding market and decreases with the uncertainty in the post-crowdfunding market.

The supplier invests resources only when there is profit from engagement. We are the first to study the impact of a profit maximizing supplier on delivery failure in crowdfunding campaigns. We show that the pledge and target in a crowdfunding campaign, besides being signals of quality (Chakraborty and Swinney 2019), also reflect a supplier's incentives. In section 2 we position in the context of existing literature and in section 3 we describe the model and introduce the notations. In sections 4 and 5 we discuss the model when the entrepreneur does not price discriminate and when she does. We conclude in section 6.

3.2 Literature Review

There are several strands of literature that are related to this study. The research question is motivated by why some, otherwise successful, campaigns fail to deliver. Belavina et al. (2019) study this issue as "fund mispppropriation," where bad actors among the entrepreneur run away with the money raised without delivering rewards to the backers. We show that entrepreneurs who fail to deliver the product to backers subsequent to a successful campaign may not necessarily be bad actors, but might simply act rationally by trading off the cost of reputation and the cost to exercise its right of "no production," with the benefit of an easily reachable target. We also show that in the absence of credible enforcement mechanisms to deter misconduct, a wholesale price contract with a "no production" penalty is effective in reducing the risk a backer faces. Chakraborty and Swinney (2019b) find that entrepreneurs are able to signal a high quality product by keeping a higher target threshold for campaign success. They assume that quality is correlated with the fixed cost of product development. However, as we show, the target and pledge amount may be reflective of the parameters in a supplier contract which makes the target, as a signal of product quality, particularly noisy.

Our paper is also closely related to the advance selling and price discrimination literature.

The impact of advance selling on strategic buying behavior is studied extensively (Prasad et al. 2011, McCardle et al. 2004). We draw parallels between crowdfunding and advance selling, and show the impact that strategic buying behavior is incumbent on backers finding waiting, till the product is successfully launched in the market, beneficial. Unlike advance selling, the underlying product in a crowdfunding campaign is not developed. If the expected product valuation in the post-campaign market compensates the loss in valuation due to waiting, backers will pledge strategically. The presence of strategic backers reduces the risk of delivery failure. We find that although strategic buying behavior reduces the profit a firm earns, in the context of crowdfunding it provides incentives to the entrepreneur to protect investors against delivery failure. Contrary to Li and Zhang (2013) we find that a better signal can increase the risk of delivery failure. In most papers published in OM journals, the retailer is treated as a newsvendor, and model second period orders accordingly. Although, we use the approach of updating prior demand estimates, we do not assume that the entrepreneur behaves likes a newsvendor. We assume that the order quantity communicated will equal the expected post-campaign market size.

We study the effect that the contingency of a fixed cost investment has on the target and pledge amount in crowdfunding. Wei and Zhang (2018) study the effect of a pre-order contingency on the participation of strategic customers. Depending on distribution of a post-campaign market, the size of which is positively correlated with the sales outcome of the campaign, we find that the degree of correlation, the size of the fixed cost investment, size and distribution of the backer population all affect the target and pledge amount.

The use of a test market to update estimates of retail demand is used for capacity planning. Tsay (1999) studies a capacity investment problem where the outcome of a first stage demand is taken as the signal for demand in a subsequent stage. There is also a sizeable literature on the option to delay the capacity investment decision to a second stage (Van Mieghem and Dada (1999), Anand and Girotra (2007), Anupindi and Jiang (2008). These papers do not consider the possibility of bankruptcy which is crucial for startups. Papers which considers aspect of capacity investment with demand uncertainty, along with bankruptcy cost are Babich (2008), Babich et al. (2007). In our paper we do not model capacity but incorporate a cost to the reputation of the entrepreneur in the event a delivery failure happens.

Barring the study of Swinney et al. (2011) and Tanrısever et al. (2012), very few studies model the impact of penalty on the optimal time to raise funds. Both studies, while arriving at optimal values of their decision variables use a threshold survival probability to determine the optimal capacity investment. In our study we assume an expected profit maximizing entrepreneur. They also do not study the strategic interaction of a supplier and entrepreneur, as we do.

Research in crowdfunding, as a signal for future market size, lies at the confluence of a publicly observable signal with no information asymmetry. Unlike most studies that treat the entrepreneur's signal about the size of a future market as private, the outcome of crowdfunding is accessible to both the supplier and the entrepreneur. Therefore, there is no asymmetry in the signal received. Among papers where a supplier's order and therefore capacity reservation depends on the quantity order by a retailer, Berman et al. (2019) show that the manufacturer (entrepreneur) has an incentive to always signal a larger market size to the supplier. They show in the presence of an option to defer the capacity reservation decision till uncertainty about the new product is resolved, the manufacturer will report their true private information. We do not model a suppliers decision to reserve capacity, instead we assume that the entrepreneur will pay a penalty if it does not honour orders when the crowdfunding campaign is successful, thereby compensating the supplier for any capacity reservation. Although we restrict ourselves solely to a wholesale price contract the efficacy of other supply chain contracts on the degree of innovation initiated by the supplier has been studied by Wang and Shin (2015). They find that revenue sharing contracts are the most efficient in obtaining the outcome of a centrally coordinated supply chain.

We do not consider the aspect of competition in our model, as the crowdfunding 'market' is a market for 'potential' demand without a physical product developed yet. In the context of instantaneous ramp-up in computing space by using 'autoscaling' in cloud computing Fazli et al. (2018) study the effect of capacity decision by two competing firms with and without the option of scaling up production after demand uncertainty is resolved. They find that capacity can strengthen competitive intensity or relax it, depending on the uncertainty associated with success of the new product.

More broadly, our paper is related to research at the interface of operations and finance, studying how a firm's financial decisions affect its operations (Buzacott and Zhang 2004, Ding et al. 2007, Chod and Zhou 2014, Chod 2017, Tunca et al. 2017, Kouvelis and Xu 2021). Closely related are those study the financing and operations strategies of startups. Chod and Lyandres (2011) examine the benefits of IPO under product market competition and demand uncertainty. More recently, Chod and Lyandres (2021) study the extent to which risk-averse entrepreneurs can transfer venture risk to fully diversified investors under ICO financing. We refer the reader to Babich and Kouvelis (2018) for a recent review of the operations-finance literature and Allon and Babich (2020) for a specific review of crowdfunding. Our work contributes to this stream of literature by showing how and why seemingly successful crowdfunding campaigns fail to deliver rewards to backers.

3.3 Model

We model a game where the total demand (Z) for the product consists of backer subscription levels in the crowdfunding market (X) and a post-campaign demand (Y) that is positively correlated with the crowdfunding subscription level. Specifically, we let total market demand be $Z = X + Y$, where X and Y are jointly bivariate normal with a correlation ρ. That is,

$$\begin{pmatrix} X \\ Y \end{pmatrix} \sim N \left[\begin{pmatrix} \mu_X \\ \mu_Y \end{pmatrix}, \begin{pmatrix} \sigma_X^2 & \sigma_{XY} \\ \sigma_{XY} & \sigma_Y^2 \end{pmatrix} \right]$$

where the covariance in the two markets, $\sigma_{XY} = \rho\sigma_X\sigma_Y$. The uncertain demand in the crowdfunding campaign is denoted by X which is normally distributed with mean μ_X and variance σ_X^2. The cumulative distribution function of the crowdfunding market demand is denote by $F_X(.)$ (the complementary cdf is denoted $\bar{F}_X(.)$), and the density by $f_X(.)$. The post-campaign demand Y is positively correlated ($\rho > 0$) with the outcome of the crowdfunding campaign. The demand in the post-campaign market is normally distributed with mean μ_Y and variance σ_Y^2. The positive correlation is representative of the fact that a higher number of pledges in the crowdfunding campaign increases the post-campaign demand. The closer the value of ρ to one, the more precise the signal. Since both the supplier and the entrepreneur assess the expected demand in the post-campaign market subsequent to the realization of demand in the crowdfunding campaign, it is imperative that we explicitly specify the expected post-campaign market size conditional on the subscription level in the crowdfunding campaign: $\mathbb{E}(Y|X = x) = \mu_Y + \rho\frac{\sigma_Y}{\sigma_X}(x - \mu_X)$. Given our assumption of a positive correlation, if the crowdfunding outcome is more than the prior mean of the campaign, then the expected posterior demand, $\mathbb{E}\left(Y|X = x\right)$, is more than the prior expected demand in the post-campaign phase, μ_Y.

We now define the variables and sequence of the game. The entrepreneur approaches the supplier with the design of the prototype and seeks a quote for each component for supply. The supplier studies the design and offers a wholesale price, w, for each component. and asks the entrepreneur to fund a fixed investment M to ensure quality. It is common practice for manufacturers of technological and hardware products to have tools and fixtures for an efficient transition to large scale production. Even for products that are less “tactile” in nature, there are often several rounds of development before a product comes to fruition. These efforts may often be wasted and come at a heavy expense. M represents the *minimum* amount that must be funded for the product to be launched in the market. There are two reasons why the supplier asks the entrepreneur for the fixed investment. The first reason is simply because the supplier has a better negotiating leverage. A supplier, typically, has a stronger bargaining position when dealing with an entrepreneur and therefore often dictates the terms of contract.[4] The second reason is because the prospect of a long term association is very uncertain. Hence, the supplier refrains from committing to a long term investment. The entrepreneur agrees to invest M, if the total market size, conditional on seeing the crowdfunding subscription levels, are large enough to recover (break-even) the investment. For some crowdfunding subscription level x and pledge amount p_c, unless $(\gamma p_c - w)x + (p_c - w)\mathbb{E}(Y|X = x) \geq M$, where $1 - \gamma$ is the commission that the platform

[4]Inspite of the rapid rise of contract manufacturers, the balance of power, when dealing with entrepreneurs, still seems to be heavily skewed in favor of the suppliers.

gets from the campaign proceeds, the entrepreneur does not invest in the development cost M. The entrepreneur sets the target T and pledge level p_c, after arranging the channel of supply. We will study a situation where the product valuation may change subsequent to the crowdfunding campaign allowing the entrepreneur to price discriminate, with the post-campaign selling price denoted p_m. A backer commits to paying p_c, which is deducted from the backer's account *only if* the aggregate pledges exceed the target T (a state in which the campaign is deemed "successful"). The entrepreneur is obligated to deliver the product to the backers if the campaign is successful. Hence, unlike traditional investment practices, in a reward based crowdfunding campaign, backers participate to get a novel product by a pre-committed time. It becomes evident that the entrepreneur, besides using the target amount T to inform the backers the amount needed for product development,[5] also serves as a parameter to protect the backers against the risk of losing their pledges if *sufficient* amount of money is not raised. We look at two cases, one in which backers are not strategic and another where backers are strategic and consider buying from the retail market once the product becomes available. The presence of strategic backers allows the entrepreneur to charge a retail price that is different than the pledge set in the crowdfunding campaign. When backers are not strategic, backers that choose not to pledge in the campaign do not consider buying in the retail market. We note that the subscription in the crowdfunding campaign, x is a part of the total demand only if the aggregate pledges exceed the target T set by the entrepreneur. That is:

$$\mathbb{E}(\Pi_e) = \begin{cases} (\gamma p_c - w)x + (p_c - w)\mathbb{E}(Y|X = x) & \text{if } x \geq \frac{T}{p_c} \\ (p_c - w)\mathbb{E}(Y|X = x) & \text{if } x < \frac{T}{p_c} \end{cases}$$

This gives a lower threshold number of backers (x^{LT}) that must subscribe to the campaign for the entrepreneur to make the investment M, when the campaign succeeds. When the

[5]It is possible that the product is already in an advanced state of development, and the only purpose of conducting a crowdfunding campaign is to test the potential market size. From our in depth study of reward based crowdfunding platforms such as Kickstarter, we find that such cases are few. For the purposes of the paper, we assume that the entrepreneur has no past sales, and depends entirely on the proceeds of a crowdfunding and a post-campaign market for sales.

campaign fails, the entrepreneur may still invest in M if a higher threshold number of backers x^{UT} subscribe to the campaign. These two thresholds are respectively:

$$\begin{cases} x^{LT}\left(p_c,w\right) = \frac{M\sigma_X-(p_c-w)(\mu_Y\sigma_X-\rho\mu_X\sigma_Y)}{(\gamma p_c-w)\sigma_X+(p_c-w)\rho\sigma_Y} \text{ and} \\ x^{UT}\left(p_c,w\right) = \frac{M\sigma_X-(p_c-w)(\mu_Y\sigma_X-\rho\mu_X\sigma_Y)}{(p_c-w)\rho\sigma_Y} \end{cases} \tag{3.1}$$

Clearly, $x^{UT} > x^{LT}$. The above mentioned conditions gives rise to a lower and upper threshold number of backers that must pledge for the campaign depending on whether the campaign is successful or not. The entrepreneur's preferred range within which to keep the critical number of backers for campaign success $(\frac{T}{p_c})$ is specified in Lemma 3.1.

Lemma 3.1. *For any target and pledge amount pair (T, p_c), an entrepreneur invests the required development cost M if the number of backers, x, pledging in the crowdfunding campaign exceeds x^{LT}. Furthermore, the entrepreneur finds it preferable to keep a target and pledge such that $\frac{T}{p_c} \leq x^{LT}$.*

As the number of backers needed for campaign success $(\frac{T}{p_c})$ increases, the expected payoff of the entrepreneur decreases. This happens, because reaching the target becomes less likely. Therefore, the entrepreneur finds it preferable to keep a target as low as possible. If the number of backers needed for campaign success $(\frac{T}{p_c})$ is strictly lower than x^{LT}, then for all backer subscription levels x where $\frac{T}{p_c} < x \leq x^{LT}$, backers are exposed to the risk of non-delivery of their rewards. In this event, although the campaign is successful in reaching the target set by the entrepreneur, it falls short of reaching the investable number to break even. Since the product cannot be manufactured for backer subscription in this range, we assume that there is a fixed cost R to the reputation of the entrepreneur. As the supplier plans to get orders based on the initial discussions with the entrepreneur, for backer subscription in the range $\frac{T}{p_c} < x \leq x^{LT}$, a penalty Γ is levied by the supplier on the entrepreneur, as the orders for which the suppliers reserved capacity don't materialize. We will refer to this penalty as the "option-premium" charged by the supplier to the entrepreneur to exercise the option of not producing. As the threshold number of backers (x^{LT} needed for the entrepreneur to make the investment M increases, the risk of delivery failure (for the same target and pledge amount) increases. Thus, the sensitivity of x^{LT}, to the environment parameters is crucial in understanding the risk of delivery failure to the backers, which we study in Lemma 3.2.

Lemma 3.2.

1. *When entrepreneur commits to keeping the same price, if $w < p_c < w^*$, $\frac{\partial x^{LT}}{\partial w} \geq 0$, $\frac{\partial x^{LT}}{\partial p_c} \leq 0$ and $\frac{\partial^2 x^{LT}}{\partial w \partial p_c} \geq 0$. If $w < w^* < p_c$, $\frac{\partial x^{LT}}{\partial w} \geq 0$, $\frac{\partial x^{LT}}{\partial p_c} \geq 0$ and $\frac{\partial^2 x^{LT}}{\partial w \partial p_c} \leq 0$. If $w^* < w < p_c$, $\frac{\partial x^{LT}}{\partial w} \leq 0$, $\frac{\partial x^{LT}}{\partial p_c} \geq 0$ and $\frac{\partial^2 x^{LT}}{\partial w \partial p} \geq 0$. The threshold price level $w^* = \frac{M(\gamma\sigma_X + \rho\sigma_Y)}{(1-\gamma)(\mu_Y\sigma_X - \rho\mu_X\sigma_Y)}$.*

2. *If the ex-ante payoff from the crowdfunding and post-campaign market exceeds the product development cost, $(\gamma p_c - w)\,\mu_X + (p_c - w)\,\mu_Y \geq M$, the crowdfunding subscription level needed for the entrepreneur to invest M increases with increases in the strength of signal, that is $\frac{\partial x^{LT}}{\partial \rho} \geq 0$. If $(\gamma p_c - w)\,\mu_X + (p_c - w)\,\mu_Y < M$, $\frac{\partial x^{LT}}{\partial \rho} < 0$. The rate of increase in the breakeven subscription level, as a result of a stronger signal, increases as the profit margin increases. That is, $\frac{\partial^2 x^{LT}}{\partial \lambda \partial \rho} \geq 0$, where $\lambda = p_c - w$.*

Proof: Refer Appendix

We observe that increasing the pledge or wholesale price can increase or decrease the threshold amount needed for the entrepreneur to invest the product development cost. With regards to the sensitivity of x^{LT} to the crowdfunding market signal as a predictor of the size of the post-campaign market, the following intuition holds. If $(\gamma p_c - w)\,\mu_X + (p_c - w)\,\mu_Y \geq M$, then the updated expected post-campaign payoff is $(\gamma p_c - w)\,x + (p_c - w)\left\{\mu_Y + \rho\sigma_Y\left(\frac{x-\mu_X}{\sigma_X}\right)\right\}$, where $x \geq \frac{T}{p_c}$ is the subscription level in the crowdfunding campaign. The updated payoff can be restated as: $(\gamma p_c - w)\,\mu_X + (p_c - w)\,\mu_Y + (\gamma p_c - w)\,(x - \mu_X) + (p_c - w)\,\rho\sigma_Y\left(\frac{x-\mu_X}{\sigma_X}\right)$. Since $(\gamma p_c - w)\,\mu_X + (p_c - w)\,\mu_Y \geq M$, the backer subscription level needed for the entrepreneur to invest is lower than the ex-ante mean crowdfunding demand, $x^{LT} < \mu_X$. All else remaining the same, as the correlation between the two markets increases, the scope of error, $\mu_X - x$, reduces. Hence, the number of backers needed to break even is closer (and therefore higher) to the prior mean of the crowdfunding backer population (μ_X). The sign of $\frac{\partial^2 x^{LT}}{\partial \lambda \partial \rho}$ is critical as it emphasizes the interaction of market signal with the margin the entrepreneur can command. This result will be particularly useful for our discussion of equilibrium results.

The backers in a crowdfunding campaign observe the target and pledge levels before making a pledge commitment. We also assume that the backers are aware of the product development cost M, and the unit cost of manufacturing the product c.[6] Hence, the backer knows that unless the entrepreneur finds it feasible to invest the development cost the component will not be developed and the promised reward to the backers will not be delivered either. All backers have a homogeneous valuation v for the product. We model the possibility that the product valuation may change after the crowdfunding campaign as a result of backer feedback after getting possession of the product. In the section on price discrimination we incorporate the potential for the product valuation to become θv where $\theta \in \{\theta_l, \theta_h\}$ with equal probability. To accommodate the possibility of the valuation increasing two folds we let $0 < \theta_l \leq \theta_h \leq 2$. When the entrepreneur price discriminates the price in the post-campaign market will be denoted p_m. If the entrepreneur finds it feasible to invest the fixed amount M, the component gets made with probability ϕ, where $1 - \phi$ represents the potential for a technical problem after the onset of production. The onset of a technical problem is independent of the demand in the crowdfunding campaign. The stages of the game is shown in Figure 3.1:

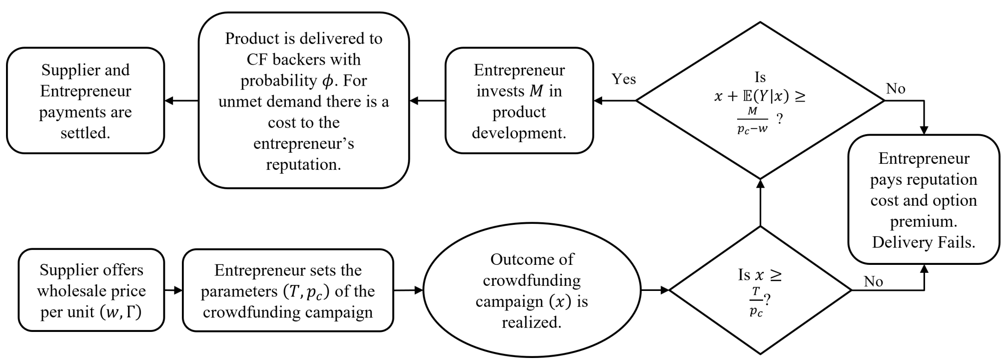


Figure 3.1: The stages in investment of a project by an entrepreneur/supplier through a crowdfunding campaign.[7]

For all subsequent calculations we use the identity for calculation of partial moments of a normal distribution with mean μ_X and variance σ_X^2 from Winkler et al. (1972), where $\int_{-\infty}^{m} x f(x)\, dx = -\sigma_X \omega(z_m) + \mu_X \Omega(z_m)$. ω and Ω are the pdf and cdf of the standard normal distribution and $z_m = \frac{m - \mu_X}{\sigma_X}$ is the standardized value. We do not standardize the

[6]If not the cost, knowing the margins that the supplier earns could also lead the backer to the value of the wholesale price.

variables to z_m, for ease of representation. For a non-standardized normal random variable, the identity becomes $\int_{-\infty}^{m} xf(x)\,dx = -\sigma_X^2 f(m) + \mu_X F(m)$. We will use the identity for all derivations.

3.4 Choice of optimal Target, Pledge and Wholesale Price with no price discrimination

We proceed with our analysis by first assuming that the entrepreneur commits to charging a post-campaign sale price that equals the pledge levels in the crowdfunding campaign. It is very common to observe that entrepreneurs try to entice backers to pledge in a campaign by suggesting that prices may increase in the post-campaign market. Assuming the pledge and prices to be the same also helps in simplifying the investment decision of the entrepreneur. Our choice of using a contingent wholesale price contract is inspired by Wei and Zhang (2018) in which production is contingent on reaching a pre-specified target. The rational for engaging in such a contract is that it safeguards both the the supplier and entrepreneur against the risk of low market subscription in the test market, and being compelled to borrow money to produce the product. We will now proceed to analyse the equilibrium.

3.4.1 Effect of Contingent Wholesale price contract *without* "No-Production" penalty (NOP regime)

Although the entrepreneur keeps a target low enough to ensure that the campaign is successful, campaign success alone may not be sufficient for the entrepreneur to invest in the fixed product development cost. If the campaign is successful but the number of pledging backers is not large enough for investment, the entrepreneur does not invest and the product is not developed. In this situation the entrepreneur incurs a 'fixed' cost to its reputation, R. Since, investment by the entrepreneur depends on whether the number of backers pledging exceed the lower threshold x^{LT}, the payoff of the entrepreneur may be expressed as:

$$\mathbb{E}\left(\Pi_e\right) = -R\int_{\frac{T}{p_c}}^{x^{LT}} f\left(x\right)dx + \gamma p_c \mathbb{E}\left(X|X \geq \frac{T}{p_c}\right) + p_c \mathbb{E}\left(Y|X \geq x^{LT}\right) - w\mathbb{E}\left(Z|X \geq x^{LT}\right) - M\bar{F}\left(x^{LT}\right) \tag{3.2}$$

where the first component represents the situation where the entrepreneur incurs a cost to its reputation on account of non-delivery of the product. The amount raised from the campaign passes to the entrepreneur as long as the target is reached, however the supplier starts production only if the entrepreneur makes the investment on reaching the lower threshold. Similarly, all post-campaign payoffs from the campaign depend on meeting the lower threshold number of backers in the crowdfunding campaign. The second component represents the payoff from the campaign conditional on raising the target. Observe that the entrepreneur pays a commission $1-\gamma$ on the amount raised to the platform. The post-campaign revenues depend on the realization of the subscription levels in the crowdfunding campaign. If the backer size is lower than the number needed for the entrepreneur to proceed with the investment, then the production does not happen. Therefore, all post-campaign revenues depend on reaching the investment threshold x^{LT}. The total cost of the components purchased from the supplier is $w\mathbb{E}\left(Z|X \geq x^{LT}\right)$, where supplies are needed only when production happens or when the subscription level in the campaign meet the minimum investable number. Since the entrepreneur pays the fixed development cost, it is deducted when production starts.

Any backer that contemplates investing in the campaign faces the uncertainty of not receiving the product even when the campaign is successful. This uncertainty consists of a technical problem at the supplier with probability $1-\phi$. Incorporating for this possibility in the backer's willingness to pay, reduces the net valuation of the product to $\phi\, v\bar{F}\left(x^{LT}\right)$. The pledge amount is lost only if the target is reached in the crowdfunding campaign. Incorporating this aspect we get the backers net payoff as:

$$\mathbb{E}\left(\Pi_b\right) = \phi\, v\bar{F}\left(x^{LT}\right) - p_c\bar{F}\left(\frac{T}{p_c}\right) \tag{3.3}$$

Knowing the payoff of the backer the entrepreneur keeps a pledge amount so that $\mathbb{E}\left(\Pi_b\right) \geq 0$. Finding the pledge amount in terms of the target from the expression and substituting in the expression for the entrepreneurs payoff gives the payoff expressed in terms of the target.

Optimizing over the target we can find the target and therefore the pledge amount in terms of the wholesale price offered by the supplier. The supplier anticipating the response from the entrepreneur keeps a wholesale price that maximizes her payoff. The payoff of the supplier is expressed as:

$$\mathbb{E}\left(\Pi_s\right) = \phi\left(w - c\right)\mathbb{E}\left(Z|X \geq x^{LT}\right) \tag{3.4}$$

Simplifying the expected payoff of the entrepreneur and supplier, we get the following expressions. In arriving at the simplified expression we use Winkler et al. (1972) for determination of partial moments of a normal distribution. For any target (T), pledge (p_c) and wholesale price (w) the payoffs of the entrepreneur and supplier are given by:

$$\begin{aligned}\mathbb{E}\left(\Pi_e\right) = \quad & -R\left\{F\left(x^{LT}\right) - F\left(\tfrac{T}{p_c}\right)\right\} + \gamma p_c\left\{\mu_X \bar{F}\left(\tfrac{T}{p_c}\right) + \sigma_X^2 f\left(\tfrac{T}{p_c}\right)\right\} + \phi p_c\left\{\mu_Y \bar{F}\left(x^{LT}\right) + \right. \\ & \left. \rho\sigma_X\sigma_Y f\left(x^{LT}\right) - \phi w\left\{\left(\mu_X + \mu_Y\right)\bar{F}\left(x^{LT}\right) + \left(\sigma_X^2 + \rho\sigma_X\sigma_Y\right) f\left(x^{LT}\right)\right\}\right. - M\bar{F}\left(x^{LT}\right)\end{aligned} \tag{3.5}$$

and

$$\mathbb{E}\left(\Pi_s\right) = \phi\left(w - c\right)\left\{\left(\mu_X + \mu_Y\right)\bar{F}\left(x^{LT}\right) + \left(\sigma_X^2 + \rho\sigma_X\sigma_Y\right) f\left(x^{LT}\right)\right\} \tag{3.6}$$

Optimizing the suppliers payoff by substituting the optimal tar get and wholesale price gives the equilibrium which is characterized in Lemma 3.3.

Lemma 3.3. *The equilibrium target, pledge amount and wholesale prices depend on the cost of reputation if the entrepreneur fails to deliver the product subsequent to a successful campaign.*

- *High Reputation Cost: When $R \geq \phi v x^{LT}(\phi v, w^*)$, the optimal pledge amount is $p_c = \phi v$ and the optimal target is, $T = \phi v x^{LT}(\phi v, w^*)$. w^* is obtained by solving $\left(\mu_X + \mu_Y\right)\bar{F}\left(x^{LT}\right) + \left(\sigma_X^2 + \rho\sigma_X\sigma_Y\right) f\left(x^{LT}\right) = \phi\left(w - c\right)\left\{x^{LT} + \mu_Y + \rho\frac{\sigma_Y}{\sigma_X}\left(x^{LT} - \mu_X\right)\right\}\frac{\partial x^{LT}}{\partial w} f\left(x^{LT}\right)$, $x^{LT} = x^{LT}\left(\phi v, w\right)$ and $\frac{\partial x^{LT}}{\partial w} = \frac{\sigma_X\{-(1-\gamma)\phi v(\mu_Y\sigma_X - \rho\mu_X\sigma_Y) + M(\sigma_X + \rho\sigma_Y)\}}{\{(\gamma\phi v - w)\sigma_X + (\phi v - w)\rho\sigma_Y\}^2}$.*
- *Low Reputation Cost: When $R < \phi v x^{LT}(\phi v, w^*)$, the optimal target is $T = \frac{R}{\gamma}$, and the optimal pledge and wholesale price is obtained by solving the constrained optimization problem:*

– $\max \mathbb{E}(\Pi_s) = \phi(w-c)\left\{(\mu_X+\mu_Y)\bar{F}\left(x^{LT}\right) + (\sigma_X^2+\rho\sigma_X\sigma_Y) f\left(x^{LT}\right)\right\}$ *such that* $\left[\phi(p_c-w)\left\{\mu_Y+\rho\sigma_Y z\left(x^{LT}\right)\right\} - \phi w x^{LT} + R - M\right]\frac{\partial x^{LT}}{\partial p_c} f\left(x^{LT}\right) = \mu_Y \bar{F}\left(x^{LT}\right) + \rho\sigma_X\sigma_Y f\left(x^{LT}\right)$ *and* $\phi v\bar{F}\left(x^{LT}\right) - p_c\bar{F}\left(\frac{R}{\gamma p_c}\right) \geq 0$. *The first constraint is obtained by equating the differential of the entrepreneur's payoff with respect to p to zero.*

It is difficult to obtain closed form expressions for the wholesale price, Target and Pledge amounts from the previous expressions. Therefore, we resort to numerical analysis in section 3.4.3 to understand how the pledge, Target, wholesale price and payoffs of the entrepreneur and supplier with the parameters of the model. Our focus is on the degree of risk exposure to the backers, as measured by $\Pr\left[\frac{T}{p_c} < x^{LT}\right]$.

3.4.2 Effect of Contingent Wholesale price contract *with* "No-Production" penalty (WOP regime)

In the previous section we looked at the optimal parameters set by the entrepreneur and the supplier, when no penalty is imposed on the entrepreneur in the event of a failure to start production. In a real situation it is highly unlikely that the supplier proceeds with a word of mouth assurance from the entrepreneur to reserve capacity for production orders. In this section, we look at a scenario where the supplier charges a fee in the event that the entrepreneur, subsequent to the outcome of the crowdfunding subscription, is unable to raise the required amount to break even. We will denote this fee Γ. This fee is applicable only when the entrepreneur does not proceed with the production order. This could be thought of as a fee to exercise of the option of no production, or as an upfront booking fee that is returned if an order is placed. This requires the following change in the payoff of the entrepreneur.

$$\begin{aligned}\mathbb{E}(\Pi_e) = -(R+\Gamma)\int_{\frac{T}{p_c}}^{x^{LT}} f(x)\,dx + \gamma p_c \mathbb{E}\left(X \middle| X \geq \tfrac{T}{p_c}\right) + \phi p_c \mathbb{E}\left(Y \middle| X \geq x^{LT}\right) - \\ \phi w \mathbb{E}\left(Z \middle| X \geq x^{LT}\right) - M\bar{F}\left(x^{LT}\right)\end{aligned} \tag{3.7}$$

Note that the entrepreneur has to pay the fee only if the backer subscription levels raise the target but are not sufficiently large to signal breaking even with participation of consumers in the post-campaign market. However, this cost is fully recovered from the entrepreneur. The expected payoff of the supplier now becomes:

$$\mathbb{E}(\Pi_s) = \Gamma \int_{\frac{T}{p_c}}^{x^{LT}} f(x)\, dx + \phi (w - c)\, \mathbb{E}\left(Z | X \geq x^{LT}\right) \tag{3.8}$$

With the incorporation of the option-premium cost, the supplier ensures that all costs associated with the entrepreneur's involvement, and any failures owing to this association is fully recovered from the entrepreneur. The supplier incorporates the best response of the entrepreneur in its own payoff to get the parameters of the contract (w, Γ). The equilibrium condition is characterized in the next lemma.

Lemma 3.4 (Equilibrium Pledge, Target, Option Premium and Wholesale Price)**.** *The equilibrium pledge, target, option premium and wholesale price are stated:*

- *The pledge is obtained by equating* $p_c = r$ *where* $\phi v \bar{F}\left(x^{LT}\right) - r\bar{F}\left(\frac{T}{r}\right) = 0$.
- *Target best response function for a given level of option premium* Γ *is* $T = \frac{R+\Gamma}{\gamma}$.
- *Option Premium* Γ *is obtained by solving for* $F\left(x^{LT}\right) - F\left(\frac{R+\Gamma}{\gamma p_c}\right) - \frac{\Gamma}{\gamma p_c} f\left(\frac{R+\Gamma}{\gamma p_c}\right) = 0$.
- *The wholesale price is obtained by maximizing the supplier's payoff from the regular season sales:* $(w - c)\left\{(\mu_X + \mu_Y)\bar{F}\left(x^{LT}\right) + \left(\sigma_X^2 + \rho\sigma_X\sigma_Y\right) f\left(x^{LT}\right)\right\}$.

3.4.3 Numerical Analysis - Same Price Regime

Due to the lack of closed form expressions of the equilibrium target, pledge amount and threshold levels; to conduct comparative statics on the risk exposure a backer faces, we take recourse in Numerical Analysis. Our primary objective is see how the impact of correlation between the two markets, and cost of reputation affect a backer's risk exposure. Throughout the analysis we have assumed that the coefficient of variation of the crowdfunding market is higher than that of the post-campaign market (i.e., $\frac{\sigma_X}{\mu_X} \geq \frac{\sigma_Y}{\mu_Y}$). This helps in ensuring that $\sigma_X\mu_Y \geq \rho\sigma_Y\mu_X$. This assumption is reasonable, as the relative variation of the crowdfunding market should be higher than the regular market in the selling season. We also assume that $\gamma c\mu_X + c\mu_Y \geq M$, to ensure the most optimistic scenario where all parties know that even if backers were to pay the marginal cost of the product, it will still be sufficient to cover for the production cost. However, as we show, the ex-ante expected payoffs do not guarantee that entrepreneur's will invest in the product development cost after observing the crowdfunding subscription levels. Our observations from the analysis are the following:

Observation 3.1 (Impact on Delivery under the same price regime)**.** *The observations apply whether or not an option premium is charged by the supplier.*

1. *As the crowdfunding market becomes a better signal of the size of the post-campaign market (as ρ increases), the risk exposure* $\Pr\left(x^{LT} - \frac{T}{p_c}\right)$*, of backers, increases.*

2. *As the cost of reputation for failing to deliver the rewards following a campaign success increases (as R increases), the risk exposure of backer* $\Pr\left(x^{LT} - \frac{T}{p_c}\right)$ *decreases. Furthermore, there always exists a high enough reputation cost at which the entrepreneur prefers to set $\frac{T}{p_c} = x^{LT}$ and $p_c = \phi v$.*

3. *There exists a γ^* such that for all revenue shares $\gamma < \gamma^*$, campaigns do not participate in crowdfunding platforms. Furthermore, increasing the entrepreneur's share of the payoffs increases the risk of delivery failure.*

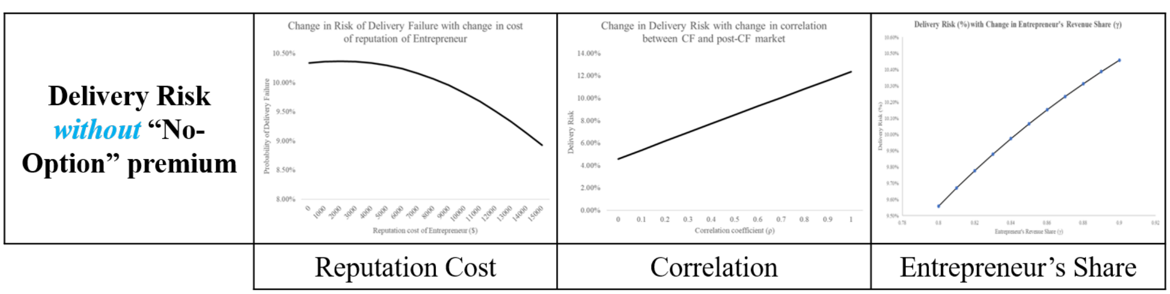


Figure 3.2: Effect of change in backer's risk exposure $Pr\left(x^{LT} - \frac{T}{p}\right)$ with increase in Reputation Cost R, Crowdfunding Signal ρ, and the Entrepreneur's Share of the campaign proceeds γ, under the **NOP** regime

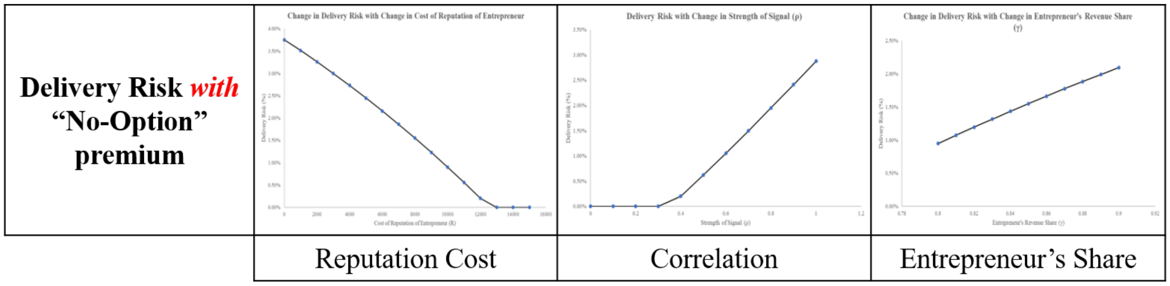


Figure 3.3: Effect of change in backer's risk exposure $\Pr\left(x^{LT} - \frac{T}{p}\right)$ with increase in Reputation Cost R, Crowdfunding Signal ρ, and the Entrepreneur's Share of the campaign proceeds γ, under the **OP** regime

The parameter values for the numerical analysis are:$\mu_X = 1400, \mu_Y = 1200, \sigma_X = 750, \sigma_Y = 300, \phi = 0.7, c = \$20, M = \$10000$. We vary the crowdfunding signal(ρ) from 0 to 1 with 0.1 increments, the cost of reputation (R) from \$0 to \$15000 in \$1000 increments, and the entrepreneur's share from 80% to 90% with 1% increments.

Figures 3.2 and 3.3 show the change in risk exposure when the entrepreneur chooses the target and pledge amount T and p_c such that the critical number of backers needed for campaign is *strictly* lower than x^{LT}. However, as noted in the second point of the remark, for a high enough cost of reputation the entrepreneur keeps the critical number of backers equal to x^{LT}. As found in Su and Zhang (2008), as the pre-order market (crowdfunding campaign) becomes a better predictor of post-campaign sales, the pledge amount is reduced thereby increasing the critical number of backers needed. Although increasing the pledge has the effect of reducing the break even number of backers as well, the drop is not as steep. Therefore, the difference between x^{LT} and $\frac{T}{p_c}$ widens.

As the cost of reputation increases the optimal target amount increases linearly as per Lemma 3.3. With a higher target there is less risk of the backers not getting delivery conditional on campaign success. Therefore, a higher pledge amount can be charged as well (when there is no premium charged by the supplier for no production orders, the pledge actually reduces until the reputation levels are sufficiently high, refer panel in Appendix). The wholesale price also increases. Although the break even quantity increases, it does not increase as fast as the critical number of backers for campaign success $\frac{T}{p_c}$. This causes the gap $x^{LT} - \frac{T}{p_c}$, and therefore the risk, to reduce.

As the correlation between the crowdfunding and the post-campaign market increases, the total size of the market for the new product, conditional on the outcome of the crowdfunding subscription levels, increases (when $\rho = 0$, the total size of the market conditional on the crowdfunding outcome is $x + \mu_Y$). For all correlation levels ρ, the expected market size increases as ρ increases). Given the equilibrium pledge amount and wholesale price, if the ex-ante payoff from the market is sufficient to cover the fixed cost of product development, from Lemma 2, we know that the crowdfunding subscription level for breaking even will be lower than the mean backer population size μ_X. However, to compensate for a more precise signal (higher ρ), the subscription level for investment moves closer to the mean backer population. In other words, $\mu_X - x^{LT}$ reduces as the signal becomes more precise, all else remaining constant.

With increase in the minimum threshold level, the expected payoff of both the supplier and entrepreneur decreases. Furthermore, an increase in the minimum subscription levels also reduces the net valuation of the product for the backer, $\phi v \bar{F}\left(x^{LT}\right)$ decreases. Given that the entrepreneur must set such a pledge and target level that compensates for the reduced value, either the pledge amount (p_c) must be reduced or the critical number of backers needed for campaign success $\left(\frac{T}{p_c}\right)$ must increase. Recall, from Lemma 4, that the optimal target of the entrepreneur increases linearly in the option premium (Γ) that the supplier charges. The supplier by increasing the option premium, not only maximizes his own payoff, but also aligns itself with the need to increase $\frac{T}{p_c}$, as $T = \frac{R+\Gamma}{\gamma}$. The supplier does not merely increase the penalty, as the wholesale price reduces more than the pledge amount so that the net impact of x^{LT} reduces. However, in equilibrium we find that the increase in correlation increases x^{LT} more than the optimal margin reduces it, with the result that x^{LT} increases overall. When the cost of reputation is low, we find that the increase in x^{LT} is more than the optimal number of critical backers $\frac{T^*}{p_c^*} = \frac{R+\Gamma^*}{p_c^*}$ needed for campaign success. As a result, the delivery risk $x^{LT} - \frac{T^*}{p_c^*}$ increases.

Comparing the two contracts of the same price regime, with and without the option premium to exercise the right of no production, we find the following result:

Proposition 3.1 (The role of suppliers in reducing delivery risk.). *All other parameters of the crowdfunding and post-campaign remaining constant, if the Entrepreneur's cost of reputation exceeds a threshold R^*, the entrepreneur will keep a "risk-free" critical number of backers for campaign success, where $\frac{T}{p_c} = x^{LT}$. Denoting, R^O and R^N as the threshold reputation costs with and without the option premium, at equilibrium $R^O < R^N$. In other words, suppliers can exert a positive externality on the crowdfunding campaigns by incentivizing low reputation players to set a risk-free critical number of backers. When there are no penalties, players with only very high cost of reputation set a risk free-number of critical backers.*

Based on a comparison of the contingent wholesale price contracts, with and without a premium for exercising the option of no production, we find that because of the discipline that the supplier imposes on the entrepreneur while setting the target and pledge amount, both the entrepreneur and the supplier are better off with a contingent wholesale contract with an exercise price for no production. This is stated in the following Proposition.

Proposition 3.2. *In a single price regime, a wholesale price contract with option premium dominates a wholesale price contract with no premium for exercising the option to not produce.*

Proof: Follows from comparison of the two regimes and the numerical analysis.

We also find that the share of the total channel profit is higher for the entrepreneur when the reputation costs are higher. Although, the total channel profits decline, the share of the total payoff in the channel increases for the entrepreneur as the cost to its reputation increases.

We note that the observations are a result of the values of the parameters chosen. When the population parameters (mean and standard deviations) of the backer and post-campaign market distributions change, such that the only feasible pledge and retail prices are such that $(\gamma p_c - w)\mu_X + (p_c - w)\mu_Y < M$, the results change. Specifically, as the correlation coefficient between the two markets increase, the probability of delivery risk *reduces* while any increase in the share of revenues of the entrepreneur results in a decrease in the probability of delivery failure.

Subsequent to the numerical analysis, we can generalize our observations by studying the contingent wholesale price contract when pledge and post-campaign prices are equal (No Price Discrimination)

Observation 3.2. *The impact of a change in cost of reputation* (R)*, strength of signal* (ρ) *and platform commission rate on the pledge* (p_c) *and wholesale price* (w)*, premium option* (Γ)*, target* (T)*, payoffs of the entrepreneur* $\mathbb{E}(\Pi_e)$*, supplier* $\mathbb{E}(\Pi_s)$ *and share of entrepreneur's payoff* $\left(\frac{\mathbb{E}(\Pi_e)}{\mathbb{E}(\Pi_e)+\mathbb{E}(\Pi_s)}\right)$*.*

- *As the cost of reputation increases both pledge and wholesale price increases* $\left(\frac{\partial p_c}{\partial R} \geq 0,\ \frac{\partial w}{\partial R} \geq 0\right)$*. Both pledge and wholesale prices increase as the crowdfunding market sends a better signal about the size of the post-campaign market* $\left(\frac{\partial p_c}{\partial \rho} \leq 0,\ \frac{\partial w}{\partial \rho} \leq 0\right)$*. As the platform decreases its commission rate (or* γ*, the entrepreneur's share, increases), the pledge level decreases and the wholesale price increases* $\left(\frac{\partial p_c}{\partial \gamma} \leq 0,\ \frac{\partial w}{\partial \gamma} \geq 0\right)$*.*
- *As the cost of reputation increase, the entrepreneur pays a lower premium to exercise the option of not pursuing production* $\left(\frac{\partial \Gamma}{\partial R} \leq 0\right)$*. A stronger crowdfunding signal increases the option premium that the supplier charges* $\left(\frac{\partial \Gamma}{\partial \rho} \geq 0\right)$*. Increasing the entrepreneur's share of campaign revenue increases the option premium charged by the supplier* $\left(\frac{\partial \Gamma}{\partial \gamma} \geq 0\right)$*.*
- *The equilibrium target set by the entrepreneur increases as the cost of reputation increases* $\left(\frac{\partial T}{\partial R} \geq 0\right)$*. Under the NOP regime the target is unaffected by a change in strength of the crowdfunding signal* $\left(\frac{\partial T}{\partial \rho} = 0\right)$*, but in a WOP regime the target increases as strength of the crowdfunding signal increases ,* $\left(\frac{\partial T}{\partial \rho} \geq 0\right)$*. With increase in the entrepreneur's share of the campaign proceeds the equilibrium target decreases in the NOP regime* $\left(\frac{\partial T}{\partial \gamma} \leq 0\right)$ *and increases in the WOP regime* $\left(\frac{\partial T}{\partial \gamma} \geq 0\right)$*.*
- *As the cost of reputation is above a threshold* R^* *any increase beyond it increases the entrepreneurs payoff increases. If* $R \leq R^*$ *the payoff decrease with increase in cost of reputation* $\left(if\ R > R^*;\ \frac{\partial \mathbb{E}(\Pi_e)}{\partial R} \geq 0\ else\ \frac{\partial \mathbb{E}(\Pi_e)}{\partial R} < 0\right)$*. The suppliers payoff decreases, total channel payoff increases and the entrepreneur's share of the total channel profit decreases with increase in the cost of reputation* $\left(\frac{\partial \mathbb{E}(\Pi_s)}{\partial R} \leq 0,\ \frac{\partial \{\mathbb{E}(\Pi_e)+\mathbb{E}(\Pi_s)\}}{\partial R} \geq 0,\ \frac{\partial}{\partial R}\left\{\frac{\mathbb{E}(\Pi_e)}{\mathbb{E}(\Pi_e)+\mathbb{E}(\Pi_s)}\right\} \leq 0\right)$*. With a better crowdfunding signal the entrepreneur's payoff increases and supplier's payoff decreases, and the entrepreneur's share of the total channel profit increases* $\left(\frac{\partial \mathbb{E}(\Pi_e)}{\partial \rho} \geq 0,\ \frac{\partial \mathbb{E}(\Pi_s)}{\partial \rho} \leq 0\right)$ *and* $\left(\frac{\partial}{\partial \rho}\left\{\frac{\mathbb{E}(\Pi_e)}{\mathbb{E}(\Pi_e)+\mathbb{E}(\Pi_s)}\right\} \geq 0\right)$*. The total channel profit increases*

for all signals $\rho < \rho^*$ and decreases after it $\left(\frac{\partial\{\mathbb{E}(\Pi_e)+\mathbb{E}(\Pi_s)\}}{\partial\rho} \geq 0 \ if \ \rho \leq \rho^* \ and \ \frac{\partial\{\mathbb{E}(\Pi_e)+\mathbb{E}(\Pi_s)\}}{\partial\rho} < 0\right)$. *A higher share of campaign revenues decreases the total channel profit at the expense of the payoff of the entrepreneur while the supplier benefits* $\left(\frac{\partial\mathbb{E}(\Pi_e)}{\partial\gamma} \leq 0, \ \frac{\partial\mathbb{E}(\Pi_s)}{\partial\gamma} \geq 0\right)$*, and* $\left(\frac{\partial\{\mathbb{E}(\Pi_e)+\mathbb{E}(\Pi_s)\}}{\partial\gamma} \leq 0, \frac{\partial}{\partial\gamma}\left\{\frac{\mathbb{E}(\Pi_e)}{\mathbb{E}(\Pi_e)+\mathbb{E}(\Pi_s)}\right\} \leq 0\right)$.

- *The risk exposure of backers decreases as the cost of reputation increases* $\left(\frac{\partial\left(x^{LT}-\frac{T}{p_c}\right)}{\partial R} \leq 0\right)$ *and increases as the strength of correlation increases* $\left(\frac{\partial\left(x^{LT}-\frac{T}{p_c}\right)}{\partial\rho} \geq 0\right)$. *With increase in the entrepreneur's share of the campaign proceeds the risk exposure of backers of not getting delivery even when losing their pledge amount increases* $\left(\frac{\partial\left(x^{LT}-\frac{T}{p_c}\right)}{\partial\gamma} \geq 0\right)$.

The above observations are based on our numerical analysis results, which are available in panels B.1, B.2, B.3 and B.4 of the Appendix.

3.5 Price Discrimination when crowdfunding backers and regular buyers have different valuation

We assume that there are consumers who will buy the product in the regular season if the product becomes available. Letting the pledge amount during the crowdfunding campaign to be p_c and the regular selling price to be p_m, the entrepreneur's decision to either invest in the fixed development cost depends on whether the expected total market size, conditional on the outcome of the campaign is large enough. That is, if, $\gamma p_c x + p_m\left\{\mu_Y + \rho\sigma_Y\left(\frac{x-\mu_X}{\sigma_X}\right)\right\} - w\left\{x + \mu_Y + \rho\sigma_Y\left(\frac{x-\mu_X}{\sigma_X}\right)\right\} \geq M$. In the first component, the revenue earned by the entrepreneur is net of the fees paid to the platform (the platform takes $1-\gamma$ of the proceeds conditional on reaching the target. Since there is a benefit from conducting a crowdfunding campaign by getting feedback from backers who get delivery, we assume that based on the feedback the value of the product changes to θv, where $\theta \in \{\theta_l, \theta_h\}$ with $\Pr(\theta = \theta_l) = \Pr(\theta = \theta_h) = \frac{1}{2}$. Backers can give negative feedback about the product which can reduce the valuation of the product to $\theta_l v$. On the upside there could be positive feedback which increases the value to $\theta_h v$ such that $0 \leq \theta_l \leq \theta_h \leq 2$. The entrepreneur does not commit on the second period price until after completing production subsequent to

finishing the campaign. The expected value for the product is $\mathbb{E}(\theta)v = \frac{\theta_l+\theta_h}{2}v$. In the range the factor (θ) can take the value, we admit the possibility that the valuation of the product may increase by two-fold (when both θ_l and θ_h take a value of 2). Therefore, conditional on the product performance, the second period price is $p_m = \theta_i v, i \in \{l, h\}$. Since, the exact impact of crowdfunding feedback is not known until the deliveries are made to the backers, the second period pledge amount is itself a random number that depends on the outcome of θ. Hence, the entrepreneur and backers can form an expectation of what the market price will be as denoted by $p_m = \mathbb{E}(\theta)v$. Substituting this value to get the expression of the threshold number of backers needed for the backer to makes an investment is:
$x^{LT} = \frac{M\sigma_X - \{\mathbb{E}(\theta)v - w\}(\mu_Y\sigma_X - \rho\mu_X\sigma_Y)}{(\gamma p_c - w)\sigma_X + \{\mathbb{E}(\theta)v - w\}\rho\sigma_Y}$.
The backer contemplating pledging in a crowdfunding campaign weighs it against buying when (and if) the product becomes available in the regular market. That is, if $\mathbb{E}(\Pi_b^c) \geq \mathbb{E}(\Pi_b^m)$ where $\mathbb{E}(\Pi_b^c) = \phi v \bar{F}\left(x^{LT}\right) - p_c \bar{F}\left(\frac{T}{p_c}\right)$ and $\mathbb{E}(\Pi_b^m) = \phi \bar{F}\left(x^{LT}\right)\{\delta v - \mathbb{E}(p_m)\}$. Note that the backer in the campaign will weigh the benefit from waiting until the product becomes available in the regular market depends on whether purchasing from the market earns a non-negative payoff. That is, if $\delta v - \mathbb{E}(p_m)$ exceeds zero. This leads us to characterize consumers as either patient or impatient.

1. Impatient Backers - Backers who lose a substantial proportion of their valuation due to waiting; $\left(\delta < \frac{\theta_l+\theta_h}{2}\right)$.
2. Patient Backers - Backers who retain a substantial proportion of their valuation even after waiting waiting; $\left(\delta \geq \frac{\theta_l+\theta_h}{2}\right)$.

The supplier offers a wholesale price and a premium to exercise an option to not produce if the raised amount is insufficient for the entrepreneur to make the investment but managed to raise the target.

Recall that the payoff of the entrepreneur is: $\mathbb{E}(\Pi_e) = -(R+\Gamma)\left\{F\left(x^{LT}\right) - F\left(\frac{T}{p_c}\right)\right\} + \gamma p_c \int_{\frac{T}{p_c}}^{\infty} x f(x)\,dx + \phi\mathbb{E}(p_m)\int_{x^{LT}}^{\infty}\left\{\mu_Y + \sigma_Y\left(\frac{x-\mu_X}{\sigma_X}\right)\right\} f(x)\,dx - \phi w \int_{x^{LT}}^{\infty}\left\{x + \mu_Y + \sigma_Y\left(\frac{x-\mu_X}{\sigma_X}\right)\right\} f(x)\,dx - M\bar{F}\left(x^{LT}\right)$. Observe that the second period price is an expectation that the entrepreneur forms based on the relative likelihood of the product turning out to be good or bad. Optimizing the expression for the optimal target gives $T^*(\Gamma) = \frac{R+\Gamma}{\gamma}$. The supplier has the same payoff as in 3.8. Incorporating the best response of the target for a given option price Γ in its own payoff, the suppliers equilibrium condition may be obtained by equating its first order condition to zero; that is $\frac{\partial \mathbb{E}(\Pi_s)}{\partial \Gamma} = F\left(x^{LT}\right) - F\left(\frac{R+\Gamma}{\gamma p_c}\right) - \frac{\Gamma}{\gamma p_c} f\left(\frac{R+\Gamma}{\gamma p_c}\right) = 0$.

The equilibrium values when the entrepreneur price discriminates is stated in the following Lemma.

Lemma 3.5 (Equilibrium Pledge, Target, Option Premium and Wholesale Price under Price Discrimination)**.** *The equilibrium second period price, target, option premium and wholesale price are obtained using the same rule, regardless of whether the backer is patient or impatient. These are given by:*

- *Regular selling price* $p_m = \theta_i v$, $i \in \{l, h\}$.
- *Target best response function for a given level of option premium* Γ *is* $T = \frac{R+\Gamma}{\gamma}$.
- *Option Premium* Γ *is obtained by solving for* $F\left(x^{LT}\right) - F\left(\frac{R+\Gamma}{\gamma p_c}\right) - \frac{\Gamma}{\gamma p_c} f\left(\frac{R+\Gamma}{\gamma p_c}\right) = 0$.
- *The wholesale price is obtained by maximizing the supplier's payoff from the regular season sales:* $(w-c)\left\{(\mu_X + \mu_Y)\bar{F}\left(x^{LT}\right) + \left(\sigma_X^2 + \rho\sigma_X\sigma_Y\right) f\left(x^{LT}\right)\right\}$.
- *The optimal pledge level depends on whether the backers in the crowdfunding campaign are patient and impatient.*
  - *When backers are impatient* $\left(\delta < \frac{\theta_l+\theta_h}{2}\right)$, *the pledge is obtained by equating* $p_c = r$ *where* $\phi v \bar{F}\left(x^{LT}\right) - r\bar{F}\left(\frac{T}{r}\right) = 0$.
  - *When backers are patient* $\left(\delta \geq \frac{\theta_l+\theta_h}{2}\right)$, *the pledge is obtained by equating* $p_c = r$ *where* $\phi v \bar{F}\left(x^{LT}\right) - r\bar{F}\left(\frac{T}{r}\right) = \phi \bar{F}\left(x^{LT}\right)\{\delta v - \mathbb{E}(p_m)\}$, *where* $\mathbb{E}(p_m) = \frac{\theta_l+\theta_h}{2} v$.

When there is a high cost of waiting the backers are impatient, that is the novelty of the product outweighs the potential benefit of waiting to see the backer feedback incorporated in the product. In this situation, the pledge amount will be kept to extract the entire surplus from the backers. This is a beneficial position for the entrepreneur as there is no chance of a spillover of backers into the regular market. However, if the backer has a low cost of waiting the entrepreneur must keep a pledge amount that ensures that there are no spillovers from the crowdfunding market to the regular market. The above conditions clearly show that the pledge level when consumer valuations in the secondary market are different than in the crowdfunding market, the pledge is *lower*, than when there is no price discrimination. Based on the above mentioned equilibrium characterization we can conduct a numerical analysis similar to the one we conducted for the same price regime.

3.5.1 Numerical Analysis - Payoffs with Price Discrimination

We highlight that discrimination is effective only when the feedback received as a result of the campaign does not *significantly* improve the product valuation. If it does, then the pledge will have to be very low to ensure that the backers do not move to the post-campaign market.

Proposition 3.3 (Entrepreneur's preference for backer types)**.** *If the cost of the entrepreneur's reputation $R < R^*$, then Entrepreneurs prefer impatient backers to patient backers in the backer population. As the proportion of patient backers increases, the entrepreneur is more likely to keep the critical number of backers for campaign success, $\frac{T}{p_c}$ equals the number of backers to break even. $R^* = \gamma\phi v x^{LT}(\phi v, w^*)$, where w^* is the wholesale price that maximizes the suppliers payoff.*

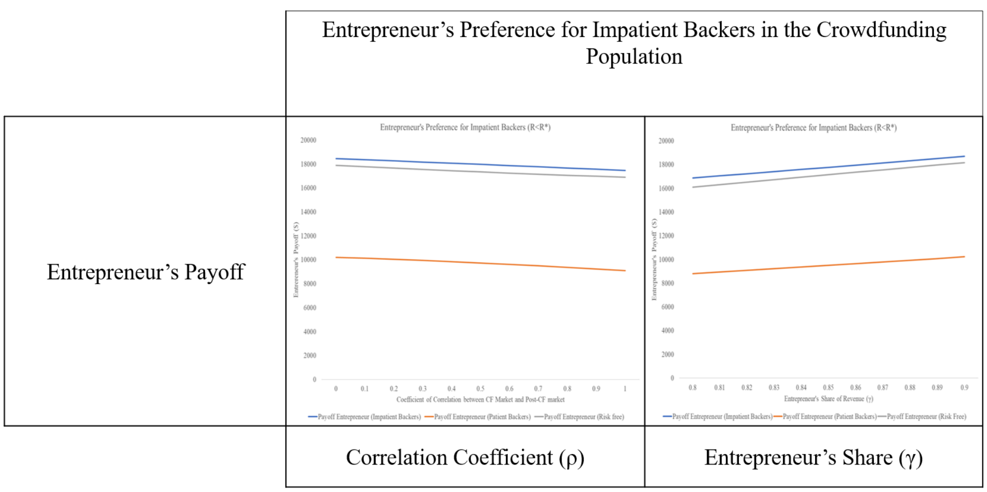


Figure 3.4: Entrepreneur's Preference for Impatient Backer's as evidenced by the highest payoff with changing Crowdfunding Signal ρ, and the Entrepreneur's Share of the campaign proceeds γ, under Price Discrimination

When backers are impatient or attach a high value to the novelty of the product it gets manifested in the heavy discounting that is done to the valuation at a later date. It is rational, therefore, to charge a higher pledge from these backers for impatience. If, however, backers are patient than the most that may be charged from the backers is capped by the expected benefit from crowdfunding. Hence, the pledge cannot be increased arbitrarily. We find, that as the cost of the reputation in case of delivery failure increases, the equilibrium option premium decreases (as it becomes less likely for delivery failure to happen). Therefore, for a sufficiently large cost of reputation, R^*, $\frac{T}{p} = x^{LT}$ where $T = \frac{R^*}{\gamma}$ as $\Gamma\left(R^*\right) = 0$ for all $R > R^*$.

Corollary 3.1 (Effect of Impatient Backer's on Risk Exposure)**.**

- *When backers are patient* $\left(\delta >= \frac{\theta_h+\theta_l}{2}\right)$ *the entrepreneur earns a higher payoff by keeping a target and pledge pair such that* $\left(\frac{T}{p} = x^{LT}\right)$*. Consequently, only impatient backers are exposed to the risk of delivery failure.*
- *The risk exposure of backers decreases as the cost of reputation increases* $\left(\frac{\partial\left(x^{LT}-\frac{T}{p}\right)}{\partial R} \leq 0\right)$ *and increases as the strength of correlation increases* $\left(\frac{\partial\left(x^{LT}-\frac{T}{p}\right)}{\partial \rho} \geq 0\right)$*. With increase in the entrepreneur's share of the campaign proceeds the risk exposure of backers of not getting delivery even when losing their pledge amount increases* $\left(\frac{\partial\left(x^{LT}-\frac{T}{p}\right)}{\partial \gamma} \geq 0\right)$*.*

When backers are patient, the entrepreneur realizes that unless pledges are significantly low the backers will prefer to wait until the product launches successfully in the regular market. The backers do not mind waiting especially because the pledge is capped by the net surplus that may be earned by an even better product. The entrepreneur is better off by extracting the full surplus by requiring that a campaign is successful only if the break-even number is reached. This is accomplished by setting the critical number of backers for campaign success equal to x^{LT}. However, the entrepreneur earns a higher payoff when backers are impatient, as the upside from waiting until the product is successfully launched is not compensated by the loss in value because of waiting. Consequently, there is greater latitude for the entrepreneur to increase the pledge levels.

Corollary 3.2. *As the proportion of impatient backers in a crowdfunding platform increases, all else remaining constant, the possibility of delivery failure increases.*

This is particularly relevant in the case of crowdfunding campaigns where backers do not usually have the experience that VCs and angel investors have. We now study the sensitivity of the risk exposure $\Pr\left(x^{LT} - \frac{T}{p_c}\right)$ when the entrepreneur can price discriminate.

Observation 3.3. *The impact of a change in cost of reputation (R), strength of signal (ρ) and platform commission rate on the pledge (p) and wholesale price (w), premium option (Γ), target (T), payoffs of the entrepreneur $(\mathbb{E}(\Pi_e))$, supplier $(\mathbb{E}(\Pi_s))$ and share of entrepreneur's payoff $\left(\frac{\mathbb{E}(\Pi_e)}{\mathbb{E}(\Pi_e)+\mathbb{E}(\Pi_s)}\right)$, and the risk exposure $\left(x^{LT} - \frac{T}{p}\right)$:*

- *As the cost of reputation increases both pledge and wholesale price increases $\left(\frac{\partial p_c}{\partial R} \geq 0,\ \frac{\partial w}{\partial R} \geq 0\right)$. Both pledge and wholesale prices increase as the crowdfunding market sends a better signal about the size of the post-campaign market $\left(\frac{\partial p_c}{\partial \rho} \geq 0,\ \frac{\partial w}{\partial \rho} \geq 0\right)$. As the platform decreases its commission rate (or γ, the entrepreneur's share, increases), the pledge level decreases and the wholesale price increases $\left(\frac{\partial p_c}{\partial \gamma} \leq 0,\ \frac{\partial w}{\partial \gamma} \geq 0\right)$.*
- *As the cost of reputation increase, the entrepreneur pays a lower premium to exercise the option of not pursuing production $\left(\frac{\partial \Gamma}{\partial R} \leq 0\right)$. A stronger crowdfunding signal increases the option premium that the supplier charges $\left(\frac{\partial \Gamma}{\partial \rho} \geq 0\right)$. Increasing the entrepreneur's share of campaign revenue increases the option premium charged by the supplier $\left(\frac{\partial \Gamma}{\partial \gamma} \geq 0\right)$.*
- *The equilibrium target set by the entrepreneur increases as the cost of reputation and strength of correlation increases $\left(\frac{\partial T}{\partial R} \geq 0,\ \frac{\partial T}{\partial \rho} \geq 0\right)$. With increase in the entrepreneur's share of the campaign proceeds the equilibrium target amount decreases $\left(\frac{\partial T}{\partial \gamma} \leq 0\right)$.*
- *As the cost of reputation increases the entrepreneurs payoff increases, the suppliers payoff decreases, total channel payoff increases and the entrepreneur's share of the total channel profit increases $\left(\frac{\partial \mathbb{E}(\Pi_e)}{\partial R} \geq 0,\ \frac{\partial \mathbb{E}(\Pi_s)}{\partial R} \leq 0,\ \frac{\partial \{\mathbb{E}(\Pi_e)+\mathbb{E}(\Pi_s)\}}{\partial R} \geq 0, \frac{\partial}{\partial R}\left\{\frac{\mathbb{E}(\Pi_e)}{\mathbb{E}(\Pi_e)+\mathbb{E}(\Pi_s)}\right\} \geq 0\right)$. With a better crowdfunding signal both the entrepreneur's and supplier's payoff decreases, but the entrepreneur's share of the total channel profit increases $\left(\frac{\partial \mathbb{E}(\Pi_e)}{\partial \rho} \leq 0,\ \frac{\partial \mathbb{E}(\Pi_s)}{\partial \rho} \leq 0\right)$, and $\left(\frac{\partial \{\mathbb{E}(\Pi_e)+\mathbb{E}(\Pi_s)\}}{\partial \rho} \leq 0, \frac{\partial}{\partial \rho}\left\{\frac{\mathbb{E}(\Pi_e)}{\mathbb{E}(\Pi_e)+\mathbb{E}(\Pi_s)}\right\} \geq 0\right)$. A higher share of campaign revenues decreases the total channel profit at the expense of the payoff of the entrepreneur while the supplier benefits $\left(\frac{\partial \mathbb{E}(\Pi_e)}{\partial \gamma} \leq 0,\ \frac{\partial \mathbb{E}(\Pi_s)}{\partial \gamma} \geq 0\right)$ and , $\left(\frac{\partial \{\mathbb{E}(\Pi_e)+\mathbb{E}(\Pi_s)\}}{\partial \gamma} \leq 0, \frac{\partial}{\partial \gamma}\left\{\frac{\mathbb{E}(\Pi_e)}{\mathbb{E}(\Pi_e)+\mathbb{E}(\Pi_s)}\right\} \leq 0\right)$.*

The comparative statics when backers are impatient are presented in Figure B.5 of the Appendix. When the entire backer population are patient the entrepreneur keeps a target and pledge amount that removes all possibility of delivery failure. Therefore, there will be no impact of a change in the cost of reputation.

Observation 3.4 (Comparative Statics when backers are patient)**.** *As stated in Proposition 3.3 when the entire backer population is patient the entrepreneur keeps a target and pledge amount that removes all possibility of delivery failure. Therefore, there will be no impact of a change in the cost of reputation. The effect of the strength of correlation (ρ) between the crowdfunding and post-campaign market and platform commission rate on the wholesale price (w), target (T), payoffs of the entrepreneur ($\mathbb{E}(\Pi_e)$), supplier ($\mathbb{E}(\Pi_s)$) and share of entrepreneur's payoff $\left(\frac{\mathbb{E}(\Pi_e)}{\mathbb{E}(\Pi_e)+\mathbb{E}(\Pi_s)}\right)$ is stated:*

- *As the platform decreases its commission rate (or γ, the entrepreneur's share, increases), the wholesale price increases $\left(\frac{\partial w}{\partial \gamma} \geq 0\right)$.*
- *The equilibrium target set by the entrepreneur increases as the strength of correlation increases $\left(\frac{\partial T}{\partial \rho} \geq 0\right)$. With increase in the entrepreneur's share of the campaign proceeds the equilibrium target amount decreases $\left(\frac{\partial T}{\partial \gamma} \leq 0\right)$.*
- *With a better crowdfunding signal both the entrepreneur's and supplier's payoff decreases, but the entrepreneur's share of the total channel profit increase $\left(\frac{\partial \mathbb{E}(\Pi_e)}{\partial \rho} \leq 0, \frac{\partial \mathbb{E}(\Pi_s)}{\partial \rho} \leq 0\right)$, and $\left(\frac{\partial \{\mathbb{E}(\Pi_e)+\mathbb{E}(\Pi_s)\}}{\partial \rho} \leq 0, \frac{\partial}{\partial \rho}\left\{\frac{\mathbb{E}(\Pi_e)}{\mathbb{E}(\Pi_e)+\mathbb{E}(\Pi_s)}\right\} \leq 0\right)$. A higher share of campaign revenues increases the total channel profit at the expense of the payoff of the entrepreneur while the supplier benefits more $\left(\frac{\partial \mathbb{E}(\Pi_e)}{\partial \gamma} \leq 0, \frac{\partial \mathbb{E}(\Pi_s)}{\partial \gamma} \geq 0\right)$, and $\left(\frac{\partial \{\mathbb{E}(\Pi_e)+\mathbb{E}(\Pi_s)\}}{\partial \gamma} \geq 0, \frac{\partial}{\partial \gamma}\left\{\frac{\mathbb{E}(\Pi_e)}{\mathbb{E}(\Pi_e)+\mathbb{E}(\Pi_s)}\right\} \leq 0\right)$.*

3.6 Conclusion

Often the reason for delivery failure when a campaign has raised a sufficient amount is attributed to the malicious intent of the entrepreneur. We find that the entrepreneur indeed trades off the benefit of failing to deliver rewards after a successful campaign, with the cost of keeping a high critical number of backers for campaign success. Keeping a target and pledge pair that makes it less likely for the campaign to be successful, comes with the benefit that the backers are insured against losing their money in the event of campaign success. However, if the cost of reputation is not too high the target and pledge is kept so as to expose backers to the risk of losing their pledge amounts.

This problem is further exacerbated because of the participation of a supplier who partakes of the profits, besides the platform which charges a commission to all successful campaigns. In the event that an entrepreneur has the choice of walking away from a commitment to make a fixed investment for quality after observing the crowdfunding outcome, we find that this makes the supplier more willing to give up a share of its revenue. The supplier knows that if it takes too much of the share from the payoffs it may not end up getting the contract, as the critical number of backers needed for campaign success will be high. Therefore, it takes a lower share of the total channel payoffs. Furthermore, against what our intuitions would suggest, as the quality of the crowdfunding signal as a predictor of the size of a future market increases, that tends to increase the risk exposure of the backers. This happens because with a high enough post-campaign mean market size, there would be too much to loose by keeping a high crticial number of backers. Thus, the prospect of a high payoffs from the post-campaign market results in such a target and pledge pair, that increases the risk exposure of the backers.

Entrepreneurs try to induce backers to pledge in a campaign by suggesting that a higher price will be charged in the regular market. For a product that is not yet developed such a claim is at best a possibility. If indeed the product turns out to be as good as promised it will command a higher price in the secondary market. However, in many cases it is seen that subsequent to deliveries there are severe criticisms of the product functioning. Since the comments that are posted are available in the public domain, it is likely that the willingness to pay (valuation) for the product will actually decrease subsequent to a campaign. If, however, backers lose substantial value due to waiting, their impatience makes it more likely for them to pay a higher pledge during the campaign. This makes it easier to reach a target which incentivizes the supplier to seek a lower exercise price for the "no-production" option. This increases the gap between the investable backer number and the critical cutoff for campaign success. Thus, unless the product improves substantially because of crowd participation and feedback, the entrepreneur cannot charge a premium in the post-campaign market but also expose the "impatient" backers to a higher risk of non-delivery subsequent to a successful campaign.

Funding agencies and venture capitalists rely on signals of various kinds to assess the potential of a new product. Crowdfunding has been shown to be an incentive compatible mechanism for such estimations. However, as the quality of the signal improves (due to a higher correlation between the crowdfunding and post-crowdfunding market), it can also expose backers to a higher risk of delivery failure. This is consequential to policy makers, regulators and all such agencies who are custodians of ensuring investor protection and safety.

Although new businesses are rife with uncertainties of various sources, the availability of funds has been the most cited source of failure. The less studied stakeholder is the supplier which is critical in not only scaling production but offering critical product development guidance that helps scaling. Often the entrepreneurs design with an outlook to create a niche in the market. The expertise for Designing for Manufacturing, a field in its own right, comes with domain knowledge and experience on either side of product development, design and manufacturing. The entrepreneurial teams although comprised of bright minds may not have the expertise to study aspects of product design that hinder large scale production or increase cost. Almost always the first exchange between a supplier and an entrepreneur ends up with a 'dose of reality' which exposes aspects of over-designing that hinder scaling and increase cost. While changing design is an ongoing process, these initial exchanges are excellent in retaining the value proposition from the 'frills.' A promising area of future research could be to investigate how the marginal benefit from implementing feedback received from a crowdfunding campaign trades off against the cost of implementing these changes by the supplier. Although we assumed that the order to the supplier is the same as the expected future market size conditional on the outcome of the campaign, studying how the results change if the "optimal order quantity" is ordered, may be interesting. Furthermore,modelling reputation cost as consisting of both a fixed and variable component and studying its role on a platform's rule of recommendation can be an interesting research direction as well. The impact of an endogenously determined minimum order size may also give interesting insights about the risk of delivery failure. We believe that unless the unique risk sources that new businesses face is incorporated, a comprehensive understanding of why "successful" campaigns fail to deliver will be at bay.

4.0 Effect of Seasonality, Sales Growth and Fiscal Year End on the Cash Conversion Cycle

Cash Conversion Cycle (CCC) measures the duration between a firm's outgoing and incoming cash flows. Firms track the CCC metric and employ it as a benchmark since lower CCC values may signal better operational and credit performance. We develop a typification of firms based on the processing lead time and credit periods negotiated with suppliers and customers, and demonstrate how these characteristics interact with sales growth rate, seasonality and fiscal year end to affect CCC. Based on our analytical models, we hypothesize that the impact of sales growth rate and the indirect effect of time on CCC can be positive or negative depending on the firm type. We also identify the crucial role that the demand pattern in the Zone of Influence, an interval that we define around the fiscal year end, plays in determining the CCC. We test our hypotheses empirically using a multi-level (random effect) model and a fixed effect model, where the levels of analyses are the specific firm types and individual firms respectively. Our results, based on quarterly financial data of 58 firms over a 12-year period, confirm the hypothesized effects of sales growth rate, fiscal year location and seasonality on CCC. Though frequently used, CCC is thus a nuanced metric and needs careful interpretation. The findings of the paper are important to facilitate more accurate longitudinal CCC analyses and benchmarking practices that account for unique differences in growth rates, location of fiscal year end, and seasonality.

4.1 Introduction

Comparing the performance of large retailers, a Harvard Business Review article (Fox 2014) states that "The key metric of a company's cash-generating prowess is the cash conversion cycle." Cash Conversion Cycle (CCC) is a pan-organizational measure of efficiency (Gitman 1974) that measures "the average days required to turn a dollar invested in raw material into a dollar collected from a customer" (Stewart 1995). Business analysts and researchers have used CCC, in conjunction with other metrics, to compare financial and operational performance. When benchmarking performance across firms, a lower CCC value is considered to imply superior performance. However, this ostensibly obvious implication may not hold since, as we show, CCC is a highly nuanced metric and requires careful interpretation. We develop a classification system for firms based on their processing lead times, and their supplier and customer credit periods. A firm's type, stemming from this classification, interacts with Sales Growth Rate (SGR), Seasonality and Fiscal Year End (FYE) in a complex fashion to affect its CCC. We show that the CCC is affected by the demand pattern only in a specific time interval around the FYE. The demand pattern outside this interval is not of any consequence, only the mean demand is. Our results show that the complexity of the relationship in the underlying factors makes it difficult to estimate intuitively the direction of change in CCC following benchmarking exercises—thereby underscoring the need for exercising caution when using the CCC metric.

Academics and practitioners have used CCC in many different contexts. For example, Hendricks et al. (2009) use CCC as a measure of operational slack and show that supply chain disruptions have a lower impact on stock returns for firms with higher operational slack. CCC is used in industry as a performance metric to determine senior executive compensation as demonstrated in DEF 14A statements.[1] C-suite executives of Apple, Coca Cola, PPG Industries, and US Steel have used "Cash Conversion Cycle" in recent analyst calls to spotlight superior performance.[2] The Association of Supply Chain Management (ASCM) lists CCC as a primary metric for measuring asset management efficiency in the SCOR model.[3] In an ASCM report (Bolstroff 2018), CCC is used to classify firms as "Laggards" if they have an average CCC that is 73 days higher than "Leaders". Likewise, The Hackett Group ranks companies using CCC based on annual fiscal year end data.

Comparing performance using annual CCC data can result in erroneous inference if we

[1]Firms file proxy statements with the U.S. Securities and Exchange Commission (SEC) in advance of annual meetings. Form DEF 14A (Definitive Proxy Statement) provides key information, including corporate governance and executive compensation to shareholders.

[2]Search results by using "Cash Conversion Cycle" in S&P Capital IQ.

[3]"The Supply Chain Operations Reference (SCOR) model provides methodology, and diagnostic and benchmarking tools that help organizations make dramatic and rapid improvements in supply chain processes." Quote from SCOR Version 12.0 document, 2017. ASCM is the largest association of supply chain professionals.

ignore Sales Growth Rate (SGR), Fiscal Year End (FYE) and Seasonality. For example, the rankings in the CFO/Hackett Group Working Capital Scorecard may not be valid unless we account for these factors. Appendix C.4 lists sample quotations with potentially incorrect comparisons and use of CCC. Next, consider Dell Inc.'s statement from its 2008 Form 424B3[4] filing (pages 55-56): "...our direct model allows us to maintain an efficient cash conversion cycle, which compares favorably with that of others in our industry." This favorable inference is based on a longitudinal CCC comparison (which is also presented in the filing) and may not be valid if SGR, FYE and Seasonality differ across the comparison set. For instance, Dell's FYE is on the Friday nearest January 31 while HP's FYE is on October 31. Overlooking this FYE difference can affect our conclusions: In 2008, HP's CCC was 16 days (about 32%) lower in January compared to in October (Appendix C.2.1). Dell only presents its own annual data, and it is not clear if it made such an adjustment for HP and other competitors. The impact of such inferences can be worsened if a firm makes major policy changes based on CCC benchmarking. For example, in 2013 PG increased the credit period extended to its suppliers from 45 days to 75 days (Esty et al. 2016, Goel and Wohl 2013, Strom 2015) to level its payment terms with industry peers and improve CCC. A major competitor, Unilever has its FYE on December 31 while P&G has its FYE on June 30. To benchmark accurately, we must compute PG's CCC on December 31. But this change increases the difference between P&G's actual and targeted CCC by 13 to 20 days during the 2012 – 2014 period (Appendix C.8).

We study how processing (inventory) lead time,[5] credit extended by suppliers and to customers interact with SGR, Seasonality and FYE to affect CCC. Our motivation for selecting these factors, among others that affect CCC, is twofold. First, the balance sheet measures used in computing CCC depend on demand (we assume demand equals sales) that is determined by SGR, Seasonality, FYE, processing lead time and the credit periods. Second, together, these factors span firm-specific, supply chain, and industry characteristics. A firm's credit policies depend on its industry, procurement and sales strategies, and supply

[4]Firms file Form 424B3 as a supplement for clarifications and updates to a firm's initial prospectus.

[5]For a manufacturer, the "processing (inventory) lead time" is the total time for manufacturing an item, and for a retailer, it is the total time that an item is held in inventory. We refer to this time as processing lead time.

chain bargaining power exercised through contractual terms negotiated with suppliers and customers. The processing lead time depends on factors such as supply chain and competitive strategies, manufacturing technology, inventory policy, and operational performance. The FYE determination depends on tax implications, auditor advice, seasonality, strategic reasons (e.g., optimal time to announce financial results), cadence for new product launches, etc. These factors are not easily changeable. For example, a firm may not be able to change its credit terms unilaterally if its customer or supplier wields more power in the supply chain relationship. Even when the firm is the dominant player, extending (shortening) payment terms for a supplier (customer) can weaken the supply chain. The relationship between these factors is complex—a firm may not be able to account simultaneously for its credit policies, processing lead time, SGR, FYE, and Seasonality when analyzing CCC values longitudinally or benchmarking with competitors. Our goal is to understand this relationship better.

We typify firms based on the processing lead time, and supplier and customer credit periods, and study the effect of a change in SGR on CCC by its Firm Type. Our analysis of a stylized demand pattern helps characterize the compound effect of FYE, Seasonality and SGR on CCC. This analysis helps develop our hypotheses. We also demonstrate that the balance sheet components of CCC depend on sales in only a subset of the fiscal cycle, which we call the Zone of Influence (ZoI). The ZoI is determined by the FYE location, processing lead time, and supplier and customer credit policies. Sales variability or growth outside of ZoI does not affect CCC, only the mean annual sales does.

To validate our hypotheses, we build two empirical models that differ in their level of analyses. The first model aggregates firms by their type and controls for the random effect of firms in the sample, while the second model investigates the fixed effect of firm while controlling for types. Since the type of a firm may change over the long run, both models allow for this change to occur for all firms during the period of analysis. Our results, based on data from 58 firms over a 12-year period, show how SGR, FYE, Seasonality influence CCC values. These factors can improve or worsen the CCC depending on the firm type and ZoI. Thus, even though these factors may be unchangeable in the short run, neglecting to incorporate them can lead to flawed recommendations and misguided managerial initiatives. We suggest improvements in the interpretation and use of CCC.

The organization of the paper is as follows. We review the literature in Section 4.2 and model the components of CCC in Section 4.3. Section 4.4 develops our hypotheses based on the analysis of different stylized demand patterns and Section 4.5 discusses the empirical validation of our hypotheses. In Section 4.6, we conclude with some managerial implications of our work. Appendix C.3 provides the proofs of the propositions, and additional details about the empirical analysis.

4.2 Literature Review

Although CCC is used frequently in practice (e.g., Appendix C.4 for a sampling of company statements) to gauge firm performance, academic research on CCC is limited. Farris and Hutchison (2002) show that a focus on CCC reduction drives firms to achieve better supply chain performance both within and outside a firm's boundaries. Using data from a Brazilian company, Zeidan and Shapir (2017) show that CCC management increases shareholder value. In the context of a firm's ability to recover from supply chain disruptions, Hendricks et al. (2009) use CCC as a proxy for operational slack: Firms with higher CCC have higher operational slack. They show that firms with greater operational slack have a less negative stock market reaction to supply chain disruptions as measured by the two-day cumulative abnormal return. Wang (2019) shows that a zero-investment portfolio constructed by buying stocks of firms with low CCC, and shorting stocks of firms with high CCC, earns a positive return beyond what is explained by traditional asset pricing models.

A firm's efforts to decrease only its own CCC may result in suboptimal decision making from a supply chain perspective. Hutchison et al. (2009) study the benefits of transferring inventory to a "low-cost-of-capital" stage and extending favorable credit terms as a way of improving supply chain profitability. They show how supply chain profitability can increase despite an increase in the CCC. Hofmann and Kotzab (2010) investigate supply chains from a single firm and collective chain perspective. They suggest that improvements in CCC from a single company's perspective may not add value to the overall supply chain because a powerful focal firm may derive all benefits of the WC improvements in the supply chain.

These papers overlook how SGR, Seasonality and FYE affect CCC.

WC is a related liquidity measure and has been studied more extensively than CCC (we show the two metrics differ in Appendix C.7). For example, studies of misspecification and measurement error in total accruals to detect earnings management (Dechow 1994, Dechow et al. 1995) control for sales growth. McNichols and Wilson (1988), and Jones (1991) introduce models which have become the standard for testing hypotheses in earnings management. These early papers use total accruals as the dependent variable and one-period lagged sales to control for sales growth. We use CCC as the dependent variable while using quarterly dummy variables for seasonality and a long-term time index to account for trend. Dechow et al. (1998) use a stochastic random walk demand primitive to explain negative serial correlation in cash flow change. Like them, we develop our hypotheses by using a demand primitive and develop an analytical expression for CCC. We find that SGR interacts with the processing lead time and credit periods to either decrease or increase CCC. Categorizing firms based on the processing lead time relative to the values of credit periods extended to suppliers and customers, we find the sensitivity of CCC to a change in SGR for each Firm Type. Classifying firms in this way, we posit that serial correlation in operating cash flow (Dechow et al. (1998)) is also affected by the credit and inventory policies of a firm. The cost of inventory, receivables and payables depend on the credit terms with suppliers and customers, the demand pattern and location of the fiscal year end. The inventory and credit policies define the interval, Zone of Influence, around the fiscal year end. Under a mild restriction, we find that the demand pattern only in this interval affects the value of CCC; the demand pattern outside of the interval is inconsequential as long as the mean annual demand is held constant.

Some papers (Banker and Chen 2006, Banker et al. 2015) find that changes in WC result from backward- and forward-looking sales. This leads to correlation in accruals. Collins et al. (2017) use a four-period (instead of one-period) lagged sales measure to account for sales growth and seasonality. In line with the critique of the assumption of uniform accrual generating process by Dopuch et al. (2012), our basis for the classification of Firm Type accommodates for heterogeneity in credit and inventory policies, both temporally and cross-sectionally across firms for benchmarking. While these papers use various controls for sales growth, none model (and test) the interaction of differing credit policies and processing lead time across firms at a granular level. Moreover, even though WC and CCC are both liquidity measures, we can show that they can move in opposite directions for the same firm, necessitating an independent investigation of CCC.

Frankel et al. (2017) study the impact of managerial compensation on abnormal WC reductions by considering inconsistent seasonal patterns (firms with lowest sales in Q4) in different sub-samples to test their hypotheses. In contrast, we investigate the variation in seasonality to show how seasonality, sales growth rate, and FYE interact. An implicit assumption in Frankel et al. (2017) is that sensitivity of WC change does not depend on the Firm Type. We postulate and validate the direction in which CCC will change for firms of different types and sales growth rates. Some companies (Facebook, US Steel, etc.) that use CCC as a metric for performance evaluation and executive compensation, must be cognizant of the degree to which Seasonality and FYE differences affect CCC. Otherwise, factors unrelated to managerial performance may confound employee appraisals.

Conducting a thorough literature review and discussing different measures of earnings quality, Dechow et al. (2010) emphasize that the decision context is as important as the metric under study. Given CCC's use for efficiency measurements, and performance and investment analysis, its vulnerability to misinterpretation increases. Pointing to the difficulty of comparing financial ratios, Lev and Sunder (1979) highlight non-linearities that may be induced due to differences in size and presence of an intercept term in the denominator. Our analysis extends this observation and we submit that Sales Growth Rate, Seasonality, and Fiscal Year End interact with the processing lead time and credit policies to affect the CCC metric. By explicitly modeling the factors that can distort interpretation of the CCC metric, our research alerts CCC users and empirical researchers in both operations management and accounting.

Specifically, the research objectives of this paper are to:

1. Highlight the complicated interaction between Sales Growth Rate, Seasonality, and Fiscal Year End and its effect on CCC.

2. Construct an analytical model to hypothesize the directional impact of the above factors

on CCC, and test the hypotheses empirically, and

3. Propose the concept of Zone of Influence, formulate it as a function of the processing time and credit policies, and investigate its role in quantifying the components that comprise CCC.

To the best of our knowledge, this paper is the first to study the effect of idiosyncratic characteristics such as Sales Growth Rate, Seasonality, and Fiscal Year End on CCC by classifying firms based on their credit periods and processing lead time. Specifically, we determine the directional impact of these factors on CCC. We contend that a lack of context in using CCC can lead to misinterpretations and append important subtleties to the "lower CCC value is better" creed.

4.3 Model and Notation

In this section, we model CCC and its components. To keep our analytical model tractable, we consider a single product, and assume that demand is deterministic and equals sales. Our model applies to both manufacturers (who procure raw materials and components for processing) and retailers (who procure finished goods to sell). We assume that the manufacturer follows a just-in-time procurement and processing strategy, acquiring the components right when needed, and shipping the finished products as soon as the processing is complete. Retailers buy the finished goods and maintain pipeline inventory at their distribution centers and retail stores. Suppliers and company personnel (e.g., employees and sub-contractors) extend "credit" to the firm for the same duration, l_s. Likewise, the credit extended to all customers, l_c, is the same. These assumptions can be relaxed.

Let $f(t)$ denote sales at time t and T the duration (in days) of a fiscal year (FY). The total sales during the FY beginning at τ (and ending at $\tau + T$) is $D_{\tau+T} = \int_{\tau}^{\tau+T} f(t)dt$, and if r denotes the product's unit selling price, the annual sales revenue is $rD_{\tau+T}$. The Cost of Goods Sold for the FYE at $\tau+T$, $COGS_{\tau+T}$ is the sum of the component and processing costs incurred during the year. Let c be the purchase cost per unit (raw material or component cost for a manufacturer; finished good cost for a retailer). Let v be processing cost per unit per time period, which consists of direct labor, direct overhead, and indirect allocated overhead, distribution and holding cost components.[6] Since the processing activity at a retailer is limited, v for a retailer may have only the holding and distribution cost components. Thus, v may be small relative to c. We assume that v remains constant during l_p, the "processing" lead time; l_p corresponds to the processing lead time for a manufacturer and to the time for which finished goods are held in inventory for a retailer. Thus, $COGS_{\tau+T} = (c + vl_p)D_{\tau+T}$.

The CCC (in days) for a FYE at time $\tau + T$ is $CCC_{\tau+T} = DSO_{\tau+T} + DIO_{\tau+T} - DPO_{\tau+T}$ where $DSO_{\tau+T}$ is the Days of Sales Outstanding, $DIO_{\tau+T}$ is the Days of Inventory Outstanding, and $DPO_{\tau+T}$ is the Days of Payables Outstanding measured at time $\tau+T$ (see, for example, Gordon et al. (2019)). Next, we derive the expressions of these components. Appendix C.5 summarizes our notation. For convenience, we assume that the parameters l_s, l_c and l_p are bounded below by zero and bounded above by the fiscal year duration T. We permit them to change during the year as long as they do not affect the computation of $DSO_t + DIO_t - DPO_t$ at $t = \tau,\ \tau + T$. To avoid special cases, we also assume that $\tau \geq T$ in the development below.

4.3.1 Days of Sales Outstanding

Let AR_t denote the accounts receivables at time t, and l_c denote the credit period that the firm grants to its customers. Then, the average of the accounts receivables at the beginning and end of a FY ending at time $\tau+T$ is $\left(\frac{AR_\tau + AR_{\tau+T}}{2}\right)$, where AR_τ equals $r\int_{t=\tau-l_c}^{\tau} f(t)dt$ and $AR_{\tau+T}$ equals $r\int_{t=\tau+T-l_c}^{\tau+T} f(t)dt$. The Days of Sales Outstanding is computed by dividing this average by the sales for the FY ending at $\tau + T$, and multiplying by T to covert the sales outstanding into days. Thus, the Days of Sales Outstanding for a FY ending at time $\tau + T$ is $DSO_{\tau+T} = \frac{T}{rD_{\tau+T}}\left(\frac{AR_\tau + AR_{\tau+T}}{2}\right)$.

[6] We assume that allocated indirect overhead includes any fixed costs and depreciation expenses relating to plant and machinery. We can relax this assumption if fixed costs are expensed rather than capitalized into inventory.

4.3.2 Days of Inventory Outstanding

The inventory at time t is the work-in-process (for a manufacturer) or the finished goods procured (for a retailer) in the interval $(t - l_p, t)$. The inventory cost at time t, IC_t is the sum of component procurement and processing costs. A just-in-time strategy implies that all procurement is done for sales arising l_p periods later. Hence, the procurement cost component of IC_τ is $c\int_{t=\tau}^{\tau+l_p} f(t)\,dt$. For modeling purposes, we assume that the unit processing per time period, v does not vary with the stage of processing (this assumption can be relaxed). Thus, a unit that spends t days (where $t \leq l_p$) in inventory contributes vt to the processing cost. Since all procurement is done for sales arising l_p periods later, the total processing cost at time τ is $v\int_{t=\tau}^{\tau+l_p} (l_p - (t-\tau))f(t)dt$ and the total inventory cost at time τ is $\text{IC}_\tau = c\int_{t=\tau}^{\tau+l_p} f(t)\,dt + v\int_{t=\tau}^{\tau+l_p} (l_p - (t-\tau))\,f(t)\,dt$. This expression also applies to a retailer, except that the processing cost component, v may be zero or small relative to c. We can express Days of Inventory for a FY ending at time $\tau + T$ as $DIO_{\tau+T} = T\left(\frac{IC_\tau + IC_{\tau+T}}{2}\right)\frac{1}{COGS_{\tau+T}}$.

4.3.3 Days of Payable Outstanding

The accounts payable at time t, AP_t is the sum of amounts outstanding for purchases and processing done during the period from $t - l_s$ to t. We assume that payments are made on their due date. Thus, the accounts payable at time τ is:

$$AP_\tau = c\int_{t=\tau-l_s+l_p}^{\tau+l_p} f(t)\,dt + v\left[\int_{t=\tau+max(l_p-l_s,0)}^{\tau+l_p} (l_p - (t-\tau))\,f(t)\,dt + l_p\int_{t=\tau+min(l_p-l_s,0)}^{\tau} f(t)\,dt\right].$$

The first term in this expression is the amount due at time τ to the suppliers for all purchases. The l_p term in the integral limits of the first term arises because purchases are made for demand l_p periods into the future. The l_s term in the lower limit of the integral accounts for the credit granted by the supplier. The second and the third terms account for the processing cost incurred on work in progress (WIP) and finished products respectively. When $l_p > l_s$, none of the parts procured from $\tau - l_s$ to τ completes the production cycle. Thus, the payables relating to the processing cost payables are only on account of WIP. However, when $l_p \leq l_s$ the processing cost is due to both WIP and finished products. The processing cost for finished products is vl_p multiplied by the quantity of finished products made; this is the third component in the expression for AP_τ. Notice that the third component becomes zero when $l_p > l_s$. A similar argument applies when the firm is a retailer. We can now express Days of Payables Outstanding for a FY ending at $\tau + T$ as $DPO_{\tau+T} = \frac{T}{COGS_{\tau+T}} \left(\frac{AP_\tau + AP_{\tau+T}}{2} \right)$.

4.4 Development of Hypotheses

In this section, we investigate factors that affect a firm's CCC and develop our hypotheses. Section 4.4.1 considers the effect of SGR and Firm Type on CCC, where Firm Type depends on l_c, l_p and l_s. For convenience, we refer to l_c, l_p and l_s, collectively, as "Operating Policy." Section 4.4.2 studies the effect of Time on CCC, and Section 4.4.3 investigates the interaction of SGR and FYE on CCC. Appendix C.3 provides the proofs of the propositions in this section.

4.4.1 Effect of Sales Growth Rate and Firm Type on *CCC*

We say that a firm's inventory performance is high (low) when l_p is low (high) relative to l_s and l_c. We use inventory performance as the basis for categorizing firms into the following four Firm Types: High (H) when $l_p < l_s - l_c$, Medium-High (MH) when $l_s - l_c \leq l_p < l_s$, Medium-Low (ML) when $l_s \leq l_p \leq l_s + l_c$ and Low (L) when $l_p > l_s + l_c$. We say that a firm is operationally efficient when $l_p < l_s - l_c$, i.e., its inventory performance is high, and it is of Firm Type H. If a firm of this type has constant demand, suppliers fund its WC needs and the CCC is negative. For Firm Types MH, ML and L, CCC is nonnegative when demand is constant. To discretize the firm types, we choose the four intervals as stated because the intervals depend on a comparison of an operational performance metric (l_p) with two credit period metrics (l_s and l_c).

To estimate the effect of SGR on CCC, we assume a linear demand form, $f(t) = \alpha + \beta t$, where α is a constant, t denotes Time, and β denotes the SGR. Figure 4.1 summarizes the sensitivity of CCC to changes in growth rate, where the threshold $\Gamma(c, v, l_p, l_c, l_s)$ equals $-3c\left(l_c + l_s - l_p\right)\left(l_c - l_s + l_p\right) + v\left\{2l_s^3 - 3l_p\left(l_c^2 + l_s^2\right) + l_p^3\right\}$.

Proposition 4.1. *The sensitivity of CCC to changes in SGR for a linear demand form, $f(t) = \alpha + \beta t$, depends on Firm Type as summarized in Table 4.1.*

Table 4.1: Sensitivity of *CCC* to change in *SGR* for a linear demand form

	Firm Type				
	$l_p < l_s - l_c$ **(High, *H*)**	$l_s - l_c < l_p < l_s$ **(Medium-High, *MH*)**	$l_s \leq l_p \leq l_s + l_c$ **(Medium-Low, *ML*)**	$l_p > l_s + l_c$ **(Low, *L*)** $\Gamma < 0$	$l_p > l_s + l_c$ **(Low, *L*)** $\Gamma > 0$
$\frac{\partial CCC_\tau}{\partial \beta}$	$+$	$-$	$-$	$-$	$+$

As the growth rate (β) increases, CCC increases for Firm Type H, decreases for Firm Types MH and ML, and may increase or decrease depending on the value of the threshold Γ for Firm Type L.

Interpretation: An increase in *SGR*, β increases the value of the snapshot measures: receivables, payables and inventory. However, since the flow measures, Sales and COGS, also change as β changes, the change in the components of CCC is not obvious. The proof of Proposition 4.1 shows that *DSO* always decreases as β increases, but the difference *DIO* – *DPO* may increase or decrease depending on the firm type. Therefore, CCC can increase or decrease as β increases. For example, when $l_p \geq l_s$, *DIO* – *DPO* always increases with β, but the net effect of increasing β on CCC depends on whether the decrease in *DSO* is greater or less than the increase in *DIO* – *DPO*. An incomplete analysis might attribute a decrease in CCC to managerial action rather than to an increase in the sales growth rate for Firm Type MH or ML. Thus, analysts might overstate the effect of managerial action when a lower CCC is observed. For Type L firms (that is, firms with $l_p > l_s + l_c$), the impact of an increase in sales growth rate on CCC depends on the purchase cost, c and the processing cost, v in addition to the Operating Policy (l_c, l_p, and l_s). This effect on CCC depends on threshold Γ, which captures the interaction of the Operating Policy and the cost parameters (c, v). As a special instance, when v is relatively small compared to c (as is likely the case for retailers), $\Gamma > 0$ and the impact of an increase in *SGR* on CCC is positive. In other words, for firms with a sufficiently long processing lead time, l_p and relatively small processing cost, v, an increase in β will increase *CCC*.

As an example, Target (TGT) and Walmart (WMT) are of the same Firm Type (L) but TGT grew faster than WMT between 2006 and 2012. If we assume that the processing cost (v) is negligible for both retailers, i.e., $\Gamma > 0$, Proposition 4.1 suggests that TGT's increase in *CCC* will be higher than that of WMT's. We observe this in the empirical results presented in Section 4.5. WMT's management, comparing its lower *CCC* change to TGT's, might overstate the effect of its improvement initiatives. Likewise, if TGT were to benchmark its *CCC* with WMT's, it should increase the reported *CCC* values of WMT as WMT grew at a lower rate. Any implications based on *CCC* comparisons across firms (e.g., as in Fox, 2014) must be done with utmost caution. Even if firms have comparable growth rates, any inter-firm differences in *CCC* changes will be confounded by Firm Type. We remark that the Operating Policy (l_c, l_p and l_s), especially l_p is unobservable. In our hypothesis validation, we use *DSO*, *DIO*, and *DPO* respectively for these parameters as approximations. *DSO*, *DIO*, and *DPO* are available for publicly held companies and can be used by analysts for classifying firms. Finally, we note that Proposition 4.1 holds when there is no seasonality. Section 4.4.3 studies the effect of a secular demand form with seasonality on *CCC*. This analysis motivates the following hypothesis.

Hypothesis 4.1. *A change in sales growth rate, (β), affects* CCC. *The direction of change in* CCC *depends on the* Firm Type *as defined in Proposition 4.1.*

4.4.2 Mediation Effect of Time through Sales on *CCC*

Even when Sales does not exhibit any seasonality, and has just a secular trend, *CCC* may change with time for two reasons. First, there may be a direct effect of Time due to, say, longitudinal industry-wide changes such as a collective push for increasingly faster payments by suppliers, quicker billing due to the introduction of progressively improving technology platforms, or introduction of modern supply chain finance methods. For example, blockchain technologies can help mitigate trade friction (Cong and He, 2019), and thus accelerate cash flow. Second, as Sales itself changes over time, it may induce an indirect effect on CCC because Sales influences COGS, DIO, DPO and DSO. This indirect (that is, mediated through Sales) effect of Time on CCC may occur even when Sales is not seasonal. Not accounting for the mediated effect of Time on CCC might distort the estimates for the direct effect of time. To formally test for the mediated effect of Time on CCC through Sales, we state Hypothesis 4.2; Appendix C.3.2 provides additional details.

Hypothesis 4.2. *Time affects CCC both directly and indirectly, that is, mediated through Sales. The mediated effect of Time on CCC through Sales depends on the Firm Type.*

Implication: For analyzing longitudinal performance improvements, firms compute and report CCC values over time. Hypothesis 4.2 states that even when a firm's Operating Policy (l_c, l_s, l_p), processing and procurement costs (v, c), and growth rate remain unchanged, and there is no direct effect of Time, CCC may change due to the mediated effect of Time through Sales. This effect depends on the company's Firm Type which is defined by its Operating Policy. Specifically, for a Type H firm, (Type MH and ML firms), an increase in Sales increases (decreases) CCC.

4.4.3 Effect of Fiscal Year End and Seasonality on CCC

We now discuss the effect of Seasonality and FYE location on CCC. We assume that the Operating Policy remains unchanged in the short term. Consider the intervals $[\tau - l_c, \tau + max\,(l_s, l_p)]$ and $[\tau + T - l_c, \tau + T + max\,(l_s, l_p)]$. Only the demand patterns in these intervals affect the CCC metric for a FYE at time $\tau + T$. The demand pattern during the rest of the year does not affect CCC, only the mean annual demand does. The reason for this observation follows from our computation of DSO, DPO, and DPO in Section 4.3. Therefore, we refer to each of these intervals as the Zone(s) of Influence (ZoI). Figure 4.1 shows the ZoI at time τ.

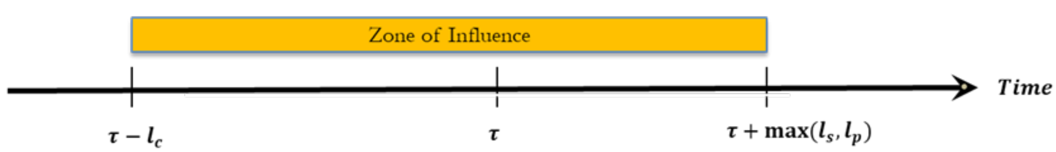


Figure 4.1: Timeline for the Zone of Influence (ZoI) relative to a Fiscal Year Ending at τ.

We assume that the demand pattern in the *ZoI* around τ is the same as the demand pattern in the *ZoI* around $\tau + T$. Thus, the comments below analogously apply to the *ZoI* around $\tau + T$, and we suppress the subscript T. We partition the *ZoI* around τ into the intervals $[\tau - l_c, \tau]$ and $[\tau, \tau + max\,(l_s, l_p)]$. The demand in the region $[\tau, \tau + max\,(l_s, l_p)]$ affects payables (AP_τ) and cost of inventory (IC_τ) while the demand in the region $[\tau - l_c, \tau)$ affects the receivables (AR_τ). When $l_p > l_s$, the difference $IC_\tau - AP_\tau$ increases as mean annual demand in the region $[\tau, \tau + l_p]$ increases and so does $DIO_\tau - DPO_\tau$. Keeping the customer credit period l_c constant, CCC_τ increases as average demand increases. However, when $l_p < l_s$ (Firm Types MH and H), an increase in mean demand in the region $[\tau, \tau + l_s]$ reduces $DIO_\tau - DPO_\tau$ and therefore *CCC*.

Proposition 4.2 compares the *CCC* values for two identical firms (i.e., firms with the same demand pattern, Operating Policy, and cost structure (v, c)). Firm i has its *FYE* at τ_i, $i = 1, 2$. The demand function has a step (up or down) at τ_1 while the demand in the *ZoI* around τ_2 is constant. Let d_a, d_b, d_u be three constants where d_u is the average demand during the year. We define a threshold $\mathrm{K}(v, c, l_p, l_c, l_p; \tau_1) \equiv \frac{2l_c}{l_p - l_s}\left\{\frac{c + vl_p}{2c + v(l_p + l_s)}\right\}$.

Proposition 4.2. *Let the demand function in the ZoI around* τ_1 *be characterized by* $\{f_1(t) = d_b, t:\ \tau_1 - l_c \leq t \leq \tau_1\}$ *and* $\{f_1(t) = d_a,\ t : \tau_1 \leq t \leq \tau_1 + max\,(l_s, l_p)\}$*, and the demand around* τ_2 *be characterized by* $\{f_2(t) = d_u,\ t : \tau_2 - l_c \leq t \leq \tau_2 + max\,(l_s, l_p)\}$*. For two firms that are identical in all respects except that Firm i has its FYE at* τ_i*, the relationship between their CCC values,* CCC_{τ_1} *and* CCC_{τ_2} *respectively, is as summarized in Table 2. Furthermore, with a stepped demand,* CCC_{τ_1} *increases if either demand contributing to receivables* (d_b) *or payables* (d_a) *increases as a proportion of mean annual demand.*

Interpretation: When benchmarking *CCC*, analysts and firms may fail to mention the effect of differing *FYE* (e.g., Fox, 2014). This omission can lead to erroneous interpretations as *FYE* and seasonality interact to affect the demand in the *ZoI* which in turn affects the *CCC* as indicated in Proposition 4.2. For example, when comparing *CCC* values of AMZN and COST, analysts must account for the difference in their *FYE* and Seasonality. AMZN's *FYE* is on December 31, and COST's on August 31. AMZNs sales in January are lower than the sales in December, and because of this step function, AMZN's *FYE* will

Table 4.2: Sensitivity of CCC to a change in FYE location

Demand parameter relationships	**Credit Policies**			
	$\boldsymbol{l_p > l_s}$		$\boldsymbol{l_p < l_s}$	
	$\frac{d_u - d_a}{d_b - d_u} > \mathrm{K}(v, c, l_p, l_c, l_p; \tau_1)$	$\frac{d_u - d_a}{d_b - d_u} < \mathrm{K}(v, c, l_p, l_c, l_p; \tau_1)$	$\frac{d_a - d_u}{d_b - d_u} > \frac{l_c}{l_s - l_p}$	$\frac{d_a - d_u}{d_b - d_u} < \frac{l_c}{l_s - l_p}$
$\max(d_b, d_a) < d_u$	$CCC_{\tau_1} < CCC_{\tau_2}$		$CCC_{\tau_1} < CCC_{\tau_2}$	$CCC_{\tau_1} > CCC_{\tau_2}$
$\min(d_b, d_a) \leq d_u \leq \max(d_b, d_a)$	$CCC_{\tau_1} \leq CCC_{\tau_2}$	$CCC_{\tau_1} \geq CCC_{\tau_2}$	$CCC_{\tau_1} \leq CCC_{\tau_2}$	
$\min(d_b, d_a) > d_u$	$CCC_{\tau_1} > CCC_{\tau_2}$		$CCC_{\tau_1} < CCC_{\tau_2}$	$CCC_{\tau_1} > CCC_{\tau_2}$

correspond to τ_1 in the model above. For AMZN, $l_p < l_s$, and since the mean annual demand is in between the December and January demands, AMZN's demand pattern corresponds to case $min\,(d_b, d_a) < d_u < max\,(d_b, d_a)$. COST has lower variation in demand around its FYE of August 31. Therefore, COST's FYE corresponds to τ_2 in the model above. Since COST's Operating Policy also satisfies $l_p < l_s$, AMZN has a lower CCC on account of its stepped demand at its FYE (i.e., $CCC_{\tau_1} < CCC_{\tau_2}$). We validate this observation empirically in Section 4.5 and show that the increase in CCC can be substantial. If differences in FYEs across firms are not accounted for, then any rankings based on CCC (e.g., The Hackett Group, cfo.com) may be incorrect. A firm's CCC might be lower due to a favorable demand pattern in the ZoI rather than due to its overall performance. Managers must exercise caution when benchmarking their company performance with the performance at other companies using the CCC metric if seasonality during the ZoI is high. Otherwise, their conclusions might only be the result of legacy (the fiscal cycle the firm follows). Indeed, the CCC values may be misleading and potential opportunities for improvement may be missed. Furthermore, executive compensation, if tied to the performance along the CCC metric, might incentivize managers to act in their own self-interest and manage only the ZoI factors that affect CCC. As Frankel et al. (2017) mention, various studies (Oyer 1998, Bushee 1998, Levy and Shalev 2017) have documented inefficient managerial action to achieve temporarily better financial figures. Such actions are indeed short-sighted and harbor classical agency problems.

Proposition 4.2 also applies if a firm facing the demand pattern as described above were to switch its FYE from τ_1 to τ_2.

Corollary 4.1 shows that their CCC values are the same if the demand pattern in the respective ZoIs for the two firms is constant.

Corollary 4.1. *Suppose two identical firms have FYEs at τ_1 and τ_2 respectively. Suppose further that the demand pattern in the ZoI for Firm 1 is $\{f(t) = d_1, t : \tau_1 - l_c \leq t \leq \tau_1 + max(l_s, l_p)\}$ and for Firm 2 is $\{f(t) = d_2, t : \tau_2 - l_c \leq t \leq \tau_2 + max(l_s, l_p)\}$. Then the CCC values for the two firms evaluated at their FYEs are equal, that is $CCC_{\tau_1} = CCC_{\tau_2}$ even if d_1 and d_2 are different.*

Interpretation: The corollary illustrates the difference between WC and CCC. Although, the WC could be higher, lower or the same for the firm with the higher demand, the CCC values for both firms are equal when the demand is constant during their respective Zones of Influence. Proposition 4.2 along with Corollary 4.1 leads us to hypothesize the effect of FYE ending and Seasonality on CCC.

Hypothesis 4.3. *The change in CCC increases as seasonality in Sales during the ZoI increases. When Sales has low seasonality, changing FYE does not significantly change CCC.*

This model helps understand how the seasonality in the ZoI affects CCC. We explore this concept further using a stylized demand which has both trend and seasonality in Section 4.4.3.1.

4.4.3.1 *CCC* for Demand with Seasonality and Secular Trend .

We now investigate how Seasonality, FYE and SGR affect CCC. Since demand in the ZoI has a crucial impact on CCC, and the ZoI duration is typically shorter than a business cycle duration, we do not incorporate the cyclical component of demand. We assume an additive demand model with trend and seasonality defined by $f(t) = \alpha + \beta t + S_t$ where α is the base demand, and βt and S_t are respectively the secular trend and the seasonal components of demand at time t. First, we set SGR (β) to zero and vary only the seasonality component keeping the total demand in the fiscal year constant. We then analyze the situation which has both positive SGR ($\beta > 0$) and Seasonality. A stylized demand form helps us change seasonality, and generate more wide-ranging seasonality patterns than the one in Section 4.4.2. We first model a demand function with only the seasonal component by a piece-wise linear function that repeats every T days. Figure 4.2 depicts the seasonal demand pattern.

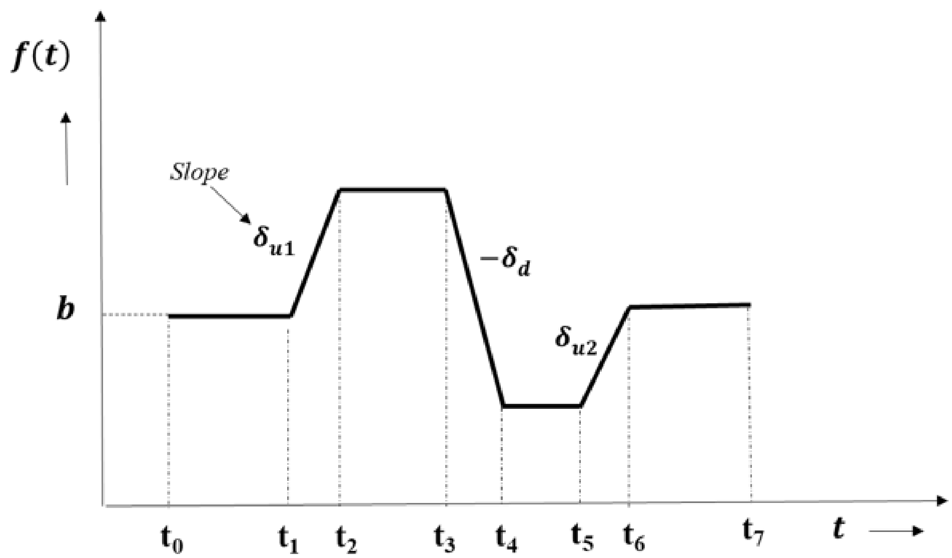


Figure 4.2: Seasonal Demand form $f(t)$

Let t_0 denote the beginning and $t_7 = T$ the end of the FY. Let b denote the base level of sales, and δ_{u1},δ_d and δ_{u2} denote the rates of increase and decrease of demand in the periods $[t_1, t_2]$, $[t_3, t_4]$, and $[t_5, t_6]$ respectively. Appendix C.3 gives the functional form of the sales. This demand function is very flexible. By changing the values of t_i ($i = 0, 1, .., 7$), δ_{u1},$-\delta_d$ and δ_{u2}, we can change the duration and the extent of seasonality. We assume $T = t_7 - t_0 = 360$ days. For our illustration, the values of $(t_0, t_1, t_2, t_3, t_4, t_5, t_6, t_7)$ are (0, 90, 150, 180, 210, 240, 330, 360) days respectively. Also, since we want $f(t) \geq 0$, we need $b + \delta_u\ (t_2 - t_1\ ) - \delta_d\ (t_4 - t_3) \geq 0$, that is, $b \geq \delta_u\ (t_6 - t_5)$ assuming $\delta_u 1 = \delta_u 2 = \delta_u$. Along the lines of (Rajagopalan 2013) we define Seasonality Index as $SI = \frac{\max f(t)\ - \min f(t)}{\min f(t)}$, $t \in t_i,\ i = 0,\ 1,\ \ldots,\ 7$. We study the CCC values for this demand function by altering the SI

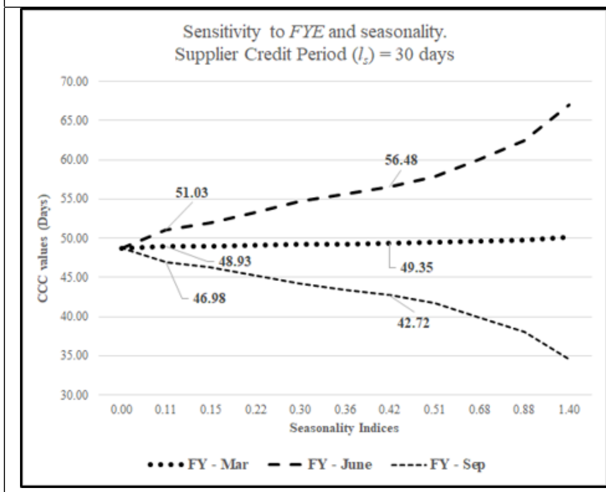
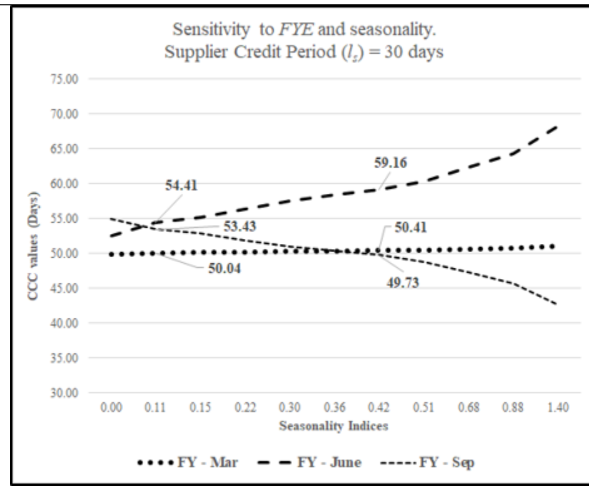
while keeping the total demand invariant. While the annual demand remains the same, the seasonality indices of the demand forms vary. We studied 22 seasonality indices ranging from 0 to 45. Only two of these demand patterns, relevant for the discussion, are given in Appendix C.4.

Table 4.2 shows the effect of seasonality and FYE for $\beta = 0$ and $\beta = 2.5$ respectively. The parameter values are $T = 360, c = \$20, v = \$1, p = \$125, l_m = 60$ days, $l_c = 30$ days, $l_s = 30$ days, and annual demand=45000 units. When t_0 corresponds to the end of December, t_1, t_3 and t_5 correspond to the end of March, June and September. We observe that both SI and FYE affect the CCC values, and increasing seasonality magnifies the difference in CCC values. An increase in seasonality may either increase or decrease the CCC depending on the FYE. For example, when the FYE is on June, increasing the SI increases CCC. Thus, a firm with a SI of 0.42 will have a CCC of 56.48 days when compared to a firm with a SI of 0.11 and CCC of 51.03 days (an increase of more than 10%). In this case, even though the firms adopt the same credit policy and have the same process lead times, an analyst may infer that the firm with the higher SI has worse operational efficiency. The situation is reversed when the FYE is on September. With this FYE, firms with higher seasonality indices have a lower CCC.

The difference between CCC of firms having the same SI but different FYEs (June and September) may be high or low. For example, the difference in CCC values at a seasonality of 0.11 is 4.1 days (51.03 – 46.98) as compared to 13.8 days (56.48 – 42.72) at a seasonality of 0.42. The magnitude of the difference depends on which FYE's are compared. When the supplier credit period increases to 90 days, the difference in CCC either due to different FYEs or seasonality reduces. In this analysis, expressions from Section 4.3 but compute them monthly.

Analysis: With seasonal demand, we see that changing the FYE affects demand in the ZoI. Even when two firms have the same total annual demand and Operating Policy, their CCC values may not be equal. Demand at t_3 and t_5 (Figure 4.2) corresponds to the maximum and minimum demand in the fiscal cycle. We vary the seasonality index by increasing the maximum demand and reducing the minimum demand so that $\frac{\max f(t) - \min f(t)}{\min f(t)}$ increases. For the chosen Operating Policy, this translates into average inventory being more than average

Table 4.3: Change in CCC with *Seasonality* and FYE.

Demand with $\beta = 0$	Demand with $\beta = 2.5$
	

payables and implies exceeds DPO. When the FYE is at t_3 and seasonality increases the difference in DIO and DPO also increases. In other words, the difference in DIO and DPO is higher for FYE at t_3 than at t_5. For the specific example, Sales (and accounts receivables) at FYE t_3 are consistently higher than Sales (and accounts receivables) at FYE t_5. An increase in Seasonality increases the difference in Sales (and accounts receivables) at t_3 and t_5. Combining these observations, we find that the change in CCC is higher for FYE at t_3 than at t_5. The time points t_3 and t_5 correspond to end of June and September in the specific example used (refer Figure C.1). This explains the increase in difference of CCC values with an increase in seasonality. The effect of seasonality is less pronounced when the ZoI does not include either the minimum or the maximum demand during the fiscal year, such as when FYE is at time t_1.

4.5 Empirical Analysis

The CCC metric unifies three fundamental areas of business and supply chains: procurement, operations, and sales. A lower CCC represents 'faster' cash recovery and operational leanness. While operational efficiency is an important factor driving CCC, different growth rates, FYEs and seasonality confound the "lower CCC is better" rationale. We model CCC as a variable dependent on $Sales$, $Time$, $FirmType$ and FYE. Since firm policy (l_c, l_p and l_s) is unobservable, we use DSO, DIO and DPO values as surrogates to classify firms into the categories defined in Figure 4.1. Companies do not report monthly balance sheet data; hence, we conduct our analysis by calendar quarters. If a FYE does not coincide with a calendar quarter, we shift it to the nearest calendar quarter end for our analysis. To validate our hypotheses, we build an aggregate-level model (at Firm Type level) and a firm-level model. We use the guidelines of Green and Tukey (1960) to make the distinction between fixed and random effects. We treat the variable Firm Types as fixed because it has a finite number of levels with all levels represented in the sample. The firms are from a larger population and therefore their idiosyncratic effects are random. We investigate the mediating effect of Sales on CCC. We also allow $Time$ to have both a direct and an indirect effect on CCC. Figure 4.3 depicts the relationships.

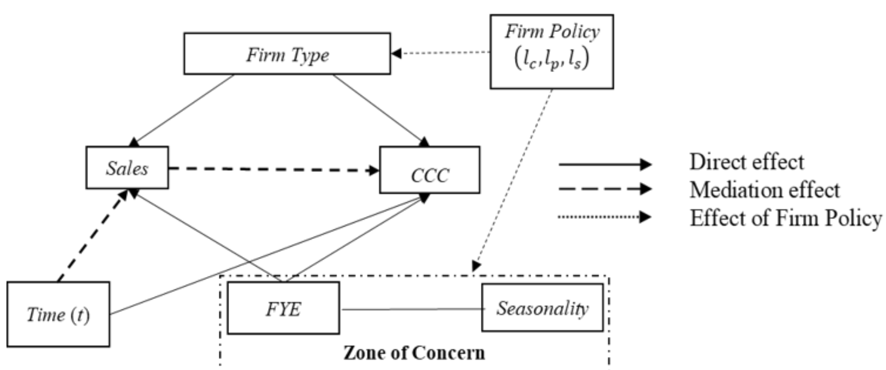


Figure 4.3: Factors Influencing CCC

Dataset: For the aggregate level analysis, we identified six industries with SIC codes 3663 (Radio and Television Broadcasting and Communications Equipment), 5311 (Department Stores), 5331 (Variety Stores), 5912 (Drug and Proprietary Stores), 5940 (Sporting Goods Stores) and 5961 (Catalog and Mail-order Housing) to test our hypotheses. We used Quarterly financial results on Accounts Payable, Accounts Receivable, Inventory, $COGS$ and Sales for 12 years (2006-2017) from the Wharton Compustat Database. The industries chosen comprise highly seasonal (Retail) and low seasonality (Drug and Proprietary Stores) firms. One important criterion in selecting industries was to ensure enough firms that did not have their FY endings at the end of calendar quarters; there were 21 such firms in our sample (Table C.11). We dropped firms which did not have all 12 years of data, had outliers with abrupt jumps in Sales and those which changed their FY endings. A total of 10 firms were removed from the analysis using these criteria (Table C.12). Note that we did not delete firms for which the Firm Type changed over time so that we could investigate the effect of change in Firm Type. There were four missing values for Sales which were replaced by the average sales of the last four quarters. The resulting sample consisted of 58 firms (Table C.12) in the six industries mentioned earlier. Costco (COST) which remained as the only firm in SIC 5399 was included in SIC 5311. We calculated the components: DSO, DIO and DPO by taking average of receivables, inventory and payables at the start and end of the calendar quarter and dividing by the sum of the previous four quarters' Sales (for DSO) and $COGS$ (for DIO and DPO). From the DSO, DIO and DPO values, we computed CCC for each calendar quarter. For example, AMZN's FYE is on December 31. We computed AMZN's CCC with December 31 as the year end, but also computed its CCC on March 31, June 30 and September 30 to understand the effect a change in AMZN's FYE might have. We replicated these quarterly calculations for all firms (58), for each of the 12 years, resulting in a dataset with 2784 observations. The summary statistics of the firms in the sample are available in Appendix C.11.

To validate our findings at the firm level, we considered a subsample of seven general retailers (SIC codes 5311, 5331, 5940 and 5961) and three pharmaceutical retailers (SIC code 5912). We selected the retail sector for several reasons. First, sales for some firms (e.g., department stores) in this sector demonstrate significant seasonality. Second, companies in the retail sector have experienced different growth rates. For example, AMZN's sales have grown at a higher rate than its competitors over the last decade, while sales of Sears have seen a decline. Finally, the firms have different FY endings. These observations indicate that using this sample as a test bench facilitates empirical validation of our findings regarding Seasonality, *SGR* and *FYE* in Section 4.4. The pharmaceutical firms are characterized by very low seasonal fluctuations and serve as a contrast to the highly seasonal (general) retail firms.

4.5.1 Model Specification and Analysis

We now describe Models *AL* and *FL* qualitatively before presenting their technical details. Model *AL* incorporates both fixed and random effects of Firm Type. The fixed effect accounts for Firm Type heterogeneity *in the sample*, while the random effect accounts for heterogeneity of Firm Type *excluded from the sample*.[7] Observe that the effect of *Sales* on *CCC* may be due to a fixed sensitivity by Firm Type or by random sensitivity by Firm. Therefore, Model *AL* includes *Sales* in both the fixed effect and the random effect components. Since Firm Type changed for more than half of the firms in our sample, the distinction between random Firm level controls and fixed Firm Type controls is necessary to validate Hypotheses 4.1 and 4.2. Model FL estimates firm-specific sensitivity to a change in SGR by incorporating fixed controls for firms. Using these fixed controls allow us to study the effect of interactions of Firm with Sales and FYE changes. These models help us validate all three Hypotheses at the Firm level over the 12-year horizon. Both models include a term for macro-economic shocks. Superscripts A and F respectively denote the coefficients (unless unique) used in Models *AL* and *FL*.

4.5.1.1 Aggregate Level Analysis (Model *AL*) . To study the impact of *SGR* by Firm Type on *CCC*, we use a random-effects model. We specify the Model *AL* below with an explanation of the Dependent, Independent and Control Variables. We follow the convention of Kutner et al. (2005), and specify the model (with vectors indicated in bold) as:

$$CCC_{it} = \Delta^A + P_{it}\delta^A + (S_{it}P_{it})\rho^A + (tP_{it})\Psi^A + T_{it}\pi^A + [\theta_i^A + Q_{it}\eta_i^A + \gamma_i S_{it} + t\beta_i^A] + \epsilon_{it}$$

[7] We use the term fixed and random effect to mean, respectively, variation on account of subjects within the sample, and on account of variation from subjects which are not a part of the sample.

In this model, the index i denotes the firm and t is a time index ranging from 1 to 48 quarters. The dependent variable CCC_{it} is the Cash Conversion Cycle of firm i at time t. Δ^A is the fixed intercept. The choice of independent variables is motivated by the need to separate aggregate sensitivity of CCC to Sales Growth by Firm Type and sensitivity to firm level characteristics such as *FYE*. In Model AL, the fixed effect part comprises the interaction of Firm Type with $Sales$ and $Time$ while controlling for macroeconomic shocks by year. A change in the credit or operational policies affects l_c, l_s or l_p that may change the $FirmType$ over the twelve-year horizon. We used Firm Type H as the reference; the variable $\mathbf{P}_{it}$ is a row vector of size three corresponding to MH, ML and L. This vector takes a value 1 corresponding to the specific Firm Type of firm i in period t and is 0 otherwise. The vector $\delta^{\mathbf{A}}$ (with components δ^A_{MH},δ^A_{ML} and δ^A_L) measures the effect of Firm Type. The interaction of $Sales$ by $FirmType$ $S_{it}\mathbf{P}_{it}$, allows us to capture the sensitivities of CCC to $Sales$ by $FirmType$, which is measured by the vector $\rho^{\mathbf{A}}$. The components of $\rho^{\mathbf{A}}$ are ρ^A_H,ρ^A_{MH}, ρ^A_{ML} and ρ^A_L. The direct effect of time is measured by the coefficient $\psi^{\mathbf{A}}$ (with components $\psi^A_H, \psi^A_{MH}, \psi^A_{ML}$ and ψ^A_L). A year specific control $\mathbf{T}_{it}$ controls for year-specific shocks which are measured by the vector π (which is a row vector of size 12, since we have 12 years of data). The random effect part of the model, demarcated by (square) parenthesis, consists of firm specific controls. Apple (AAPL) is used as the reference firm and $Q1$ (Calendar Quarter 1) as the reference calendar quarter. The coefficients θ^A_i corresponds to the random intercept of firm i. When reporting the results, we add the mean, μ_θ of the random intercepts to the fixed intercept to get the overall intercept value. The coefficients $\eta^{\mathbf{A}}_i$ correspond to random slopes for calendar quarter ends, γ_i corresponds to $Sales$ and β^A_i corresponds to $Time$. These random parameters follow a multivariate normal distribution as defined in Appendix C.5. ε_{it} is a normally distributed error term. To validate our hypotheses, $Sales$ is regressed on $Time$ and $FirmType$ in Model S.

$$S_{it} = \Delta^S + \mathbf{P}_{it}\delta^{\mathbf{S}} + (t\mathbf{P}_{it})\,\lambda + \mathbf{T}_{it}\pi^{\mathbf{S}} + \left[\theta^S_i + \mathbf{Q}_{it}\eta^{\mathbf{S}}_i + +\beta^S_i t\right] + \varepsilon^S_{it}$$

S_{it} is the sales of firm i at time t, λ_j is the effect of Time by Firm Type $j\,(it)$ (after controlling for average firm-level heterogeneity). We included this variable because the firm policy (l_c, l_p, *and* l_s) affects Sales. The remaining independent variables are similar to

Model AL and distinguished by the use of superscript S. Let $j\,(it)$ denote the $FirmType$ of Firm i in period t. The sign of $\rho^{A}_{j(it)}$ in Model AL helps validate Hypothesis 4.1 since $\frac{\partial CCC_{it}}{\partial \lambda_{j(it)}} = \frac{\partial CCC_{it}}{\partial S_{it}} * \frac{\partial S_{it}}{\partial \lambda_{j(it)}} = \rho^{A}_{j(it)} t$ and t is always positive. Thus, the directional impact of SGR by Firm Type j is measured by the sign of ρ_j. To test Hypothesis 4.2, the indirect effect of Time, $\rho^{A}_{j}\lambda_j$ is tested for significance for firm type j. The significance of the product $\rho^{A}_{j}\lambda_j$ is tested by generating empirical distributions of the product of the growth rate in $Sales$, λ, and the sensitivity of CCC to $Sales$, $\rho^{\mathbf{A}}$ from Model AL as suggested in Rungtusanatham (2014).

4.5.1.2 Firm Level Analysis (Model FL)

. To validate the effect of change in SGR at the level of firms, we test Model FL which uses fixed control for firms. We study seven retail firms (AMZN, WMT, DKS, TGT, COST, JCP, SHLD) that present a mix of different FY endings and varying growth rates, and three Pharmaceutical chains (CVS, RAD, WBA). The relatively stable $Sales$ at these three firms offers a contrast to the highly seasonal nature of the retail firms – an observation we exploit to validate Hypothesis 4.3. We regress CCC on $Sales$ and $Time$ while controlling for $FirmType$ and $Year$ for year-specific shocks. Since the sensitivity of sales growth to CCC is of interest at the level of the firm, we put fixed controls for firms that vary with $Sales$, $Time$ and Calendar Quarter end. We refer to this model as Model FL.

$$CCC_{it} = \Delta^{F} + \mathbf{P}_{it}\delta^{\mathbf{F}} + \mathbf{Q}_{it}\eta^{\mathbf{F}}_{i} + \rho^{F}_{i} S_{it} + \psi^{F}_{i} t + (S_{it}\mathbf{P}_{it})\,\varphi + + \mathbf{T}_{it}\pi^{\mathbf{F}} + \varepsilon_{it}$$

The firm specific intercept for firm i in period t, $\Delta^{F}_{it} = \Delta^{F} + \eta^{F}_{it}$ where η^{F}_{it} adjusts for the difference in FYE between the benchmark firm and firm i in period t. This adjustment parameter η^{F}_{it} is tested for significance to validate Hypothesis 4.3. For this model, we use Q4 as the reference quarter for all firms and $\mathbf{Q}_{it}$ is a vector of size three. At any time t, if Firm i's FYE is in the same quarter as the benchmark firm (TGT) then the corresponding element in $\mathbf{Q}_{it} = 0$, and $\mathbf{Q}_{it} = 1$ otherwise. The sensitivity to sales coefficients ρ^{F}_{i} for each firm is reported in Table which is used to validate Hypothesis 4.1. To address changes in Firm Type, we put a fixed control for Firm Type in vector $\mathbf{P}_{it}$. As with Model AL, the elements of $\mathbf{P}_{it}$ take a value 1 corresponding to Firm Type of firm i in period t and 0 otherwise.

The coefficient φ_i is added to ρ_i^F to adjust for a change in Firm Type while estimating the sensitivity of CCC to $Sales$, S_{it}. ψ_i^F is the trend component of firm i after controlling for firm type and π^F are the year specific shock similar to Model AL.

We regress $Sales$ to $Time$ and indicators for calendar quarters while placing fixed controls for firms interacted with $Time$, $Sales$ and $CalendarQuarter$. This model is similar to Model S but with fixed control for firms. As earlier, Model S is used to validate our hypotheses. It is not explicitly stated to save space. Similar to Model AL, the empirical distributions of SGR and CCC sensitivity to $Sales$, i.e., the product $\rho_i^F \beta_i^F$, is used to get the indirect effect of SGR to validate Hypothesis 4.2 for Firm i.

4.5.2 Results

We now present the empirical results for Models AL and FL. Section 4.5.2.1 describes the results for Model AL and Section 4.5.2.2 gives the results for Model FL.

4.5.2.1 Model AL Results . The unconditional model, with random control for firms only, has an Intra Class Correlation (ICC) of 0.84 which suggests high firm level heterogeneity that should be controlled for, thus validating our model specification. Firm level heterogeneity can also affect CCC in interaction with $Sales$ and FYEs. The Base Model (refer Figure 6) has $Sales$ and $Time$ as the independent variables (and no interaction effects), Model $AL1$ uses random (intercept) control for firms θ_i^A, Model $AL2$ uses control for firms varying by $Sales$ (θ_i^A and β_i^A), Model $AL3$ uses control for firms varying by $Sales$ and $Time$ (θ_i^A,γ_i^A and β_i^A) and Model $AL4$ uses control for firms varying by $Sales$ and $CalendarQuarter$ (θ_i^A,β_i^A and η_i^A). While we would have preferred a model with random slopes for sales, trend and calendar quarter, the estimation algorithm failed to converge (we used lme4 in R; Bates, 2010.) We now discuss the fixed effect of the independent variables (Figure 6). In a Base Model with $Sales$ (no interaction with $FirmType$) and $Time$ as independent variables, while placing fixed controls for $CalendarQuarters$, $FirmType$ and random intercept for $Firms$, we find that $Sales$ is indeed a significant predictor of CCC. Since we are interested in validating the sensitivity of CCC to growth rate for each $FirmType$, we include $Sales$

interacted with $FirmType$ in all subsequent models. We observe that sensitivity of CCC to $Sales$ is significant for all $FirmTypes$. For Model $AL1$, the sales coefficients for firm types H $\left(\rho_H^A = -0.4\right)$, MH $\left(\rho_{MH}^A = -0.82\right)$, ML $\left(\rho_{ML}^A = -0.76\right)$ and L $\left(\rho_L^A = -1\right)$ are all significant. The coefficients are significant for Models $AL2$ through $AL4$ as well. All the predicted signs match except for Type H firms for which Proposition 1 suggested a positive sensitivity to sales growth. This shows that all firm types, on average, will report a higher CCC value if they do not experience increasing $Sales$. Hypothesis 4.1 is supported for ML and MH type firms. To validate the sensitivity of growth rate on CCC for an L type firm, the value of (average) Γ is needed (Proposition 1). The unavailability of processing and purchase costs (needed for computing the average value of Γ), makes validating Hypothesis 4.1 for L type firms difficult. To validate Hypothesis 4.2, we first look at the direct effect of $Time$. This direct effect is positive and significant for Firms Types MH, ML and L (C.1) in Model $AL1$ with the coefficients being $\psi_{MH}^A = 0.53$, $\psi_{ML}^A = 0.43$, $\psi_L^A = 0.25$. The effect is not significant for Firm Type H. The direct effect is observed to be significant in all models $AL1$ through $AL4$. To validate how $Time$ is mediated through sales, following the suggestion of Rungtusanatham (2014), we generate empirical distributions of $\rho_j^A \lambda_j^A$ for each Firm Type j. The coefficients ρ_j^A from Model $AL1$ and λ_j from Model S follow a normal distribution with standard deviation equal to the (reported) standard errors which were used to generate the distributions. 100,000 simulations of the product $\rho_j^A \lambda_j^A$ were used to empirically generate the 95% confidence intervals for each Firm Type j (4.4). We find that $Time$ has a negative mediating effect for Firm Types H, ML and L while the effect of mediation is insignificant for Firm Type MH. 4.4 reports the 2.5 (LL) and 97.5 percentiles (UL) for the average mediating effects. Hypothesis 4.2 is therefore supported for the effect of Time.

Table 4.4: Results of **Model *AL*** variants with *CCC* as the dependent variable and for Model *S*.

	Base Model	**Model *AL*1**	**Model *AL*2**	**Model *AL*3**	**Model *AL*4**	**Model *S***
Dependent Variable	***CCC***	***CCC***	***CCC***	***CCC***	***CCC***	***Sales***
Intercept $(\Delta^{A} + \mu_{\theta})$	18.1* (8.26)	18.71* (8.24)	17.87* (8.95)	18.96* (9.19)	17.51* (8.93)	-7.29** (2.2)
Sales	-0.55*** (0.12)	-	-	-	-	-
Time (ψ^{A}_{H})	0.13* (0.06)	-0.27 (0.16)	-0.15 (0.17)	0.22 (0.23)	-0.17 (0.17)	Refer footnote 8
Type MH (δ^{A}_{MH})	35*** (3.67)	35.07*** (3.72)	47.23*** (3.94)	46.69*** (3.97)	46.87*** (3.94)	14.61*** (0.74)
Type ML (δ^{A}_{ML})	46.69*** (3.68)	46.8*** (3.71)	53.57*** (3.87)	50.01*** (3.92)	53.77*** (3.87)	13.12*** (0.71)
Type L (δ^{A}_{L})	56.76*** (3.94)	58.63*** (3.99)	59.43*** (4.05)	58.16*** (4.31)	59.13*** (4.06)	10.34*** (0.71)
Qtr. = Q2 $\left(\mu_{\eta^{A}_{2}}\right)$	-0.36 (1.46)	-0.6 (1.46)	-0.57 (1.38)	-0.56 (1.28)	-0.55 (1.38)	0.05 (0.21)
Qtr. = Q3 $\left(\mu_{\eta^{A}_{3}}\right)$	1.47 (1.47)	1.48 (1.46)	1.42 (1.38)	1.42 (1.29)	1.42 (1.47)	0.13 (0.21)
Qtr. = Q4 $\left(\mu_{\eta^{A}_{4}}\right)$	3.85** (1.48)	3.68* (1.47)	3.23* (1.44)	3.01* (1.36)	3.01* (1.54)	1.00*** (0.21)
Sales×Type H (ρ^{A}_{H})	-	-0.4** (0.14)	-16.99* (7.44)	-22.01* (9.52)	-17.32* (7.15)	-
Sales×Type MH (ρ^{A}_{MH})	-	-0.82*** (0.21)	-23.01** (7.35)	-27.59** (9.43)	-23.36** (7.07)	-
Sales×Type ML (ρ^{A}_{ML})	-	-0.76*** (0.19)	-23.05** (7.35)	-27.55** (9.43)	-23.41** (7.07)	-
Sales×Type L (ρ^{A}_{L})	-	-1.00*** (0.2)	-23.18** (7.35)	-27.66** (9.43)	-23.53** (7.06)	-
Random Effects						
Group (Variance)						
Firm – Intercept		3099.58	3703.98	3898.18	3692.86	255.47
Firm – Sales			2392.07	3814.07	2264.64	
Firm – Calendar Q2					0.89	
Firm – Calendar Q3					15.43	
Firm – Calendar Q4					18.63	
Firm – Time				0.56		
Residual		735.21	656.32	564.89	648.37	14.66
Model Fit Statistics						
ICC – Firm	0.810	0.810	0.850	0.870	0.850	0.950
AIC	26585.02	26587.79	26422.83	26155.45	26429.80	15824.37
BIC	26709.58	26730.15	26577.05	26327.47	26655.20	15960.79
Conditional R^2	0.094	0.117	0.159	0.146	0.171	0.029
Marginal R^2	0.825	0.829	0.999	0.999	0.999	0.947

Table 4.5: Mediation Effect of $Time$ on CCC by $FirmType$ (95% Confidence Interval)

Firm Type	LL	UL	Mean
H	-0.38	-0.064	-0.22
MH	-0.022	0.026	0.0019
ML	-0.065	-0.0047	-0.031
L	-0.083	-0.014	-0.045

4.5.2.2 Model FL Results To analyze effects at firm level we refer the results obtained from Model FL. We found evidence of heteroskedasticity and autocorrelation of the error terms and therefore a straightforward use of OLS standard errors would have led to incorrect inference. Therefore, we use the Newey-West robust standardized error for statistical inference as used in Oyer, 1998. To address endogeneity issues from omitted variables, we find the coefficients of Model FL by regressing CCC_{it} to the estimated sales. There was no significant difference in magnitude and no difference in the signs of the estimates. We build Model $FL1$ through $FL5$ by progressively putting controls for Firms (Model $FL1$), interaction of $Firms$ and $Sales$ (Model $FL2$), $Firms$ and $Time$ (Model $FL3$), $Firms$ and FYE (Model $FL4$) and finally adding $FirmType$ (Model $FL5$). C.2 summarizes these results. From the results of Model $FL5$, we observe that only three firms (TGT, CVS and WBA) have significant sensitivity to $Sales$ $\left(\rho^F_{TGT} = 4.32, \rho^F_{CVS} = -1.35, \rho^F_{WBA} = -1.13\right)$, and we focus on these three firms next to check for Hypothesis 4.1 and Hypothesis 4.2. 4.5 summarizes the observed and hypothesized signs sensitivity of CCC to SGR.

Recall from Section 4.4 that $\Gamma > 0$ for retail firms since the value-added parameter, v is small. Thus, for TGT, the predicted sensitivity of CCC to SGR is positive. This matched the observed sensitivity. The Firm Type of CVS changed from Medium-Low (ML) in 2013 to Low (L) and shows a negative sensitivity to sales growth thus providing evidence for Hypothesis 4.1. WBA's Firm Type changed from Medium-Low (ML) in 2014 to Medium-High (MH) in 2016 (perhaps due to its acquisition of Alliance Boots). The sign of the coefficient $\rho^F_{WBA} = -1.13$ matches the predicted sensitivity in Hypothesis 4.1. TGT's type changed to L in 2014. Thus, CCC shows significant sensitivity to $Sales$ and we find support for Hypothesis 4.1 for these firms.

We test for the direct effect of $Time$ as stated in Hypothesis 4.2 (please see Table C.3 in Appendix C.1). We find that the direct effect of time is significant for TGT and CVS ($\psi^F_{TGT} = -1.00,\ \psi^F_{CVS} = 0.91$) but not for WBA.

Table 4.6: Model FL: Effect of SGR on CCC (Details in Appendix C.2)

	Sales Growth Rate	Firm Type	Predicted results (Hypothesis 4.1)	Sensitivity to $CCC(\rho)$	Result of Validation (Hypothesis 4.1)
TGT	+	L	+	+ 4.32	Match
CVS	+	ML	-	- 1.35	Match
WBA	+	ML, MH	-	- 1.13	Match

Testing for the indirect effect of $Time$ using the same approach as for Model AL. Table 4.6 gives the 95% confidence intervals of $\rho^F_j \lambda^F_j$ for all three firms. All three coefficients are significantly different from zero, thus lending support to Hypothesis 4.2. To check for Hypothesis 4.3, we specify CVS as the reference firm. CVS (and the other pharmaceutical firms, RAD and WBA) has low seasonality facilitating the measurement of FYE changes. As Figure 7 shows, retail firms have different FYEs. Figure 7 also lists the effect of changing

Table 4.7: Model FL: Firm Level Mediating Effect of $Time$ on CCC (95% Confidence Interval)

	LL	UL	Mean
TGT	0.034	0.57	0.29
CVS	-1.4	-0.47	-0.96
WBA	-0.65	-0.37	-0.51

the FYE for each retailer from Q4, the reference quarter. For example, changing AMZN's FYE from Q4 to Q1 will increase its estimated CCC by 17.79 days. These results follow from Model FL, where the three components of vector $\eta_i^{\mathbf{F}}$ for firm i measures the impact of changing the FYE quarter from Q4. The reported values in Figure 7 are the change from Q4 ($CCC_{ij} - CCC_{i,Q4}$), where j is one of the other three quarters. We note that $\eta_{CVS}^{\mathbf{F}}, \eta_{RAD}^{\mathbf{F}}$ and $\eta_{WBA}^{\mathbf{F}}$ are not significant. This supports Hypothesis 4.3 since CVS, RAD and WBA have very low seasonality. Consequently, comparisons of pharmaceutical firms based on annual CCC would be valid even if these firms have different FYEs. For five of the remaining seven firms, changing the FYE does have a significant impact on the CCC (at a significance value of 0.10). Hypothesis 4.3 is thus, supported at the firm level. This ability to calculate CCC values by changing the FYE quarter helps us look at the results as a counterfactual (e.g., how much would the CCC of AMZN change if it shifted its FYE from December 31 to June 30). Such counterfactuals are crucial for meaningful benchmarking when firms have different FYEs. A firm benchmarking AMZN's CCC must recalibrate its targets if its FYE is different from AMZN's. As an example, COST which has its FYE in August (i.e., the nearest previous quarter is Q2) should recalibrate its targets when benchmarking its CCC with AMZN's. Results from Figure 7 indicate COST should add 18.8 days on average to AMZN's CCC to adjust for the difference in FYEs. As previously given examples illustrate, managers, business consultants, financial analysts and academic researchers often do not make such a correction.

Table 4.8: **Model *RC***. The impact of change in FYE from Q4 end

Firm FYE coefficients	Current FYE	Q_1	Q_2	Q_3
$\boldsymbol{\eta}^{\mathbf{F}}_{AMZN}$	December	17.79*** (2.76)	18.80*** (2.77)	15.56*** (2.75)
$\boldsymbol{\eta}^{\mathbf{F}}_{COST}$	August	-0.40 (2.78)	0.15 (2.63)	1.2 (4.83)
$\boldsymbol{\eta}^{\mathbf{F}}_{DKS}$	January	9.31* (4.56)	6.76* (3.46)	1.32 (4.83)
$\boldsymbol{\eta}^{\mathbf{F}}_{JCP}$	January	3.92 (3.88)	4.19 (3.74)	15.44*** (3.56)
$\boldsymbol{\eta}^{\mathbf{F}}_{SHLD}$	January	-0.59 (3.51)	1.04 (3.18)	8.02* (3.44)
$\boldsymbol{\eta}^{\mathbf{F}}_{WMT}$	January	2.06 (3.90)	1.56 (3.31)	5.61 (3.64)
$\boldsymbol{\eta}^{\mathbf{F}}_{TGT}$	January	16.11** (5.86)	16.84** (5.66)	19.73*** (5.60)
$\boldsymbol{\eta}^{\mathbf{F}}_{CVS}$ §	December	-0.96 (1.86)	-2.02 (1.84)	-1.92 (1.85)
$\boldsymbol{\eta}^{\mathbf{F}}_{RAD}$	February	-1.51 (2.62)	-1.52 (2.59)	1.75 (2.61)
$\boldsymbol{\eta}^{\mathbf{F}}_{WBA}$	August	1.38 (2.63)	-0.16 (2.16)	0.03 (2.6)

4.5.3 Robustness Checks

In Sections 4.5.1 and 4.5.2, we used quarterly data because firms do not publish balance sheet and income statement data more frequently. However, seasonality does not have a quarterly cadence, and so spikes and troughs will get smoothened when we aggregate data by quarters. Second, we offset the FYE to the nearest calendar quarter when needed. Third, there may also be idiosyncratic industry variations. We now do robustness checks to address these issues. We consider a model, Model RC, that includes $Industry$ as a variable to account for industry-level changes in CCC. Also, we do not change the FYE to the previous quarter. None of the 52 firms in the sample have Fiscal Years ending in May, October and

November. Hence, we used eight binary variables to control for the FYE effects and January as the base. As in Oyer (1998), adding $CalendarQuarter$ makes no significant difference to the results. In Model RC, k an index for the industry. The model assumes that firm-level heterogeneity does not explain the variance in CCC anymore than does $FirmType$. Thus, $FirmType$ constitutes a unit of analysis and the average sensitivity of CCC to change in sales growth may be obtained by controlling for the industry effects only. We consider discuss Model RC in which random controls are put for firms nested within industries.

$$CCC_{ikt} = \Delta^R + \rho^R S_{it} P_{it} + \delta^R P_{it} + \gamma_i F_{it} + \Pi^R T_{it} + \theta_k(i) + \gamma_i S_{it} + \lambda_k(i)t + \theta k + \lambda_k t + \varepsilon_{it}$$

While independent and control variables have similar meaning as in Models AL and FL (the coefficients use the superscript R), there are two main differences. First, every firm i is nested within its industry k, the random intercept $\theta_{k(i)}$ incorporates the structure of firm i nested within industry k and θ_k is a random intercept for industry. To correct for an overall industry trend in CCC, we model the random slope coefficients $\lambda_{k(i)}$ and λ_k similarly. Since $Sales$ is recorded at the level of a firm, the random slope γ_i varies by firm. The variable $\mathbf{F}_{it}$ controls for all eight FY months in the sample instead of simply Calendar Quarters. We build Model RC progressively by first adding industry level controls (Model $RC1$) and then add controls for firms nested within industry (Model $RC2$). The size of covariance matrix of Model $RC2$ increases in proportion to estimates of firm-industry level correlations. C.14 in the Appendix F shows the results of Model RC. For Model $RC1$, a firm of type H is not sensitive to $Sales$ $\left(\rho^R_H = -0.19\right)$. For all other credit policies, the coefficients are significant $\left(\rho^R_{MH} = 0.46,\ \rho^R_{ML} = 0.33,\ \ \rho^R_L = -0.55\right)$. FY month ends are significant (i.e., $\gamma_9 = -52.77$ when FY ends in September). The significance of the parameters were calculated using the Satterthwaite method of finding p-values. When we include the firm level controls as well (Model $RC2$), we find that the signs of the coefficients of sales are the same as the signs obtained in Model AL $\left(\rho^R_{MH} = -17.36, \rho^R_{MH} = -23.26, \rho^R_{ML} = -23.21, \rho^R_L = -23.33\right)$. While $Time$ is insignificant as a direct effect, we test for the indirect effect of $Time$ as mediated through $Sales$. As with Model AL we find support for mediation. Model $RC1$ shows significant results for all months but Model $RC2$ shows significant sensitivity only in FYE ending September. We conjecture that this is due to the unavailability of monthly financial data. As mentioned previously, $January$ sees a distinctive drop in monthly sales following the December holiday season. However, this drop gets subdued by aggregation in our sample when firms, following a January end fiscal cycle, do not report their sales in December. Thus, although accounting for different FYEs the level of $Sales$ is of the same order as $Sales$ ending in December (that is the seasonal effects are the same). It is more apt, therefore, to refer to Model FL results to assess the degree of recalibration to correct for a difference in FYE. Overall, no departure from results obtained in Sections 4.5.1 and 4.5.2 is observed. This observation indicates that our model is robust given the granularity at which the data was obtained.

4.6 Conclusion

The analysis in this paper shows that even when two firms have the same Operating Policy (defined by supplier credit period, processing lead time and customer credit period) and the same mean demand, CCC values may differ because of differing Sales Growth Rates (SGRs). When the demand patterns are the same, the CCCs of the two firms could be significantly different because of the interaction of Seasonality and Fiscal Year End (FYE). We also show that demand in only a subset of the fiscal cycle, the Zone of Influence (ZoI), affects the CCC values. Hence, even when discounting for differences in SGR, an optimally located FYE may confer the benefit of the "right mix" of demand seasonality in the ZoI, resulting in a lower CCC. Additionally, even when a firm does not have any demand seasonality, the sensitivity of CCC to changes in SGR can be positive or negative depending on the Firm Type (which depends on Operating Policy). If a company's Firm Type changes due to a change in its Operating Policy, because of modified credit terms, improved processing time or better inventory management, the impact on CCC will depend on the firm's original and new Firm Type. We emphasize that only the relative supplier and consumer credit terms, and processing lead time, and not their absolute values, determine the Firm Type. We also find that Time affects CCC both directly and indirectly through Sales. The interactions between these factors complicate the interpretation of CCC. For example, even when a firm implements process improvements to decrease *CCC*, an increase in *SGR* may increase *CCC* depending on its Firm Type. This suggests that we need to exercise caution when comparing *CCC* values for firms of different types.

The collective impact of *SGR*, Seasonality and *FYE* on *CCC* depends on the Operating Policy, cost parameters and demand pattern. These factors interact in a complex way to affect the *CCC*. We offer three rules of thumb, suitable for well-behaved demand forms. First, higher demand seasonality of the focal or benchmarked firm increases the importance of measuring *CCC* at a point in time where seasonality is comparable. Second, as we found in our computations, the impact of Seasonality and *FYE* is higher than the impact of *SGR*. Third, any change in the Seasonality outside the *ZoI* does not affect the *CCC* as long as the mean demand is constant.

Next, for a more granular comparison of *CCC* values of two firms that have different *FYE*s, we make certain assumptions to ensure parity in all other parameters. Specifically, we assume that the firms have the same Operating Policy with supplier credit period being greater than the processing lead time. Furthermore, the two firms have the same procurement and processing costs, selling price, annual demand, *SGR* and Seasonality. The firms differ only in the location of their *FYE*. A firm which has its *FYE* located where demand is increasing will report a lower *CCC* compared to a firm which has its *FYE* located where the demand is decreasing. This is because although the width of the *ZoI* is the same, the excess payables over inventory cost is higher when demand is increasing. Finally, consider the case where the two firms have different seasonality indices (as measured by the spread in the demand), and both firms have their *FYE*s at their lowest demand values. If the peak demand for both firms falls within their respective *ZoI*s and occurs after the lowest demand, the firm with higher seasonality will have a higher *CCC*. Because of the complexity of the underlying relationship, it is difficult to estimate intuitively even directionally, let alone numerically, the movement of *CCC* when changes occur in *SGR*, *FYE* and Seasonality.

Decision makers, analysts and consultants may use *CCC* values without considering differing *FYE* locations, Seasonality, and *SGR*. Neglecting to account for these factors could lead to incorrect conclusions and inaccurate targets for performance improvements. Consequently, *CCC* benchmarking-driven efforts by a firm to improve operational efficiencies might be unwarranted.

Finally, we note that there is increasing emphasis on the use of secondary financial data in academic research (Rabinovich and Cheon 2011). Researchers of such data sources often use annual or quarterly firm-level accounting data to draw conclusions. The reason is a systemic limitation: Balance sheet data is publically available only on an annual or quarterly basis. In contrast, the duration of the "seasonality" can be shorter. Therefore, it is difficult to account for aberrations caused by the interaction between Seasonality and FYE location when benchmarking CCC and other such metrics across companies. Promising future research directions include investigating whether adjusting CCC components by detrending and deasonalizing results in a metric that more accurately captures differences in operational efficiencies across companies. The codependence between the factors we have studied, such as how the Operating Policy itself changes with Sales, might also be interesting. One could also study how managerial incentives and decisions are affected when an adjusted CCC metric is used rather than an unadjusted one. Another line of avenue for research might be to investigate if managers indulge in CCC management, as they do in earnings management, when CCC is an input in the compensation formula. For accurate benchmarking, it is imperative that interpretation and use of metrics, such as CCC, be appropriate for the context being evaluated.

5.0 Conclusions

In my thesis, I investigate the reasons of why campaigns that reach their target amounts, fail to deliver the products to the backers. Specifically, I find that entrepreneurs with a low cost of reputation will participate in a crowdfunding campaign and keep a target that is lower than the product development cost. The participation of a supplier, and a penalty for the contingency of not following through on initial order commitments, disciplines the entrepreneur. However, even with the imposition of a penalty the entrepreneur will keep a target and pledge amount that expose backers to the risk of delivery failure, if reputation costs are very low. The main contributions of chapters 2 and 3 is to look at how, a platform by following a specific threshold induces the entrepreneur to keep a low target, and how a suppliers involvement in the product development process can restrain the entrepreneur against opportunistic target setting.

In chapter 4, we find evidence that firms which rely on Cash Conversion Cycle for drawing conclusions about their operating efficiency may wrongfully infer better operating efficiency. It is possible that factors exogenous to a firm's operations, demand seasonality, growth rate and Fiscal Year differences may cause CCC values to be lower. The results of the chapter are particularly relevant to a large stream of operations management literature that uses accounting metrics uncritically as proxies of operational slack, efficiency and financial contagion to name a few. By addressing about the extent of wrongful misattribution we make a case for a cautious use of accounting metrics.

The theme of the dissertation was to show how parameters; target amount in crowdfunding and CCC, intended for the benefit of investors may not serve their intended objective. We provide evidence for it by including the motives of platform and suppliers in a crowdfunding context; and by including differences in growth rate, seasonality and Fiscal Year differences for the Cash Conversion Cycle.

Moving forward I will continue to research at the interface of Operations Management and Finance, with a particular focus on novel mechanisms to raise funds and ensure transparency. Particularly, the use of Blockchains and Initial Coin Offerings have become popular with investors. The design of these mechanisms, although intended to provide transparency and therefore reduce risk, may expose investors to risk the same way as crowdfunding has. I believe, incorporating aspects of Operations Management will bring in a realistic assessment of these mechanisms.

Appendix A

Chapter 2

A.1 Tables and Figures

Table A.1: Variable and parameter definitions

Decision Variables	
p	Pledge level that backers pay to be entitled to the product – chosen by entrepreneur
T	Target amount to be raised by the campaign – chosen by entrepreneur
γ	Entrepreneur's share of campaign revenues – chosen by platform (platform's share is 1-γ)
α	Threshold percentage of target that entitles campaigns for promotion – chosen by platform
Parameters	
v	Valuation of the product
s	Backer's altruistic utility from supporting a campaign
M	Development cost of the product
N	Random variable indicating the number of informed backers in the campaign
$\bar{N}$	Total size of informed backers in the population
Z	Total size of uninformed backers in the population
k	Probability of technical success when sufficient funds to cover development cost are available
δ	Expansion factor of backer population conditional on campaign promotion
π	Profit in the external market, post campaign, if product is successfully produced
j	L, I, H, corresponding to low, intermediate and high fractional threshold values
Π_b^j	Payoff of Backers for $j = L, I, H$

Π_e^j	Payoff of Entrepreneur for $j = L, I, H$
Π_p^j	Payoff of Platform for $j = L, I, H$
T_e^{j*}	Optimum target that maximizes payoff to the Entrepreneur for $j = L, I, H$
T_p^{j*}	Optimum target that maximizes payoff to the Platform for $j = L, I, H$
R_e	Reputation cost incurred by entrepreneur on failing to deliver the product to backers
R_p	Reputation cost incurred by the platform if the entrepreneur fails to deliver the product

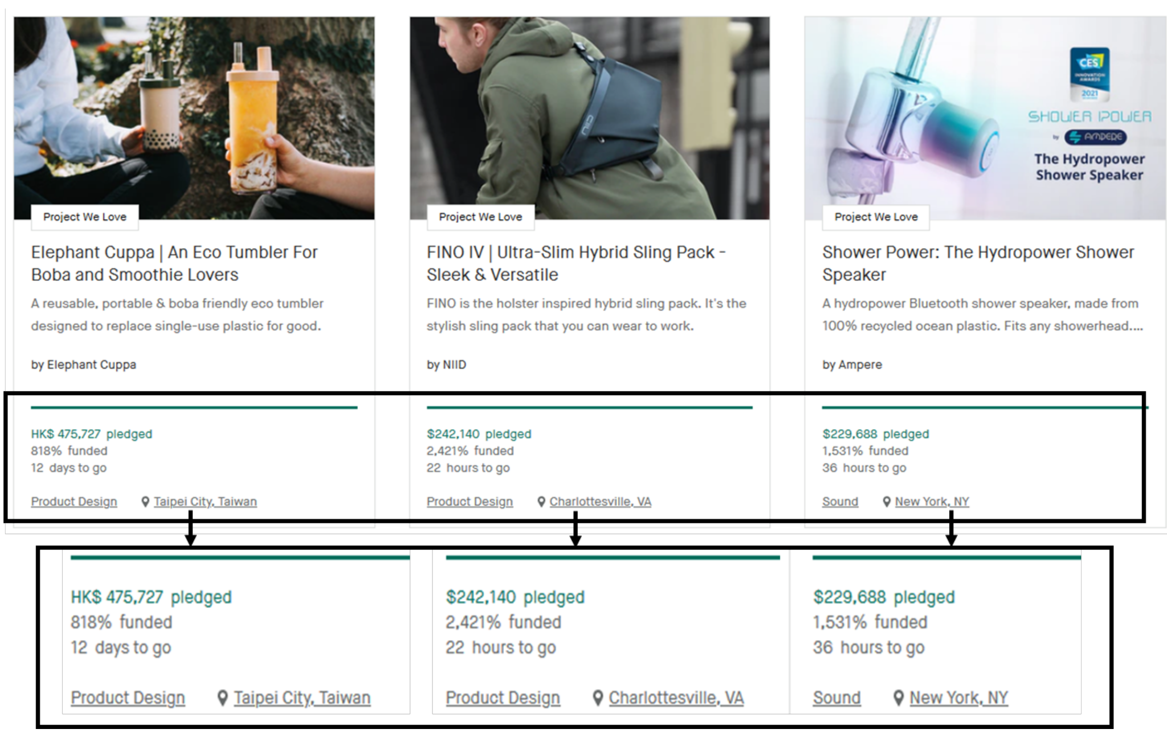


Figure A.1: A snapshot of recommended projects in Kickstarter[1]

[1] Examples of Promoted Campaigns on Kickstarter (as on December 24, 2020)

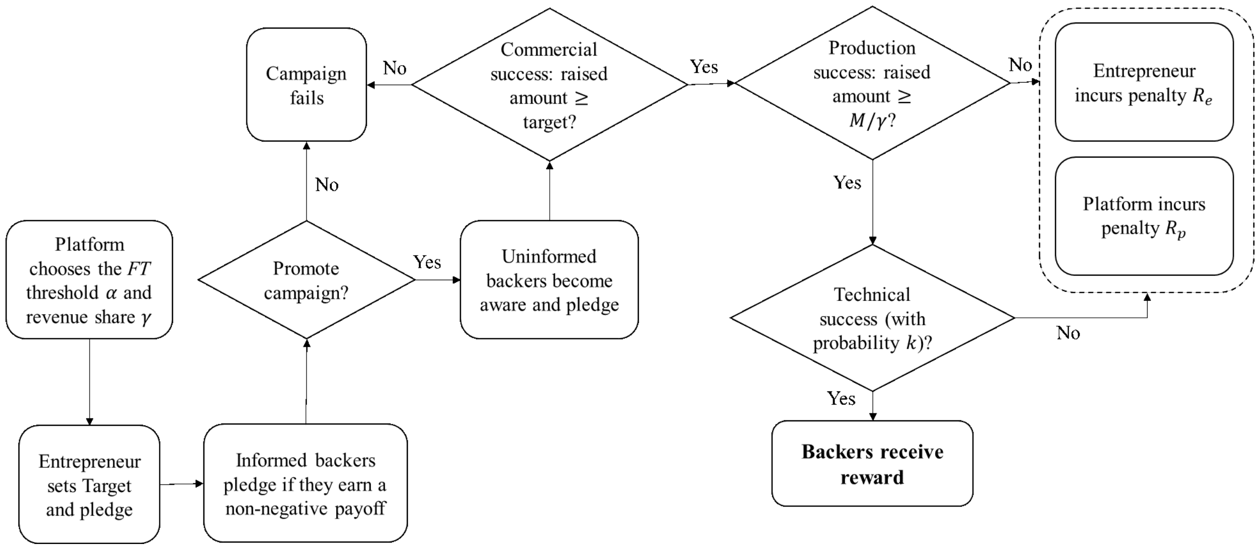


Figure A.2: Stages of a crowdfunding campaign

A.2 Proofs of Propositions, Lemmas and Corollaries

A.2.1 Proof of Proposition 1

Differentiating the expected payoff expression with respect to T, we obtain: $\frac{\partial \mathbb{E}\left(\Pi_e^L\right)}{\partial T} = \frac{[R_e-\gamma T]}{(1+\delta)p\bar{N}} + \frac{\partial p}{\partial T}\left[\frac{\gamma(1+\delta)\bar{N}}{2} + \frac{T^2\gamma}{2(1+\delta)p^2\bar{N}} + \frac{[k\pi-(1-k)R_e-M]M+R_e(M-\gamma T)}{\gamma(1+\delta)p^2\bar{N}}\right]$, where $\frac{\partial p}{\partial T} =$

$$\frac{\left[(1+\delta)(v+s)\bar{N}+T\right]+\sqrt{\left[(v+s)\left((1+\delta)\bar{N}\right)-T\right]^2-4\left[(1+\delta)\bar{N}\right]\left[v\frac{M}{\gamma}-(v+s)T\right]}}{2(1+\delta)\bar{N}\sqrt{\left[(v+s)\left((1+\delta)\bar{N}\right)-T\right]^2-4\left[(1+\delta)\bar{N}\right]\left[v\frac{M}{\gamma}-(v+s)T\right]}} = \frac{p}{\sqrt{\left[(v+s)\left((1+\delta)\bar{N}\right)-T\right]^2-4\left[(1+\delta)\bar{N}\right]\left[v\frac{M}{\gamma}-(v+s)T\right]}}.$$

The expression for $\frac{\partial p}{\partial T}$ is obtained from (2). When $T = \frac{Mv}{\gamma(v+s)}$, the biggest value consistent with the region $T \leq \frac{Mv}{\gamma(v+s)}$, $p = v+s$ and $\frac{\partial p}{\partial T} = \frac{v+s}{\left[(1+\delta)(v+s)\bar{N}-\frac{vM}{\gamma(v+s)}\right]}$. Evaluating $\frac{\partial \mathbb{E}\left(\Pi_e^L\right)}{\partial T}$ at the biggest value of $T = \frac{Mv}{\gamma(v+s)}$ for the region, yields that $\frac{\partial \mathbb{E}\left(\Pi_e^L\right)}{\partial T} > 0$. Given the concavity of the payoff function, it follows, therefore, that the highest payoff for the region is obtained when the target is $\frac{Mv}{\gamma(v+s)}$.

Next, we consider the possibility that $T > \frac{Mv}{\gamma(v+s)}$. In this case, the pledge level is a constant independent of the value of T, and is equal to $p = v+s$. Differentiating the expected payoff expression with respect to T, for values of $T > \frac{Mv}{\gamma(v+s)}$, yields $\frac{\partial \mathbb{E}\left(\Pi_e^L\right)}{\partial T} = \frac{[R_e-\gamma T]}{(1+\mu)(v+s)\bar{N}}$.

Setting this expression to zero yields a target value of $R_e \frac{}{\gamma.}$

The above analysis implies that optimal target value for the low fractional threshold case to be $T_e^{L^*} = \max\left\{\frac{Mv}{\gamma(v+s)}, \frac{R_e}{\gamma}\right\}$, as reported in the Proposition.

A.2.2 Proof of Proposition 2

From (7), $\frac{\partial \mathbb{E}\left(\Pi_e^I\right)}{\partial T} = \frac{\alpha[R_e-\gamma T\alpha(1+\delta)]}{p\bar{N}} + \frac{\partial p}{\partial T}\left[\frac{\gamma(1+\delta)\bar{N}}{2}\left(1+\left(\frac{\alpha T}{p\bar{N}}\right)^2\right) + \frac{[k\pi-(1-k)R_e-M]M+R_e(M-\gamma T\alpha(1+\delta))}{\gamma(1+\delta)p^2\bar{N}}\right]$, where $\frac{\partial p}{\partial T} = \frac{\alpha p}{\sqrt{\left[(v+s)\bar{N}-\alpha T\right]^2 - 4\bar{N}\left[\frac{vM}{\gamma(1+\delta)}-(v+s)\alpha T\right]}}$.

The expression for $\frac{\partial p}{\partial T}$ is obtained from (6). When $T = \frac{vM}{\gamma(v+s)\alpha(1+\delta)}$, the biggest value consistent with the region $T \leq \frac{vM}{\gamma(v+s)\alpha(1+\delta)}$, $p = v+s$ and $\frac{\partial p}{\partial T} = \frac{\alpha(1+\delta)(v+s)}{\left[(1+\delta)(v+s)\bar{N}-\frac{vM}{\gamma(v+s)}\right]}$. Substituting these values yields $\frac{\partial \mathbb{E}\left(\Pi_e^I\right)}{\partial T} > 0$ at $T = \frac{vM}{\gamma(v+s)\alpha(1+\delta)}$, the biggest value of the target in the region. Given the concavity of the payoff function, it follows that the highest payoff for the region is obtained when the target value is $\frac{vM}{\gamma(v+s)\alpha(1+\delta)}$.

Next, we consider the region define by $T > \frac{vM}{\gamma(v+s)\alpha(1+\delta)}$. In this case, the pledge level, p is a constant and equals $v+s$. Differentiating the expected payoff expression with respect to T, for values of $T > \frac{vM}{\gamma(v+s)\alpha(1+\delta)}$, yields $\frac{\partial \mathbb{E}\left(\Pi_e^I\right)}{\partial T} = \frac{\alpha[R_e-\gamma T\alpha(1+\delta)]}{(v+s)\bar{N}}$. This implies that the optimal target level for the region $T > \frac{vM}{\gamma(v+s)\alpha(1+\delta)}$ equals $\frac{R_e}{\gamma\alpha(1+\delta)}$.

The above analysis implies that $T_e^{I^*} = Max\left\{\frac{vM}{\gamma(v+s)\alpha(1+\delta)}, \frac{R_e}{\gamma\alpha(1+\delta)}\right\}$, as reported in the Proposition 2.

A.2.3 Proof of Proposition 3

Substituting the optimal values of target and pledge levels from Propositions 1 and 2 into the payoff functions of the platform in (4) and (8), respectively, yields that the payoff of the platform in the regions specified is the same for both Cases 1 and 2.

A.2.4 Proof of Corollary 1

With the RS rule, as with the FT rule, uninformed backers observe the realization of the random number of informed contributors, n, before contributing. Using this number as a signal, the population of backers expands by the multiplicative factor δ. Hence, if the pre-promotion revenues collected in the campaign are pn, the post-promotion revenues are $np\,(1+\delta)$. Therefore, the total revenues raised by the campaign with the RS rule equal the total revenues raised with the FT rule. Since γ is the same, the expected commission retained by the platform is the same for both the FT and the RS rules. Moreover, as discussed in the remarks following Proposition 2, the probability of product non-delivery is also the same for both these rules under Cases 1 and 2. This implies that the platform's expected reputational cost from a project is the same for the FT and the RS rules. Therefore, the platform's expected payoff from each project is the same under both the FT and the RS rules for Cases 1 and 2 (i.e., when production success is not guaranteed) and γ is kept the same. Hence, the platform is indifferent between using these two rules.

A.2.5 Proof of Proposition 4

Cases (i) and (ii). According to Proposition 3 the expected profits of the platform are the same in Cases 1 and 2. Substituting the equilibrium target and pledge levels into (4) or (8) yields $\mathbb{E}\left(\Pi_p^L\right) =$

$$\begin{cases} \frac{(1-\gamma)(1+\delta)(v+s)\bar{N}}{2}\left[1-\left(\frac{\frac{vM}{\gamma(v+s)}}{(1+\delta)(v+s)\bar{N}}\right)^2\right]-(1-k)\,R_p\left(1-\frac{\frac{M}{\gamma}}{(1+\delta)(v+s)\bar{N}}\right)-\frac{R_p\left(\frac{sM}{\gamma(v+s)}\right)}{(1+\delta)(v+s)\bar{N}} & when\ R_e<\frac{Mv}{(v+s)} \\ \frac{(1-\gamma)(1+\delta)(v+s)\bar{N}}{2}\left[1-\left(\frac{\frac{R_C}{\gamma}}{(1+\delta)(v+s)\bar{N}}\right)^2\right]-(1-k)\,R_p\left(1-\frac{\frac{M}{\gamma}}{(1+\delta)(v+s)\bar{N}}\right)-\frac{R_p\left(M\gamma-\frac{R_e}{\gamma}\right)}{(1+\delta)(v+s)\bar{N}} & when\ R_e\geq\frac{Mv}{(v+s)} \end{cases}$$

Comparing (A.1) with the equilibrium profits in (9) for Case 3, yields the cutoff values of R_p reported in the Proposition.

A.2.6 Proof of Corollary 2

Enforcement of production success is more likely when the minimal cutoff levels on R_p reported in Proposition 4 decline. In Case (i) of Proposition 4, the cutoff level declines if s or γ go up, or when v or M go down. In Case (ii) of Proposition 4, the cutoff level declines if M or R_e go down or when γ goes up.

A.2.7 Proof of Proposition 5

Follows from the discussion preceding the Proposition.

A.2.8 Proof of Proposition 6

To obtain the comparative statics results, we use the Implicit Function Theorem by deriving the total differential of the first order condition (12). To obtain the sign of $\frac{\partial \gamma}{\partial f}$, where f is any parameter of the model the total differential is: $d\left[\frac{\partial \mathbb{E}(\Pi_p)}{\partial \gamma}\right] = \frac{\partial \mathbb{E}^2(\Pi_p)}{\partial \gamma^2} d\gamma + \frac{\partial \mathbb{E}^2(\Pi_p)}{\partial \gamma \partial f} df = 0$. As a result, $\frac{\partial \gamma}{\partial f} = -\frac{\frac{\partial \mathbb{E}^2(\Pi_p)}{\partial \gamma \partial f}}{\frac{\partial \mathbb{E}^2(\Pi_p)}{\partial \gamma^2}}$. Because $\mathbb{E}\left(\Pi_p\right)$ is a concave function of γ, it follows that $\frac{\partial \mathbb{E}^2(\Pi_p)}{\partial \gamma^2} < 0$ and the sign of $\frac{\partial \gamma}{\partial f}$ is determined by the sign of $\frac{\partial \mathbb{E}^2(\Pi_p)}{\partial \gamma \partial f}$. Partial differentiation of the expression for $\frac{\partial \mathbb{E}(\Pi_p)}{\partial \gamma}$ with respect to any parameter, yields, therefore, the results reported in the Proposition.

A.2.9 Proof of Lemma 2

i. Because $\frac{\partial M^*}{\partial \gamma} > 0$, when $M^* < \overline{M}$, this part follows.

ii. The entire population participates in one of two cases:

   a. If the term inside the radical of the expression for M^* is negative, namely if $s\mu\left[(\mu + 2\lambda)(2v + s) - 2R_e(v + s)\right] > \left[\lambda(v + s) + R_e s\right]^2$, there is no real solution to the equation $W(M^*) = 0$. This is more likely to happen when the expected revenues in the campaign, μ are relatively high, when the altruistic benefit, s derived by backers is high, and when the reputation cost, R_e incurred by the entrepreneur for non-delivery of the product is low.

   b. When the real solution derived for M^* in (13) is bigger than $\overline{M}$. Once again, this is more likely when μ and s are relatively big and R_e is relatively small.

iii. When μ and s are relatively small and R_e is relatively big, the solution for M^* in (13) may be smaller than $\underline{M}$.

iv. Substituting $s = 0$ into the solution for M^* in (13), yields the result.

A.2.10 Proof of Proposition 7

Cases (i)(a) and (i)(b) follow from the first order condition for γ in (13). Case (ii) follows because, from (16), $\frac{\partial M^*}{\partial s} > 0$, and from Lemma 2, $M^* = \mu$ when $s = 0$. Hence, when $s > 0$, $M^* > \mu$. As a result, entrepreneurs facing development cost in the interval $M \in (\mu, M^*]$ will be active on the platform despite never being able to deliver the promised product. For these entrepreneurs, $M > \gamma (1 + \delta) (v + s) \bar{N}$, where the right-hand-side of the last inequality measures the maximum revenues that can ever be raised in the campaign.

A.3 Extensions of the model

A.3.1 Allowing informed backers to withdraw pledges when few other informed backers participate

In this extension, we consider the possibility that when the number of informed backers is revealed post promotion, some informed backers who have already pledged may change their mind and withdraw their pledges. We formulate this possibility by assuming that the total number of backers after the promotion is $[n (1 + \delta) - \beta\delta]$. Hence, if $n < \beta$ the total size of the backer population actually declines because some informed withdraw their pledges. In this case, the campaign definitely fails commercially, given our assumption that $(v + s) \overline{N} < T$. Hence, promotion leads to an expansion of the backer population only if $n > \beta$. In this case, the threshold level on α that determines the three cases we considered in the main case are as follows:

i. $\alpha < \left(1 + \frac{\delta\beta p}{T}\right) / (1 + \delta)$ (Commercial success is not guaranteed).

ii. $\left(1 + \frac{\delta\beta p}{T}\right) / (1 + \delta) \leq \alpha < \left(\frac{M}{\gamma T} + \frac{\delta\beta p}{T}\right) / (1 + \delta)$ (Commercial success guaranteed but production success is not guaranteed).

Most of the qualitative results we obtained in the main text, when $\beta = 0$, remain similar, with the exception being that the expected profits of the platform may be different in Cases

A.1 and A.2 compared to Cases 1 and 2 in the main text, respectively. The next Proposition reports the comparison of the expected profits of the platform in these two cases.

Proposition A.1 (Low Fractional Threshold)**.** *For a fixed sharing rule γ of campaign revenues:*

i. *When $R_e < \left[\frac{Mv}{(v+s)} - \delta\beta s\gamma\right]$ or when $R_e \geq \left[\frac{vM}{(v+s)} + v\gamma\delta\beta\right]$, the platform's expected profits are the same irrespective of whether the threshold value α selected by the platform ensures the commercial success of the campaign (Cases i or ii).*

ii. *When $\left[\frac{Mv}{(v+s)} - \delta\beta s\gamma\right] < R_e < \left[\frac{vM}{(v+s)} + v\gamma\delta\beta\right]$, the expected profits of the platform are higher when the threshold level for promotion selected by the platform cannot ensure the commercial success of the campaign (Case i) if $R_p > \frac{1-\gamma}{2}\left[\frac{Mv}{\gamma(v+s)} - \delta\beta s + \frac{R_e}{\gamma}\right]$. Otherwise the platform prefers to choose the threshold to ensure the commercial success of the campaign.*

Hence, only for intermediate values of the reputational cost incurred by the entrepreneur, reported in part (ii) of the Proposition, the platform may have a strict preference between Cases (i) and (ii). Because of this different result, the decision of the platform of whether to enforce production success changes as well, as we report in Proposition A.2.

Proposition A.2 (Intermediate Fractional Threshold)**.** *For a fixed value of γ, there exist threshold levels R^*_{p1} and R^*_{p2} indicating indifference between ensuring and not ensuring production success so that:*

i. *When $R_e < \left[\frac{Mv}{(v+s)} - \delta\beta s\gamma\right]$:*

  a. *If $R_p < R^*_{p1}$, the platform chooses α in a manner that does not guarantee production success (Cases i or ii).*

  b. *$R_p \geq R^*_{p1}$, the platform chooses α to ensure production success.*

ii. *When $\left[\frac{Mv}{(v+s)} - \delta\beta s\gamma\right] \leq R_e < \left[\frac{vM}{(v+s)} + v\gamma\delta\beta\right]$:*

  a. *If $R_p < \frac{1-\gamma}{2}\left[\frac{Mv}{\gamma(v+s)} - \delta\beta s + \frac{R_e}{\gamma}\right]$, the platform chooses α in a manner that guarantees commercial success but does not guarantee production success (Case ii).*

  b. *If $\frac{1-\gamma}{2}\left[\frac{Mv}{\gamma(v+s)} - \delta\beta s + \frac{R_e}{\gamma}\right] \leq R_p < R^*_{p2}$, the platform chooses α in a manner that does not guarantee either commercial or production success (Case i).*

c. *If* $R_p \geq R^*_{p2}$*, the platform chooses* α *to ensure the production success of the campaign.*

iii. *When* $R_e \geq \left[\frac{vM}{(v+s)} + v\gamma\delta\beta\right]$*:*

a. *If* $R_p < R^*_{p2}$*, the platform chooses* α *in a manner that does not guarantee production success (Cases i or ii).*

b. *If* $R_p \geq R^*_{p2}$*, the platform chooses* α *to ensure the production success of the campaign.*

iv. *When* $R^*_{p1} < R^*_{p2}$*. The threshold levels decrease with the values of the parameters* s*,* γ*,* δ*,* β *and increase with the values of the parameters* v*,* M*, and* R_e*.*

R^*_{p1} *and* R^*_{p2} *are defined as follows: When* $R_e < \left[\frac{Mv}{(v+s)} - \delta\beta s\gamma\right]$*,*
$R^*_{p1} \equiv \frac{(1-\gamma)\left[(1+\delta)(v+s)\bar{N}\right]^2}{2\left(\frac{sM}{\gamma(v+s)}+\delta\beta s\right)}\left[\frac{\left(\frac{sM}{\gamma(v+s)}+\delta\beta(v+2s)\right)\left(\frac{(2v+s)M}{\gamma(v+s)}+\delta\beta v\right)}{\left[(1+\delta)(v+s)\bar{N}\right]^2} - \frac{\delta\beta}{(1+\delta)\bar{N}}\left(2-\frac{\delta\beta}{(1+\delta)\bar{N}}\right)\right]$*. When* $R_e \geq \left[\frac{vM}{(v+s)} + v\gamma\delta\beta\right]$*,* $R^*_{p2} \equiv \frac{(1-\gamma)\left[(1+\delta)(v+s)\bar{N}\right]^2}{2\left(\frac{M-R_c}{\gamma}\right)}\left[\frac{\left(\frac{M-R_c}{\gamma}+\delta\beta(v+s)\right)\left(\frac{M+R_c}{\gamma}+\delta\beta(v+s)\right)}{\left[(1+\delta)(v+s)\bar{N}\right]^2} - \frac{\delta\beta}{(1+\delta)\bar{N}}\left(2-\frac{\delta\beta}{(1+\delta)\bar{N}}\right)\right]$*.*

The results implied by Proposition A.2, are similar to those reported in Proposition 2.4 of the main text. Specifically, the platform is more likely to enforce production success when R_e is relatively small and/or when R_p is relatively large (note that $R^*_{p1} < R^*_{p2}$), when s and γ are big, and when M and v are small. The only difference with the case that $\beta = 0$ is that for intermediate levels of reputational cost incurred by the entrepreneur (in part (ii) of the Proposition), the platform has a strict preference of ensuring commercial success over not ensuring such success when $R_p < \frac{1-\gamma}{2}\left[\frac{Mv}{\gamma(v+s)} - \delta\beta s + \frac{R_e}{\gamma}\right]$ and the opposite when $\frac{1-\gamma}{2}\left[\frac{Mv}{\gamma(v+s)} - \delta\beta s + \frac{R_e}{\gamma}\right] \leq R_p < R^*_{p2}$.

A.4 General distribution function of the informed backer population

In this section, we explore whether the results derived for the uniform distribution can be extended to other distribution functions. For simplicity, we assume that the probability of technical success is one, namely k=1, $\beta = 0$, and the reputational cost of the platform is sufficiently small, so that the threshold level of promotion does not guarantee the commercial success of the campaign. Let $f(n)$ and $F(n)$ denote the density and cumulative distribution functions, respectively, of the number of informed backers. The expected payoff of the informed backers is: $\mathbb{E}\left(\Pi^L_b\right) = \left\{v\left[1 - F\left(\frac{M}{\gamma(1+\delta)p}\right)\right] - p\left[1 - F\left(\frac{T}{(1+\delta)p}\right)\right] + s\right\}$. The entrepreneur sets the highest pledge possible to ensure that the informed backer obtain a nonnegative payoff. This pledge can never exceed the maximum willingness to pay of backers $v+s$. Setting $\mathbb{E}\left(\Pi_b^L\right)=0$ for $p\leq v+s$, yields two observations. First, the maximum pledge of v+s is attained at a target level $T^u<\frac{M}{\gamma}$ when $s>0$.

Specifically, $T^u=(1+\mu)\,(v+s)\,F^{-1}\left[\frac{v}{v+s}F\left(\frac{M}{\gamma(1+\delta)(v+s)}\right)\right]<\frac{M}{\gamma}$ if $s>0$. Hence, as in the case of a uniform distribution, the pledge reaches its maximum value at a target level strictly lower than the funds necessary to cover the development costs. Second, we can obtain the the expression for $\frac{\partial p}{\partial T}$ by total differentiation of the equation $\mathbb{E}\left(\Pi_b^L\right)=0$, for $p\leq v+s$. Define $x\equiv\ \frac{T}{(1+\delta)p}$ and $y\equiv\frac{M}{\gamma(1+\delta)p}$, then $\frac{\partial p}{\partial T}=\frac{f(x)x\frac{p}{T}}{[1-F(x)]+f(x)x-vf(y)\frac{y}{p}}$. However, when $\mathbb{E}\left(\Pi_b^L\right)=0$, $F\left(x\right)=\frac{vF(y)-(v+s-p)}{p}$, implying that $f\left(x\right)=\frac{v}{p}\frac{M}{\gamma T}f\left(y\right)$. Substituting into the derivative, we obtain that $\frac{\partial p}{\partial T}=\frac{f(x)x}{[1-F(x)](1+\delta)}>0$. Hence, as in the case of the uniform distribution, a higher target level allows the entrepreneur to set a higher pledge. Moreover, for $T\geq T^u$, the pledge is a constant equal to the maximum willingness to pay $(v+s)$. The expected payoff of the entrepreneur is: $\mathbb{E}\left(\Pi_e^L\right)=(1+\mu)\,p\gamma\int_x^{\bar{N}}nf\left(n\right)dn+(\pi-M)\left[1-F\left(y\right)\right]-R_e\left[F\left(y\right)-F\left(x\right)\right]$.

When $T\geq T^u$, the pledge level is a constant equal to $v+s$. Hence, in this case, the optimal level of the target satisfies the first order condition $f\left(\frac{T}{(1+\delta)(v+s)}\right)\left[\frac{R_e-\gamma T}{(1+\delta)(v+s)}\right]=0$, yielding the solution $T_{opt}^e=\frac{R_e}{\gamma}$ if $\frac{R_e}{\gamma}\geq T^u$. When $\frac{R_e}{\gamma}<T^u$, the optimal solution for the target level falls in the region where $p<v+s$. We differentiate the expected profits of the entrepreneur with respect to the target level:
$\frac{\partial\mathbb{E}\left(\Pi_e^L\right)}{\partial T}=\gamma xf\left(x\right)\left[\mathbb{E}\left(N|\,N\geq x\right)-1+\frac{xf(x)}{1-F(x)}\right]+\frac{(\pi-M)[xf(x)]^2}{(1+\delta)(1-F(x))v}+\frac{R_cf(x)}{p(1+\delta)}\left[1+\frac{x^2f(x)}{1-F(x)}\left(\frac{p}{v}-1\right)\right]>0$. Because the profits of the entrepreneur increase with T throughout the region, it follows that $T_{opt}^e=T^u$ when $\frac{R_e}{\gamma}<T^u$. To summarize:

$$T_{opt}^e=\begin{cases}T^u\text{ when}\frac{R_e}{\gamma}<T^u\\ \frac{R_e}{\gamma}\text{ if }\frac{R_e}{\gamma}\geq T^u\end{cases}$$

The solution is very similar to that derived under the uniform distribution.

A.5 Empirical Analysis for Kickstarter Data

Our conclusions about the effect of campaign promotion rule on the optimal target and pledge amount, rely on the assumption that campaigns which raise a high 'Percentage of Target' are more likely to be promoted.[2] It is well established in the literature that people rely on results on the first few pages of a search engine to determine which pages to visit (Ghose et al. 2014, Agarwal et al. 2011, Ghose and Yang 2009, Ursu 2018). We extend this search rationale to a crowdfunding platform. Campaigns that have a lower rank appear in the first pages, and therefore, draw a larger backer population. To empirically establish whether a higher 'Percentage of Target' results in promotion, we compile a dataset comprising of campaigns that are promoted, based on specific sorting categories, in the first 10 pages of Kickstarter.[3] Each page consists of 12 campaigns. We took six samples every day from June 27 to August 15 at randomly chosen time points to avoid a consistent pattern of browsing and time zone effects. There are many potential search categories that one can use to browse through the different campaigns in Kickstarter. A prospective backer can do a focused search for a campaign, browse for products under the various 'product categories', or get 'suggestions' from the platform. These 'suggestions' are further sorted depending on a backer's preference for products which are 'just launched', 'popular', 'recommended' or 'staff picks'.[4] Our intention in choosing all the potential product categories is to show that, regardless of how the backers choose to navigate the crowdfunding platform, campaigns that raise a higher 'Percentage of Target' have a lower (better) rank. Since there are 120 (10×12) campaigns for each sorting category and four sorting categories, there are 480 campaigns in each sample. The raw data size we started with had a size of 480 x 50 x 6 observations.

The metrics we tracked for each campaign were:

Name: Campaign name which also serves a unique identifier.[5]

[2]Because crowdfunding platforms use the "Load More" or "Show More" buttons at the bottom of each page of recommended campaigns to continue displaying additional campaigns from the recommended list, we use improvement in the ranking of a campaign as a measure of the recommendation in this investigation.

[3]Kickstarter does not list campaigns in distinct pages but appear as one scrolls down the page. The page numbers, however, appear in the HTML script.

[4]The Kickstarter platform uses the following names for sorting the campaigns, 'Trending' for 'Popular' campaigns, 'Everything' for 'Recommended' campaigns and 'Project We Love' for 'Staff Picks'.

[5]The name of the entrepreneur and a short description of the dataset are also available

Demographic details: Country of Origin and Location of the campaign.

Amount Pledged: $ amount pledged, including for campaigns that originate outside the US.[6]

Backer Count: Number of backers who have already pledged.

Launch Date: Date when the campaign was launched.

End Date: Date when the campaign is scheduled to end.

Target: Amount to be raised through the campaign.

Sorting Category: Specific category (recommended, popularity, staff pick, or just launched) in which the campaign is ranked.

Rank: Order in which the campaigns are presented to an unregistered onlooker, for the specific sorting category.

Percentage Funded: Amount raised as a percentage of the target level.

Product Category: Specific category in which the campaign is listed.

Time Stamp: Time epoch when the sample is taken.

We tracked 724 distinct campaigns over the 50-day period. In our sample, around 75% of the campaigns had met their targets at some point, and 25% had raised 10 times (1000%) of the target amount. Among the 108 product categories, the highest number (90) of campaigns were listed under Tabletop Games followed by products in Product Design (67). Products under the "Product Design" category are technologically intensive and require substantial development cost. Hardware on average had the highest backer count. Most listed campaigns originated in the United States (58%) followed by United Kingdom (14%). 77% of the campaigns had a target level less than $20,000. We now describe the models that guide our research questions.

Because our objective is to validate how the rank of a campaign is affected by the Percentage of Target, we designate the rank of a campaign as the dependent variable, where $Rank_{it}$ is the rank of campaign i at time t. The independent variables are as follows: $CampDur_i$ measures the duration of the campaign, $DaysToEnd_{it}$ measures a potential "end effect" for the campaign as cited in Burtch et al. (2020) and Chakraborty and Swinney (2019a). We also control for the target that each campaign keeps $Target_i$. We include both a continuous variable for the lagged percentage of target raised, $PercFun_{i(t-1)}$, and a binary

[6]Rather than converting foreign currencies ourselves, we rely on the $ amount that Kickstarter provides.

variable Threshold Percent Funded TPF_{it} which equals one if campaign i has reached a specific threshold percentage of target at time t. We use three different percentage threshold values: 100%, 300% and 500%. The variable X_i controls for the product category to which the campaign belongs, and the specific sorting method a backer uses (i.e., 'just launched', 'popularity', 'recommended' and 'staff picks'.) Unlike Godes and Silva (2012), we could not control for the backer's identity as it is confidential. The model is given below:

$$Rank_{it} = \beta_0 + \beta_1 CampDur_i + \beta_2 DaysToEnd_i + \beta_3 PercFun_{i(t-1)} + \beta_4 Target_i + \beta_5 TPF_{it} + \gamma X_i + \epsilon_{it}$$

The results in Table 9 clearly show that an increase in the Percentage of Target raised results in an improvement (reduction) of rank. The rank of a campaign improves (reduces) by 1.5 units when the campaign is funded three times over ($TPF = 300\%$), all the other variables held constant. Interestingly, we observe that the campaign ranking worsens (increases) when the campaign is just funded ($TPF = 100\%$). It may be that because the platform is assured of its commissions, once a campaign is fully funded, the platform prefers giving priority to other campaigns that raise a higher amount, thus guaranteeing higher commission for itself. With a higher threshold than 300%, the impact on rank becomes progressively stronger (i.e., for $TPF = 500\%$, all else constant, rank reduces by 3 units). Furthermore, the continuous lagged percentage variable is significant and negative, implying that a unit increase in percentage has the effect of improving the rank of a campaign. We also find that there is an improvement in the rank of a campaign as the campaign draws to a close (*Days To End*). Campaigns with a longer duration have a lower rank. We also find that campaigns are ranked 9 points lower, on average, when a backer alters his sorting category from campaigns that are 'just launched' to 'recommended' campaigns. These results are robust both in direction and statistical significance if either of the two variables (but not both), the continuous lagged percentage funded variable and the threshold percent funded, are included as independent variables.

Table A.2: Results from Data Analysis of Kickstarter Recommended Campaigns

Effect of increase in Percentage Target on Campaign Rank

	Dependent Variable: Rank of Campaign			
	Estimate	Std. Error	LL (95% CI)	UL (95% CI)
Intercept	150.969***	20.014	111.739	190.196
Campaign Duration	-0.421***	0.112	-0.639	-0.202
Days to End	-0.402***	0.014	-0.431	-0.374
Percent Funded (Lagged)	-0.0003***	9.45E-05	-0.0005	-0.0001
Target	-0.008**	0.0036	-0.015	-0.0008
Threshold Percent Funded (TPF = 300%)	-1.531***	0.527	-2.563	-0.498
Sort by "Popularity"	9.077***	0.647	7.808	10.346
Sort by "Recommended"	-18.517***	0.575	-19.644	-17.39
Sort by "Staff Picks"	28.973***	0.711	27.579	30.366

Appendix B

Chapter 3

B.1 Proofs

Proof of Lemma 3.2.

We know that $x^{LT} = \frac{M\sigma_X - \{p_c - w\}(\mu_Y\sigma_X - \rho\mu_X\sigma_Y)}{(\gamma p_c - w)\sigma_X + \{p_c - w\}\rho\sigma_Y}$. Taking the derivative with respect to the pledge we find that $\frac{\partial x^{LT}}{\partial p_c} = \frac{(1-\gamma)w\sigma_X(\mu_Y\sigma_X - \rho\mu_X\sigma_Y) - M\sigma_X(\gamma\sigma_X + \rho\sigma_Y)}{\{(\gamma p_c - w)\sigma_X + \{p_c - w\}\rho\sigma_Y\}^2}$. Assuming $\frac{\sigma_X}{\mu_X} \geq \frac{\sigma_Y}{\mu_Y}$ (the post-campaign market is relatively more stable than the crowdfunding market) so long as $w \geq w^* = \frac{M(\gamma\sigma_X + \rho\sigma_Y)}{(1-\gamma)(\mu_Y\sigma_X - \rho\mu_X\sigma_Y)}$, $\frac{\partial x^{LT}}{\partial p_c} \geq 0 else \frac{\partial x^{LT}}{\partial p_c} \leq 0$. Given the value of our parameters in the numerical analysis $w < w^*$, therefore, $\frac{\partial x^{LT}}{\partial p_c} \leq 0$. Furthermore, $\frac{\partial^2 x^{LT}}{\partial w \partial p_c} \geq 0$. That is a as pledge amount reduces and so does the whole sale price it has the effect of increasing the threshold investment number. Taking the derivative of x^{LT} with respect to the wholesale price we get, $\frac{\partial x^{LT}}{\partial w} = \frac{(1-\gamma)\sigma_X(\mu_Y\sigma_X - \rho\mu_X\sigma_Y)(w^* - p_c)}{\{(\gamma p_c - w)\sigma_X + \{p_c - w\}\rho\sigma_Y\}^2}$. Therefore, so long as, $p_c < w^*$, $\frac{\partial x^{LT}}{\partial w} > 0$ else $\frac{\partial x^{LT}}{\partial w} \leq 0$. The other signs follow from the relative position of the pledge amount p_c and wholesale price w relative to the threshold w^*.

Taking the differential of the threshold number of backer for investment with respect to the strength of the crowdfunding market signal ρ, we get, $\frac{\partial x^{LT}}{\partial \rho} = \frac{(\gamma p_c - w)(p_c - w)\mu_X\sigma_X\sigma_Y - \{M\sigma_X - (p_c - w)\mu_Y\sigma_X\}(p_c - w)\sigma_Y}{\{(\gamma p_c - w)\sigma_X + (p_c - w)\rho\sigma_Y\}^2}$. Therefore, $\frac{\partial x^{LT}}{\partial \rho} \geq 0 \Leftrightarrow (\gamma p_c - w)\,\mu_X + (p_c - w)\,\mu_Y \geq M$. For the sake of simplicity if we let $\gamma = 1$, we can simplify $\frac{\partial x^{LT}}{\partial \rho}$ to $\frac{\partial x^{LT}}{\partial \rho} = \frac{\mu_X\sigma_X\sigma_Y - \left\{\frac{M}{p_c - w}\sigma_X - \mu_Y\sigma_X\right\}\sigma_Y}{\{\sigma_X + \rho\sigma_Y\}^2}$. Observe that as the margin, $p_c - w$ increases the increase in the threshold number of backers needed for the entrepreneur to invest increases even more. That is, $\frac{\partial^2 x^{LT}}{\partial \lambda \partial \rho} \geq 0$, where $\lambda = p_c - w$.

B.1.1 Proof of Lemma 3.3

At the boundary setting $\frac{T}{p_c} = x^{LT}$ assures the backer that conditional on campaign success, the investment will be made for sure which will also ensure that the product is delivered. Therefore, the backer will be ready to give up $p_c = \phi v$ in this situation. The target therefore, is simply $T = \phi v x^{LT}$. Since the entrepreneur will decide the optimal wholesale price in response to the pledge amount the entrepreneur sets, the supplier will maximize its own payoff. That is, by maximizing 3.4, w.r.t. the wholesale price gives

$$\frac{\partial \mathbb{E}\left(\Pi_s\right)}{\partial w} = \sigma_X^2 f\left(x^{LT}\right) + \left(\mu_X + \mu_Y\right)\bar{F}\left(x^{LT}\right) - (w-c)\left(\mu_Y + x^{LT}\right)\frac{\alpha M}{\left(p_c - w\right)^2} f\left(x^{LT}\right)$$

where $x^{LT} = x^{LT}(\phi v, w)$. Equating $\frac{\partial \mathbb{E}(\Pi_s)}{\partial w}$ to zero, gives the condition as stated in Proposition 1.1.

B.1.2 Proof of Lemma 3.4

For all target amounts that are *strictly* lower than the minimum amount of backers needed for the entrepreneur to invest in the fixed cost, there could potentially be a cost to the reputation of the entrepreneur if the campaign succeeds but the entrepreneur fails to deliver the product. This is true for all realizations in the range $\frac{T}{p_c} \leq x < x^{LT}$. Differentiating the payoff of the entrepreneur in 3.2 w.r.t. the target amount gives:

$$\frac{\partial \mathbb{E}\left(\Pi_e\right)}{\partial T} = \frac{R - \gamma T}{p_c} f\left(\frac{T}{p_c}\right)$$

Equating $\frac{\partial \mathbb{E}(\Pi_e)}{\partial T}$ to zero, gives the optimal target. Once the target is known, the payoff maybe calculated as a function (best-response) of the wholesale price offered by the supplier. That is, substituting the optimal value of the target in the expression for the net payoff of the backer in 3.3, and equating to zero, we get:

$$\phi v \bar{F}\left(x^{LT}\right) - p_c \bar{F}\left(\frac{R}{\gamma p_c}\right) = 0$$

The supplier incorporates the best response of the entrepreneur, in its own payoff (3.4) and maximizes it w.r.t to the wholesale price w. By using Winkler's rule of partial moments (Winkler et al. 1972), we can rewrite the payoff of the supplier as:

$$\mathbb{E}\left(\Pi_s\right) = (w-c)\left[\sigma_X^2 f\left(x^{LT}\right) + \left(\mu_X + \mu_Y\right)\bar{F}\left(x^{LT}\right)\right]$$

Differentiating the above expression with respect to the wholesale price, and simplifying gives:

$$\frac{\partial \mathbb{E}\left(\Pi_s\right)}{\partial w} = \sigma_X^2 f\left(x^{LT}\right) + \left(\mu_X + \mu_Y\right)\bar{F}\left(x^{LT}\right) - (w-c)\left(\mu_Y + x^{LT}\right)\frac{\alpha M}{\left(p_c - w\right)^2} f\left(x^{LT}\right)$$

Equating $\frac{\partial \mathbb{E}(\Pi_s)}{\partial w}$ to zero while incorporating the net payoff of the backer gives the optimal pledge and wholesale price as stated in Proposition 1.

B.2 Figures - Comparative Statics without Price Discrimination

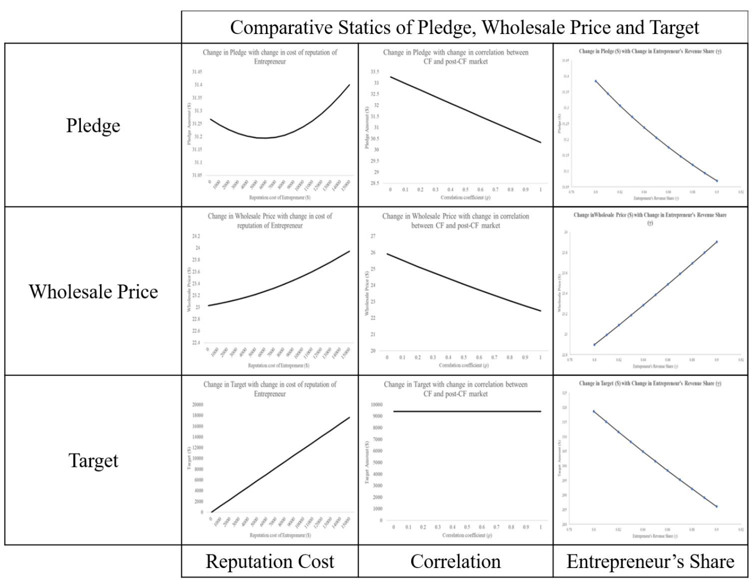


Figure B.1: Effect of change in Pledge, Wholesale Price and Target with increase in Reputation Cost R, Crowdfunding Signal ρ, and the Entrepreneur's Share of the campaign proceeds γ, under the **NOP** regime

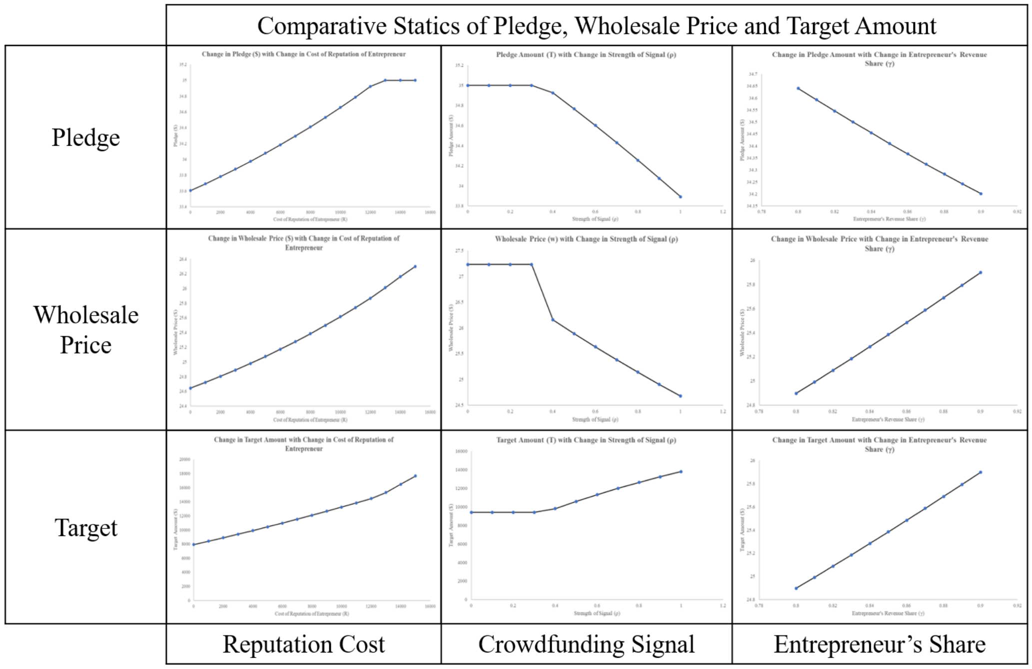


Figure B.2: Effect of change in Pledge, Wholesale Price and Target with increase in Reputation Cost R, Crowdfunding Signal ρ, and the Entrepreneur's Share of the campaign proceeds γ, under the **WOP** regime

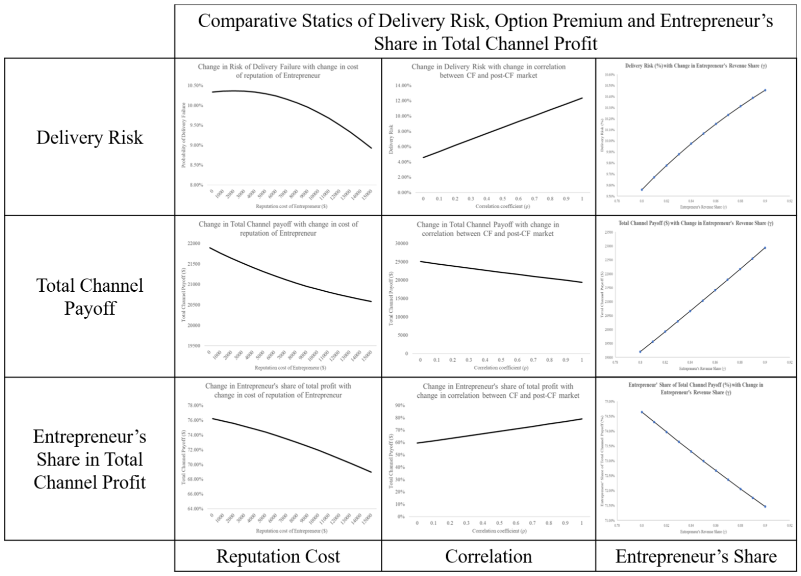


Figure B.3: Effect of change in Total Channel Profit and Entrepreneur's Share in Total Channel Profit, under the **NOP** regime

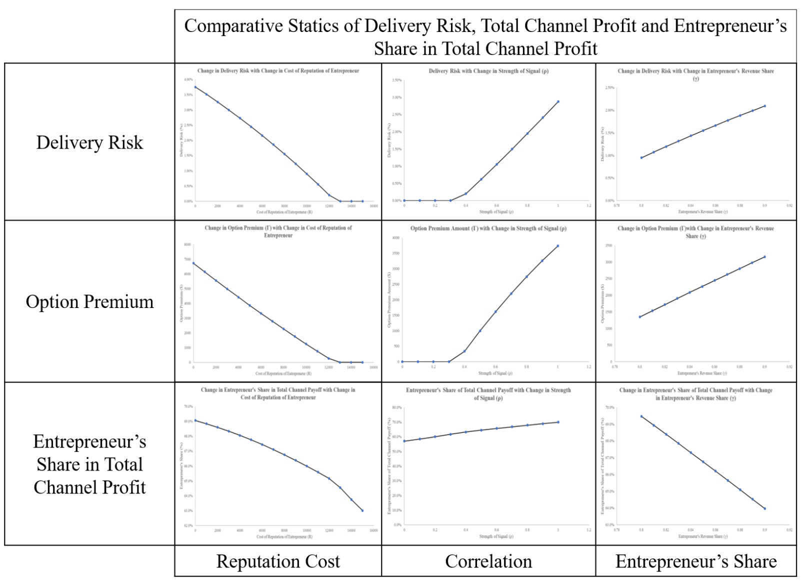


Figure B.4: Effect of change in Total Channel Profit and Entrepreneur's Share in Total Channel Profit, under the **WOP** regime

B.3 Figures - Comparative Statics with Price Discrimination

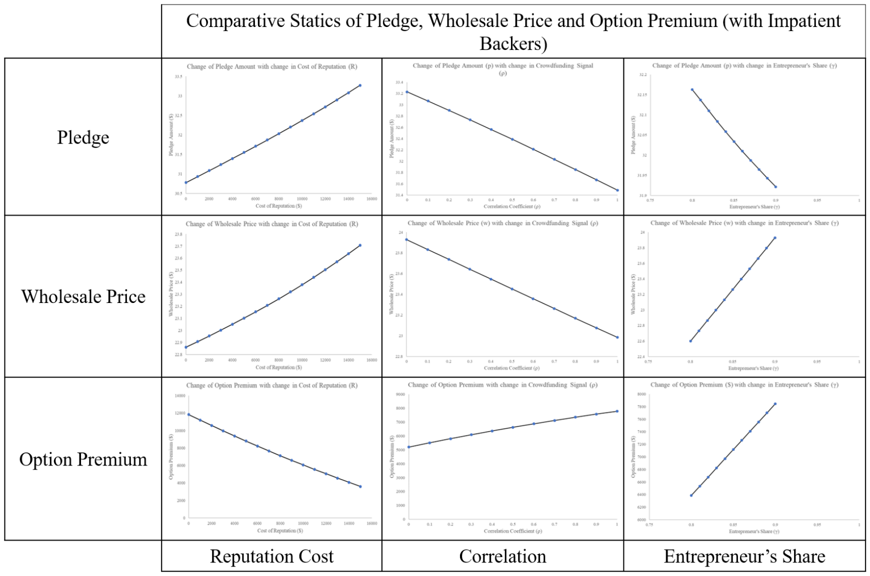


Figure B.5: Effect of change in Pledge, Wholesale Price and Option Premium under Price Discrimination in the **WOP** regime

Appendix C

Chapter 4

C.1 Detailed Results

Table C.1: Model AL. Sensitivity of CCC to $Time$

		Model $AL1$	Model $AL2$	Model $AL3$	Model $AL4$
	Dependent Variable	CCC		CCC	CCC
IVs	$Time \times Type\ H\ (\psi_H^A)$	-0.27 (0.16)	-0.15 (0.17)	0.22 (0.23)	-0.17 (0.17)
	$Time \times Type\ MH\ (\psi_{MH}^A)$	0.53** (0.17)	0.42* (0.18)	-0.22 (0.24)	0.06 (0.18)
	$Time \times Type\ ML\ (\psi_{ML}^A)$	0.48** (0.18)	0.36* (0.2)	0.3 (0.24)	0.44* (0.18)
	$Time \times Type\ L\ (\psi_L^A)$	0.25 (0.18)	0.05 (0.18)	-0.29 (0.23)	0.38* (0.19)

[§] t-values were calculated using the Satterthwaite method. ***$p \leq 0.01$, **$p \leq 0.05$, *$p \leq 0.10$

Table C.2: Model FL. Effect of SGR on CCC

		Model $FL1$	**Model $FL2$**	**Model $FL3$**	**Model $FL4$**	**Model $FL5$**
	Dependent Variables	***CCC***	***CCC***	***CCC***	***CCC***	***CCC***
Independent Variables	AMZN: *Sales* (ρ^{F}_{AMZN})	-0.25*** (0.05)	-0.15* (0.08)	-0.56*** (0.15)	0.04 (0.15)	0.04 (0.15)
	TGT: *Sales* (ρ^{F}_{TGT})	-	-0.51 (0.4)	1.82*** (0.38)	3.8*** (1.04)	4.32*** (1.03)
	COST: *Sales* (ρ^{F}_{COST})	-	0.35* (0.17)	0.15 (0.28)	-0.02 (0.56)	0.01 (0.55)
	CVS: *Sales* (ρ^{F}_{CVS})	-	-0.36** (0.12)	-0.67* (0.38)	-1.42*** (0.34)	-1.35*** (0.31)
	DKS: *Sales* (ρ^{F}_{DKS})	-	2.68 (2.21)	-10.8** (3.93)	8.8 (8.1)	8.85 (8.24)
	JCP: *Sales* (ρ^{F}_{JCP})	-	-7.41*** (1.02)	-1.71 (1.07)	-0.62 (1.78)	-0.56 (1.81)
	RAD: *Sales* (ρ^{F}_{RAD})	-	0.84 (0.95)	0.84 (0.83)	0.13 (0.74)	-0.41 (0.7)
	SHLD: *Sales* (ρ^{F}_{SHLD})	-	-1.33*** (0.37)	-0.23 (0.59)	-1.04 (0.85)	-0.99 (0.85)
	WBA: *Sales* (ρ^{F}_{WBA})	-	-1.47*** (0.22)	-0.53 (0.38)	-1.19*** (0.34)	-1.13*** (0.29)
	WMT: *Sales* (ρ^{F}_{WMT})	-	0.2* (0.1)	0.53** (0.18)	-0.09 (0.24)	-0.1 (0.2)
	Sales×Type MH (φ_{MH})	-	-	-	-	-0.08** (0.03)
	Sales×Type ML (φ_{ML})	-	-	-	-	-
	Sales×Type L (φ_{L})	-	-	-	-	-0.01 (0.02)
	Model Fit Statistics					
	AIC	3295.91	3174.55	2979.19	2859.74	2853.17
	BIC	3371.04	3287.25	3129.45	3122.69	3124.47
	LogLik	-1629.96	-1560.28	-1453.59	-1366.87	-1361.58
	Adjusted R^2	0.95	0.96	0.97	0.98	0.98

[1] Newey-West robust standardized error ***$p \le 0.01$, **$p \le 0.05$, *$p \le 0.10$.

Table C.3: Model FL. Effect of $Time$ on CCC

		Model *FL3*	Model *FL4*	Model *FL5*
	Dependent Variables	***CCC***	***CCC***	***CCC***
Independent Variables	AMZN: *Time* (ψ^F_{AMZN})	0.26 (0.14)	-0.23 (0.13)	0.04 (0.14)
	TGT: *Time* (ψ^F_{TGT})	-1.24*** (0.15)	-0.92*** (0.16)	-1.00*** (0.16)
	COST: Time (ψ^F_{COST})	-0.12 (0.18)	0.19 (0.26)	0.28 (0.26)
	CVS: *Time* (ψ^F_{CVS})	0.24 (0.29)	0.85** (0.26)	0.91*** (0.26)
	DKS: *Time* (ψ^F_{DKS})	0.08 (0.18)	-0.01 (0.27)	-0.01 (0.28)
	JCP: *Time* (ψ^F_{JCP})	0.11 (0.16)	0.69*** (0.16)	0.69*** (0.17)
	RAD: *Time* (ψ^F_{RAD})	-0.51*** (0.15)	-0.02 (0.14)	0.03 (0.14)
	SHLD: *Time* (ψ^F_{SHLD})	-0.28 (0.19)	0.17 (0.22)	0.17 (0.22)
	WBA: *Time* (ψ^F_{WBA})	-0.46* (0.19)	0.06 (0.18)	0.07 (0.18)
	WMT: *Time* (ψ^F_{WMT})	-0.28 (0.17)	0.23 (0.21)	0.30 (0.22)
	Model Fit Statistics			
	AIC	2979.195	2859.742	2853.175
	BIC	3129.452	3122.691	3124.471
	LogLik	-1453.598	-1366.871	-1361.587
	Adjusted R^2	0.970	0.980	0.980

§ Newey-West robust standardized error ***$p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$.

Table C.4: List of sample quotes (for the first half of 2019)

Company	Date	Designation	Quote	Reference
Novartis AG	May 23, 2019	CEO	"…within our industry, we are bottom quartile in cash conversion cycle…"	(May 23, 2019 Thursday)Meet Novartis AG Management Investor Event CEO Introduction (Day 2) - Final. *FD (Fair Disclosure) Wire.*
Extreme Networks Inc	February 13, 2019	CFO	"… and you know some of our competitors, HP for example, are at a much lower cash conversion cycle. Part of the reason that you see this high number is the introduction of vendor-managed inventory…"	(February 13, 2019 Wednesday). Extreme Networks Inc Corporate Analyst Meeting - Final. *FD (Fair Disclosure) Wire.*
HP Inc	February 28, 2019	President, CEO & Director	"… when we look at the other factors in the business, we think about cash conversion cycles. At the Securities Analyst Meeting, we said that, that would be minus 32 days. In quarter 1, it was negative 35…"	(February 28, 2019 Thursday). HP Inc at Morgan Stanley Technology, Media & Telecom Conference - Final. *FD (Fair Disclosure) Wire.*

Newell Brands Inc.	February 15, 2019	Executive VP & CFO	"... When we look at the cash conversion cycle, our – and benchmark versus our competitors, our days sales outstanding are relatively high, our days of inventory are relatively high and our days payable are relatively low. And so we are putting – and have put, but are putting a aggressive push on each of those areas. And we think that there is opportunity to go after each of them..."	(February 15, 2019 Friday). Q4 2018 Newell Brands Inc Earnings Call - *FD (Fair Disclosure) Wire.*
McCormick & Company Inc.	January 24, 2019	Chairman, President & CEO	"...For the fiscal year, our cash conversion cycle was significantly better than the year-ago period, down 21 days, as we executed against programs to achieve working capital reductions, such as extending payment programs with our suppliers and inventory management programs..."	(January 24, 2019 Thursday). Q4 2018 McCormick & Company Inc Earnings Call - Final. *FD (Fair Disclosure) Wire.*

Table C.5: Summary of Notations

Notation	Description
c	Purchase cost per unit
v	Processing (e.g., manufacturing, distribution, holding) cost per unit per time period
l_c	Credit period granted to consumers (in time periods)
l_s	Credit period negotiated with suppliers (in time periods)
l_p	Processing lead time (in time periods)
r	Selling price per unit
T	Duration of a Fiscal Year
FY	Fiscal Year
FYE	Fiscal Year End
τ, τ'	Fiscal year end (FYE) locations
$D_\tau + T$	Total annual demand between τ and $\tau + T$
b	Average annual demand
t	Time
$f(t)$	Demand at time $t = 0$, $f(t) = \alpha + \beta t + S_t$
α	Constant in the demand function
β	Sales Growth Rate (SGR)
S_t	Seasonality at time t
SI	Seasonality Index
d_a, d_b, d_u	Specific demand levels
AR_t	Accounts receivables at time t
IC_t	Inventory Cost at time t
AP_t	Accounts Payable at time t
DSO_t	Days of Sales Outstanding at time t
DIO_t	Days of Inventory Outstanding at time t
DPO_t	Days of Payables Outstanding at time t

$COGS_t$	Cost of Goods Sold for Fiscal Year beginning at time t
CCC_t	Cash Conversion Cycle at time t

C.2 Method of Firm Classification

Table C.6: Basis of Firm Type Classification

Firm Type Classification	**Classification Method**
High (H)	$DIO < DPO–DSO$
Medium High (MH)	$DPO–DSO < DIO < DPO$
Medium Low (ML)	$DPO < DIO < DPO+DSO$
Low (L)	DPO + $DSO < DIO$

We use the DIO as proxy for l_m, DPO as proxy for l_s and DSO as proxy for l_c. Therefore, to identify a High firm type, we find those that have $DSO + DIO–DPO < 0$ or CCC is negative. For all other firm types the CCC is positive. One could argue that there be a binary type with just two firm types, ones that have a negative CCC and those that have a positive CCC. However, we find that the impact of growth rate on the firms that have a positive CCC when the firm type is L and H, an increase in growth rate increases the CCC. All other firms that have a positive CCC have a negative sensitivity to increase in sales growth. Therefore, a binary classification system will not work. Also, because we are using the current CCC values to study the impact on CCC, some may argue that there will be problems with collinearity. This is, however, not true. We are using the relative values of DIO, DSO and DPO to categorize the firms only. These are not continuous variables. The idea is to see, that given a particular level of cash recovery, what effect does increase in sale has on CCC, and does it improve or worsen the CCC values.

C.2.1 *CCC* Comparison - Hackett Group

Dell's *FYE* is on the Friday nearest January 31. By recalibrating its *FYE* to match its peer HP's *FYE* on October 31, we observe that there is a decrease of 0.5 days (Table C.7, *FYE CCC* highlighted in yellow; adjusted in grey). The reason that Dell's *CCC* does not change significantly is because Dell's sales does not exhibit much seasonality, probably because of its direct sales model and dynamic pricing strategy.

Table C.7: *CCC* Analysis of Dell

Data Date	Fiscal Year	Fiscal Quarter	Ticker Symbol	Sales/Turnover (Net)	DSO	DIO	DPO	CCC
04/30/2008	2008	1	DELL	16077	40	7	74	-27
07/31/2008	2008	2	DELL	16434	42	7	76	-27
10/31/2008	2008	3	DELL	15162	42	8	73	-24
01/31/2009	2008	4	DELL	13428	42	7	72	-23

HP has its *FYE* on October 31. Therefore, if it wanted to undertake a benchmarking exercise of *CCC* it must align its *FYE* to match that, for example, of Dell's *FYE* on January end. Doing so results in a decrease of approximately 16 days (Table C.8).

Table C.8: *CCC* Analysis of HP

Data Date	Fiscal Year	Fiscal Quarter	Ticker Symbol	Sales/Turnover (Net)	DSO	DIO	DPO	CCC
1/31/2008	2008	1	HP Inc	28467	47	37	51	32
4/30/2008	2008	2	HP Inc	28262	49	33	53	29
7/31/2008	2008	3	HP Inc	28032	49	35	56	28
10/31/2008	2008	4	HP Inc	33603	72	33	53	51
1/31/2009	2009	1	HP Inc	28807	49	32	46	35

Similarly, P&G has its *FYE* on June 30 while Unilever has its *FYE* on December 31. P&G's *DPO* on December 2013 was 10 days lower than its *DPO* in June 2013 (Table C.9). Also, if PG benchmarked itself against Unilever's *DPO* in June, they would have targeted an even steeper value of 105 days instead of 75 days. Therefore, unless P&G adjusted for the differences in fiscal year end, it either overestimated its performance or targeted a much more ambitious *CCC* value.

Table C.9: Model AL. Sensitivity of CCC to $Time$

Data Date	Fiscal Year	Fiscal Quarter	Ticker Symbol	Sales/Turnover (Net)	DSO	DIO	DPO	CCC
09/30/2011	2012	1	PG	21530	28	72	66	34
12/31/2011	2012	2	PG	21744	29	68	60	38
03/31/2012	2012	3	PG	20194	27	68	61	35
06/30/2012	2012	4	PG	20212	27	65	74	18
09/30/2012	2013	1	PG	20739	29	72	69	32
12/31/2012	2013	2	PG	22175	30	69	65	34
03/31/2013	2013	3	PG	20598	28	67	66	29
06/30/2013	2013	4	PG	20655	27	63	77	13
09/30/2013	2014	1	PG	20174	29	68	69	28

C.3 Proofs of Propositions 4.1 and 4.2

C.3.1 Proof of Proposition 4.1

We will compute the CCC at time period $\tau+T$. Since $f(t)=\alpha+\beta t$, the demand during the period τ to $\tau+T$ is $D_{\tau+T}=\int_{\tau}^{\tau+T} f(t)\,dt=\left\{T\alpha+\beta\left(-\frac{\tau^2}{2}+\frac{1}{2}(T+\tau)^2\right)\right\}$ and the Cost of Goods Sold is $COGS_{\tau+T}=(c+vl_p)\int_{\tau}^{\tau+T} f(t)\,dt=(c+vl_p)\left\{T\alpha+\beta\left(-\frac{\tau^2}{2}+\frac{1}{2}(T+\tau)^2\right)\right\}$.

DSO at time $\tau+T$. We now use the expressions from Section 3.1 to compute $AR_\tau=\frac{1}{2}rl_c(2\alpha-\beta l_c+2\beta\tau)$ and $AR_{\tau+T}=-\frac{\beta r l_c^2}{2}+rl_c(\alpha+\beta(T+\tau))$. Substituting the values from the expressions above we get, $DSO_{\tau+T}=\frac{T}{rD}\left(\frac{AR_\tau+AR_{\tau+T}}{2}\right)=l_c-\frac{\beta l_c^2}{2\alpha+\beta(T+2\tau)}$. Note from this expression that $DSO_{\tau+T}$ equals l_c adjusted by $\frac{\beta l_c^2}{2\alpha+\beta(T+2\tau)}$ to address changing demand between τ and $\tau+T$.

Difference between DIO and DPO at time $\tau+T$ when $l_p<l_s$.

Expressions from Sections 3.2 and 3.3 give $IC_\tau-AP_\tau=\frac{1}{2}(l_s-l_p)(c+vl_p)\{-2\alpha+\beta(l_s-l_p-2\tau)\}$ and $IC_{\tau+T}-AP_{\tau+T}=\frac{1}{2}(l_s-l_p)(c+vl_p)\{-2\alpha+\beta(l_s-l_p-2(T+\tau))\}$.

Now, $\frac{T}{COGS_{\tau+T}}\left(\frac{IC_\tau-AP_\tau}{2}+\frac{IC_{\tau+T}-AP_{\tau+T}}{2}\right)=\frac{T}{COGS_{\tau+T}}\left(\frac{IC_\tau+IC_{\tau+T}}{2}-\frac{AP_\tau+AP_{\tau+T}}{2}\right)=$

$DIO_{\tau+T} - DPO_{\tau+T}$. Substituting the values, we get $DIO_{\tau+T} - DPO_{\tau+T} = l_p - l_s + \frac{\beta(l_p-l_s)^2}{2\alpha+\beta(T+2\tau)}$. Note that due to a reasoning similar to above, $DIO_{\tau+T} - DPO_{\tau+T}$ is not just $l_p - l_s$ but is also affected by the demand change between τ and $\tau + T$.

Adding $DSO_{\tau+T}$ to the above expression we get $CCC_{\tau+T} = -\frac{(l_c-l_s+l_p)(-2\alpha+\beta(l_c+l_s-l_p-T-2\tau))}{2\alpha+\beta(T+2\tau)}$. To observe the sensitivity to growth rate, we differentiate the expression w.r.t β to get $\frac{\partial CCC_{\tau+T}}{\partial\beta} = -\frac{2\alpha(l_c+l_s-l_p)(l_c-l_s+l_p)}{\{2\alpha+\beta(T+2\tau)\}^2}$.

Difference between DIO and DPO at time $\tau + T$ when $l_p \geq l_s$. Using the results from Section 3.1 when $l_s \leq l_p$ we get $DIO_{\tau+T} - DPO_{\tau+T} = \frac{(l_p-l_s)\left[6c+3v(l_p+l_s)+\frac{2\beta(l_p-l_s)\{3c+v(2l_s+l_p)\}}{2\alpha+\beta(T+2\tau)}\right]}{6(c+vl_p)}$. We add $DSO_{\tau+T}$ to the expression above to get $CCC_{\tau+T} = \frac{6c(l_c-l_s+l_p)\{2\alpha+\beta(l_p-l_c-l_s+T+2\tau)\}+v\left[4l_s^3\beta-3l_s^2\{2\alpha+\beta(2l_p+T+2\tau)\}+l_p\left\{12\alpha l_c+6\alpha l_p-6\beta l_c^2+6\beta l_c(T+2\tau)+\beta l_p(2l_p+3T+6\tau)\right\}\right]}{6(c+vl_p)(2\alpha+\beta(T+2\tau))}$.

Differentiating $CCC_{\tau+T}$ w.r.t. β we get, $\frac{\partial CCC_{\tau+T}}{\partial\beta} = \frac{2\alpha\left[-3c(l_c+l_s-l_p)(l_c-l_s+l_p)+v\left\{2l_s^3-3l_p\left(l_c^2+l_s^2\right)+l_p^3\right\}\right]}{3(c+vl_p)\{2\alpha+\beta(T+2\tau)\}^2}$.

Observe that $3c\,(l_c + l_s - l_p)\,(l_c - l_s + l_p) \geq 0 if l_s \leq l_p \leq l_s + l_c$. Under the same conditions $v\left\{2l_s^3 - 3l_p\left(l_c^2 + l_s^2\right) + l_p^3\right\} \leq 0$ which can be seen by factoring $2l_s^3 - 3l_p\left(l_c^2 + l_s^2\right) + l_p^3$ into $(l_s - l_p)\left(2l_s^2 - l_p^2 - l_sl_p\right) - 3l_c^2l_p \leq 0$. If, however, $l_p > l_s + l_c$ the condition as stipulated in the proposition has to hold for $\frac{\partial CCC_{\tau+T}}{\partial\beta}$ to change direction. When $l_s = l_p$, $\frac{\partial CCC_{\tau+T}}{\partial\beta} = \frac{-2\alpha l_c^2}{\{2\alpha+\beta(T+2\tau)\}^2} < 0$.

C.3.2 Development of Hypothesis 4.2

Suppose Sales is not seasonal, and just has a secular trend. The changing Sales will affect Cost of Goods Sold, Accounts Receivables, Accounts Payables and Inventory. These changes will affect CCC. In addition, CCC may change over time because of implementation of increasingly faster payment systems, industry push to adopt better inventory management methods (and thereby reduce inventory), faster information transmittal and retrieval, and better process management (for, say, incoming quality inspection or invoice approval). We refer to the second effect of $Time$ on CCC as a direct effect, and the former effect as an indirect effect, that is, the effect of Time mediated through Sales. Figure 4.3 in the paper depicts this relationship between Time and CCC graphically. The direct and indirect effects can occur even when there is no seasonality. To determine the impact of $Time$ on CCC, that is, to find $\frac{\partial CCC}{\partial t}$, we denote CCC at time t as CCC_t and express it as a function of

Sales and *Time*. That is, we define $CCC_t = CCC(Sales(t), t)$, and by the rule of total partial differential, we obtain $\frac{dCCC_t}{dt} = \frac{\partial CCC}{\partial t} + \frac{\partial CCC}{\partial Sales} \times \frac{dSales(t)}{dt}$.

The first term on the right-hand side is the direct effect of time, and the second term on the right hand side is the mediated effect of *Time* on *CCC* through Sales. Computing the mediated effect of Time is important to account for the effect of a secular change in *Sales* on *CCC*.

C.3.3 Proof of Proposition 4.2

Let $AR_{\tau'}, AP_{\tau'}$ and $IC_{\tau'}$ denote the receivables, payables and cost of inventory when the FY ends at τ'. Let AR_{τ}, AP_{τ} and IC_{τ} have similar interpretations when FY ends at τ. From Section 3 we have, $IC_{\tau} = c\int_{t=\tau}^{\tau+l_p} f(t)dt + v\int_{t=\tau}^{\tau+l_p}(l_p - (t-\tau))f(t)dt = cl_pd_a + vd_a\int_{t=\tau}^{\tau+l_p}(l_p - (t-\tau))dt$. The reason why the condition holds is because $f(t) = d_a$ when $\tau \leq t < \tau + \max(l_s, l_p)$. When $l_p > l_s$, $AP_{\tau} = c\int_{t=\tau-l_s+l_p}^{\tau+l_p} f(t)dt + v\int_{t=\tau-l_s+l_p}^{\tau+l_p}(l_p + \tau - t)f(t)dt = cl_sd_a + vd_a\int_{t=\tau-l_s+l_p}^{\tau+l_p}(l_p+\tau-t)dt$. The rationale for the above is the same as for the inventory cost. Lastly, $AR_{\tau} = r\int_{t=\tau-l_c}^{\tau} f(t)dt = rd_bl_c$. The comparison of *CCC* for seasonal and constant demands essentially reduces to the comparison of the three elements of *CCC*. We may write the full expression of CCC_{τ} as $CCC_{\tau} = \frac{1}{D_{\tau}}\left[d_bl_c + \frac{cd_a(l_p-l_s)+vd_a\int_{\tau}^{\tau-l_s+l_p}(l_p+\tau-t)dt}{(c+vl_p)}\right]$. Comparing the expression with *CCC* for a constant demand in the ZoC where $CCC_{\tau'} = \frac{1}{D_{\tau'}}\left[d_ul_c + \frac{cd_u(l_p-l_s)+vd_u\int_{\tau'}^{\tau'-l_s+l_p}(l_p+\tau'-t)dt}{(c+vl_p)}\right]$. Note that $D_{\tau} = D_{\tau'}$ and $\int_{\tau}^{\tau-l_s+l_p}(l_p+\tau-t)\,dt = \int_{\tau'}^{\tau'-l_s+l_p}(l_p+\tau'-t)\,dt. When d_a < d_u < d_b, AR_{\tau'} < AR_{\tau}$.

CCC$_{\tau'} > CCC_{\tau}$ if $d_ul_c + \frac{cd_u(l_p-l_s)+vd_u\int_{\tau}^{\tau-l_s+l_p}(l_p+\tau-t)dt}{(c+vl_p)} > d_bl_c + \frac{cd_a(l_p-l_s)+vd_a\int_{\tau}^{\tau-l_s+l_p}(l_p+\tau-t)dt}{(c+vl_p)} \Rightarrow \frac{c(d_u-d_a)(l_p-l_s)+v(d_u-d_a)\int_{\tau}^{\tau-l_s+l_p}(l_p+\tau-t)dt}{(c+vl_p)} > (d_b - d_u)\,l_c \Rightarrow \frac{d_u-d_a}{d_b-d_u} > \frac{(c+vl_p)l_c}{c(l_p-l_s)+v\int_{\tau}^{\tau-l_s+l_p}(l_p+\tau-t)dt}{}_{\tau'} > CCC_{\tau}$.

However, if $l_p < l_s$, then $AP_{\tau} = cl_sd_a + vd_a\int_{\tau}^{\tau+l_p}(l_p+\tau-t)dt + vd_al_p(l_s-l_p)$. Substituting the values of AR_{τ} and IC_{τ} we get $CCC_{\tau} = \frac{1}{D_{\tau}}[d_bl_c - (l_s-l_p)\,d_a]$. Comparing the expression with $CCC_{\tau'} = \frac{1}{D_{\tau'}}[d_ul_c - (l_s-l_p)\,d_u]$, $CCC_{\tau} > CCC_{\tau'}$ if $d_bl_c - (l_s-l_p)\,d_a > d_ul_c - (l_s-l_p)\,d_u \Rightarrow (d_b-d_u)\,l_c > (l_s-l_p)(d_a-d_u) \Rightarrow \frac{d_a-d_u}{d_b-d_u} < \frac{l_c}{l_s-l_p}$. When $min\,(d_b, d_a) > d_u or max\,(d_b, d_a) < d_u$, $CCC_{\tau} > CCC_{\tau'}$ if $\frac{d_a-d_u}{d_b-d_u} < \frac{l_c}{l_s-l_p}$. Furthermore, we conclude that $CCC_{\tau} > CCC_{\tau'}$ when $d_a < d_u < d_b$ and $CCC_{\tau} < CCC_{\tau'}$ when $d_b < d_u < d_a$.

C.4 Demand Patterns

The explicit form of demand with only seasonality is given below. Recall in this case $f(t) = \alpha + S_t$. For tractability, we assume demand at time period t where $t_0 t < t_1$ and $t_6 t t_7$ equals d, and $\delta_u 1 = \delta_u 2$. This leads to a necessary condition between the rate of positive change in demand and the rate of negative change in demand; specifically, we have $\delta_d = ((t_2 - t_1) + (t_6 - t_5))/((t_4 - t_3))\delta_u$.

$$f(t) = \begin{cases} b & \text{when } t_0 \le t < t_1 \\ b + \delta_{u1}(t - t_1) & \text{when } t_1 \le t < t_2 \\ b + \delta_{u1}(t_2 - t_1) & \text{when } t_2 \le t < t_3 \\ b + \delta_{u1}(t_2 - t_1) - \delta_d(t - t_3) & \text{when } t_3 \le t < t_4 \\ b + \delta_{u1}(t_2 - t_1) - \delta_d(t_4 - t_3) & \text{when } t_4 \le t < t_5 \\ b + \delta_{u1}(t_2 - t_1) - \delta_d(t_4 - t_3) + \delta_{u2}(t - t_5) & \text{when } t_5 \le t < t_6 \\ b + \delta_{u1}(t_2 - t_1) - \delta_d(t_4 - t_3) + \delta_{u2}(t_6 - t_5) & \text{when } t_6 \le t < t_7 \end{cases}$$

Figure C.1 has twelve data points corresponding to end-of-month demand. For illustration, we compare the demand patterns of two firms which have the same total annual demands but different seasonality (0.11 and 0.42 respectively).

Figure C.1: Demand with seasonality indices of 0.11 and 0.42

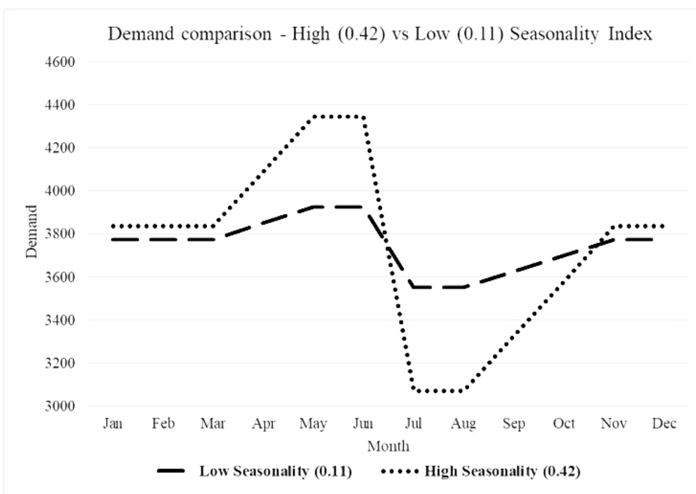


Table C.10: 12 month Demand for seasonality indices of 0.11 and 0.42

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Seasonality Index
3775	3775	3775	3850	3925	3925	3550	3550	3625	3700	3775	3775	0.11
3835	3835	3835	4090	4345	4345	3070	3070	3325	3580	3835	3835	0.42

C.5 Variance-Covariance Table for Model AL

In Model AL, the means of the effect of calendar quarter are denoted by the vector μ_η corresponding to Quarters 2, 3, and 4. The parameter μ_θ denotes the mean for the random intercept for firms, and μ_γ denotes the mean random slopes of CCC sensitivity to Sales, and μ_β is the mean trend for firms. We drop the firm specific index i for conciseness. The variance-covariance matrix consists of random variables partitioned into $\eta = \begin{bmatrix} Q_2 & Q_3 & Q_4 \end{bmatrix}'$ and $\boldsymbol{\Omega} = \begin{bmatrix} \theta & \gamma & \beta \end{bmatrix}'$. Each of the covariance matrices Σ_η, $\Sigma_{\eta\boldsymbol{\Omega}}$ and $\Sigma_{\boldsymbol{\Omega}}$ are square matrices of size three. The distribution of the random parameters is denoted below.

$$\begin{bmatrix} \eta \\ \theta \\ \gamma \\ \beta \end{bmatrix} N \left(\begin{bmatrix} \mu_\eta \\ \mu_\theta \\ \mu_\gamma \\ \mu_\beta \end{bmatrix}, \begin{bmatrix} \Sigma_\eta & \Sigma_{\eta\boldsymbol{\Omega}} \\ \Sigma'_{\eta\boldsymbol{\Omega}} & \Sigma_{\boldsymbol{\Omega}} \end{bmatrix} \right)$$

where the variance-covariance matrix details are as follows:

$$\Sigma_\eta = \begin{bmatrix} \sigma^2_{\eta_2} & 0 & 0 \\ 0 & \sigma^2_{\eta_3} & 0 \\ 0 & 0 & \sigma^2_{\eta_4} \end{bmatrix}, \Sigma_{\eta\boldsymbol{\Omega}} = \begin{bmatrix} \sigma_{\eta_2\theta} & \sigma_{\eta_2\gamma} & \sigma_{\eta_2\beta} \\ \sigma_{\eta_3\theta} & \sigma_{\eta_3\gamma} & \sigma_{\eta_3\beta} \\ \sigma_{\eta_4\theta} & \sigma_{\eta_4\gamma} & \sigma_{\eta_4\beta} \end{bmatrix} \text{ and } \Sigma_{\boldsymbol{\Omega}} = \begin{bmatrix} \sigma^2_\theta & \sigma_{\theta\gamma} & \sigma_{\theta\beta} \\ \sigma_{\gamma\theta} & \sigma^2_\gamma & \sigma_{\gamma\beta} \\ \sigma_{\beta\theta} & \sigma_{\beta\gamma} & \sigma^2_\beta \end{bmatrix}$$

We use η_k to denote η_{Q_k} for conciseness and ease of readability.

C.6 Computational Tables

Table C.11: Summary statistics of industries with average *CCC* and *Sales* by *FYE*

SIC Code	**Description**	***FYE***	**Count**	**Average (Days)**	**Average Sales by Quarter (Mn of $s)**
3663	Radio and Television Broadcasting and Communications Equipment	February	1	57.60	50.72
		March	1	98.65	252.47
		July	1	135.82	119.98
		September	1	-35.01	32562.00
		December	17	123.43	1349.35
5311	Department Stores	January	5	65.81	5206.81
		August	1	3.51	23658.43
5331	Variety Stores	January	6	44.65	22612.55
		August	1	7.31	484.75
		December	1	0.59	6423.27
5912	Drug Stores and Proprietary Stores	February	1	50.00	6190.55
		March	1	38.44	56.01
		June	1	34.42	30.34
		August	1	30.57	19629.88
		December	3	21.52	15227.11
5940	Sporting Goods Stores and Bicycle Shops	January	2	78.64	805.55
		December	2	71.72	1694.06
5961	Catalog and Mail-Order Houses	January	2	59.36	599.14
		June	1	25.52	218.24
		September	1	31.56	82.29
		December	8	20.12	2543.24

Table C.12: List of firms used in this study with Ticker Symbols

Serial No.	COMPANY NAME	TICKER SYMBOL
1	1-800-FLOWERS.COM	FLWS
2	ACORN INTERNATIONAL INC -ADR	ATV
3	AMAZON.COM INC	AMZN
4	APPLE INC	AAPL
5	ARRIS INTERNATIONAL PLC	ARRS
6	BIG 5 SPORTING GOODS CORP	BGFV
7	BIG LOTS INC	BIG
8	BK TECHNOLOGIES	BKTI
9	BLONDER TONGUE LABS INC	BDR
10	CALAMP CORP	CAMP
11	CERAGON NETWORKS LTD	CRNT
12	CHINA TECHFAITH WIRELESS-ADR	CNTF
13	COMTECH TELECOMMUN	CMTL
14	COSTCO WHOLESALE CORP	COST
15	CVS HEALTH CORP	CVS
16	DICKS SPORTING GOODS INC	DKS
17	DILLARDS INC -CL A	DDS
18	DOLLAR GENERAL CORP	DG
19	DOLLAR TREE INC	DLTR
20	DOUGHERTYS PHARMACY INC	MYDP
21	DSP GROUP INC	DSPG
22	ELECTRONIC SYSTEM TECH INC	ELST
23	EVINE LIVE INC	EVLV
24	EXPRESS SCRIPTS HOLDING CO	ESRX
25	FREDS INC	FRED

26	GILAT SATELLITE NETWORKS LTD	GILT
27	HARMONIC INC	HLIT
28	HIBBETT SPORTS INC	HIBB
29	KOHL'S CORP	KSS
30	LIQUIDITY SERVICES INC	LQDT
31	MACY'S INC	M
32	MOTOROLA SOLUTIONS INC	MSI
33	NOKIA CORP	NOK
34	NUTRISYSTEM INC	NTRI
35	OFFICE DEPOT INC	ODP
36	OVERSTOCK.COM INC	OSTK
37	PARKERVISION INC	PRKR
38	PC CONNECTION INC	CNXN
39	PCM INC	PCMI
40	PCTEL INC	PCTI
41	PENNEY (J C) CO	JCP
42	PETMED EXPRESS INC	PETS
43	PRICESMART INC	PSMT
44	QURATE RETAIL INC	QRTEA
45	RITE AID CORP	RAD
46	SEARS HOLDINGS CORP	SHLD
47	SOCKET MOBILE INC	SCKT
48	SUNLINK HEALTH SYSTEMS INC	SSY
49	TARGET CORP	TGT
50	TELEFONAKTIEBOLAGET LM ERICS	ERIC
51	US AUTO PARTS NETWORK INC	PRTS
52	UTSTARCOM HOLDINGS CORP	UTSI
53	VIASAT INC	VSAT

54	WAL MART DE MEXICO SA	WMMVY
55	WALGREENS BOOTS ALLIANCE INC	WBA
56	WALMART INC	WMT
57	WILLIAMS-SONOMA INC	WSM
58	WIRELESS TELECOM GROUP INC	WTT

Table C.13: Summary statistics of *CCC* for Retailers

Quarter	Firm	Mean	Std. Dev.	Min	Median	Max
Q4	TGT	34.07	15.11	12.21	40.58	50.05
Q1	TGT	30.13	15.55	10.87	37.46	49.93
Q2	TGT	29.68	16.86	9.14	38	50.79
Q3	TGT	31.94	18.25	8.8	40.43	54.89
Q4	AMZN	-40.42	2.63	-45.99	-40.1	-36.54
Q1	AMZN	-22.79	3.85	-28.6	-24.42	-17.58
Q2	AMZN	-23.97	4.52	-34.2	-24.09	-19.36
Q3	AMZN	-27.43	5.17	-40	-26.72	-21.22
Q4	COST	4.49	1.31	2.04	4.34	5.94
Q1	COST	2.5	0.91	1.43	2.27	3.94
Q2	COST	3.37	0.97	2.16	3.31	5.97
Q3	COST	3.85	0.34	2.97	3.88	4.3
Q4	DKS	60.39	6.27	52.1	61.55	73.38
Q1	DKS	64.51	7.12	53.12	66.31	73.07
Q2	DKS	62.27	5.1	53.23	64.23	68.72
Q3	DKS	75.17	5.83	65.95	75.57	83.57
Q4	JCP	71.51	6.14	63.95	69.38	82.04
Q1	JCP	74.97	8.57	63.83	75.71	89.65

Q2	JCP	74.88	8.65	62.99	75.4	84.77
Q3	JCP	86.55	9.08	74.47	83.99	98.64
Q4	SHLD	69.19	3.62	61.6	69.87	74.2
Q1	SHLD	71.57	4.16	65.03	71.7	79.38
Q2	SHLD	71.58	4.27	64.36	70.75	77.2
Q3	SHLD	79.34	3.6	70.98	80.18	83.65
Q4	WMT	9.82	1.68	7.14	9.7	12.16
Q1	WMT	10.66	1.9	8.21	10.45	13.55
Q2	WMT	9.38	2.06	6.26	9.74	12.54
Q3	WMT	12.79	2.22	8.8	13.56	15.89

Table C.14: Model RC. Parameter estimates for Models $RC1$ and $RC2$

		Model *RC*1	Model *RC*2
	Dependent Variable	***CCC***	***CCC***
Independent Variables	*Intercept* (Δ^R)	-38.76* (13.21)	26.54 (16.28)
	Type MH $\left(\delta^{R}_{MH}\right)$	39.81*** (3.74)	46.13*** (3.97)
	Type ML $\left(\delta^{R}_{ML}\right)$	68.38*** (3.6)	49.67*** (3.92)
	Type L $\left(\delta^{R}_{L}\right)$	127.23*** (3.55)	58.53*** (4.35)
	Time $\left(\mu_{\lambda_j} + \mu_{\lambda_{i(j)}}\right)$	0.08 (0.15)	0.11 (0.11)
	FY2 (Υ_2)	-25.57*** (5.37)	-16.16 (33.66)
	FY3 (Υ_3)	-21.57*** (5.39)	-33.32 (36.48)
	FY6 (Υ_6)	14.42** (5.39)	-42.6 (32.71)
	FY7 (Υ_7)	-2.26 (6.86)	-62.04 (46.23)
	FY8 (Υ_8)	-26.65*** (4.2)	-37.42 (22.62)
	FY9 (Υ_9)	-52.77*** (5.71)	-69.84* (30.32)
	FY12 (Υ_{12})	15.32*** (3.19)	-11.6 (15.81)
	Sales×Type H $\left(\rho^{R}_{H}\right)$	-0.19 (0.17)	-17.36* (9.49)
	Sales×Type MH $\left(\rho^{R}_{MH}\right)$	0.46* (0.21)	-23.26* (9.42)
	Sales×Type ML $\left(\rho^{R}_{ML}\right)$	0.33** (0.12)	-23.21* (9.42)
	Sales×Type L $\left(\rho^{R}_{L}\right)$	-0.55*** (0.06)	-23.33* (9.41)
	Random Effects		
	Group	Variance	Variance
	Industry - Intercept	936.78	540.20
	Industry - Time	0.11	0.00
	Industry: Firm - Intercept	-	723.40
	Firm - Intercept	-	2079.61
	Firm - Sales	-	3470.91
	Industry: Firm - Time	-	0.56
	Residual	1720.01	568.40
	Model Fit Statistics		
	ICC – Industry	0.35	0.14
	ICC – Firm	-	0.53
	ICC – Industry × Firm	-	0.18
	AIC	28627.01	26074.29
	BIC	28745.61	26228.48
	Conditional R^2	0.400	0.118
	Marginal R^2	0.654	0.999

C.7 A Note on the Difference between Cash Conversion Cycle and Working Capital

The Cash Conversion Cycle and the Working Capital is used interchangeably in the Operations Management literature. In this paper, we highlight ways in which these two metrics may differ despite measuring the same objective, liquidity. The Cash Conversion Cycle measures the average cash turnaround time, and therefore is an efficiency metric while Working Capital is a more static measure which measures the ability of a firm to pay its short term debts. We show, using analytical models how the two metrics may move in opposite direction when an underlying factor changes.

C.7.1 Introduction

We investigate the difference in the impact of Sales Growth Rate, fiscal year end (FYE), and *Seasonality* on Working Capital (WC) and Cash Conversion Cycle (CCC). Both WC and CCC are liquidity measures and some of the data elements needed for their computations are the same. While changes in sales growth rate, seasonality and FYE location affect both WC and CCC, the effect is different. The fundamental reason for the different effects is that WC uses snapshot (balance sheet) data for a specific point in time while CCC uses snapshot data for two points in time and flow (income statement) data. For computing CCC, we use the flow measure corresponding to the time period, T between these two snapshots. This time period is not standard and both quarter and years have been used by industry professionals and researchers. When sales and $COGS$ are constant, the chosen time period does not affect the CCC.

To demonstrate that SGR, *Seasonality* and FYE can affect WC and CCC differently, we assume that current assets consists of only accounts receivables and inventory, and current liabilities consists of only accounts payables. Removing entities such as cash, short term securities, and short-term loans, which affect WC but not CCC, makes the comparison between WC and CCC more informative.

We study different scenarios defined by (i) three demand forms and, (ii) two conditions relating l_s and l_p. Recall that l_s is credit period extended by suppliers and l_p is the manufacturing lead time (or stocking period for retailers). Specifically, we consider the following demand forms:

$$\begin{cases} \text{constant demand:} f(t) = D_i \text{ for } \tau - T < t \leq \tau \\ \text{seasonal demand:} f(\tau + T) = f(\tau) \text{ and} \\ \text{linearly increasing demand:} f(t) = \alpha + \beta t \end{cases}$$

Recall that τ is the FYE location. The first demand form helps us identify the merit of comparing CCC across businesses that differ in size, as measured by sales and cost of sales; the second demand form helps us identify the effect of the interaction between FYE and *Seasonality*, while the third demand form shows the interaction of FYE and growth rate. It is also critical to incorporate the two conditions, $l_s > l_p$ and $l_s \leq l_p$ as they determine how shifting the FYE affects the changes in WC and CCC. For the second two demand forms, we focus on the changes in WC and the CCC values, rather than their absolute values. Dechow et al. (2010) and Dopuch et al. (2012) both study the change in WC, and therefore our approach is consistent with the accounting literature.

C.7.2 Effect of changing *FYE* on Working Capital and *CCC* for constant demand.

Suppose two firms, l, and h, have identical unit revenue, r, and unit costs, i.e., c, v, values (with no economies of scale), credit policies (l_s, l_c), and lead time (l_p). Further, suppose that both firms have constant but different levels of demand. Let $CCC_\tau^i$and (WC_τ^i) denote the Cash Conversion Cycle (Working Capital) for firm $i, i = \{l, h\}$ at FYE location τ. The following discussion establishes the relationship between CCC_l and CCC_h, and WC_l and WC_h. We consider two cases:

i. Case (i) looks at CCC, where $CCC_\tau^l = CCC_\tau^h$ for all τ, and
ii. Case (ii) looks at WC. For all τ,
   - $l_s > l_p$. $WC_\tau^l < WC_\tau^h$ if and only if $rl_c - (c + vl_p)(l_s - l_p) > 0$.
   - $l_s \leq l_p$. $WC_\tau^l < WC_\tau^h$ regardless of the parameter values.

Let $f_i(t) = D_i$, $i = \{l, h\}$, $0 < \tau - T \leq \tau$ denote the demand for the two firms with $D_l < D_h$. Since the demand functions are constant, the FYE location τ will not affect either the CCC or the WC values for either firm.

For $i = \{l, h\}$, from Sections 3.1-3.2, $AR_\tau^i = r\int_{t=\tau-l_c}^{\tau} f_i(t)dt = rD_il_c$, and $IC_\tau^i = c\int_{t=\tau}^{\tau+l_p} f_i(t)\,dt + v\int_{t=\tau}^{\tau+l_p}(l_p - (t-\tau))\,f_i(t)\,dt$. When $l_s > l_p$, $AP_\tau^i = c\int_{t=\tau-l_s+l_p}^{\tau+l_p} f_i(t)\,dt + v\left[\int_t^{\tau+l_p}(l_p-(t-\tau))\,f_i(t)dt + l_p\int_{t=\tau+l_p-l_s}^{\tau} f_i(t)\,dt\right]$. Therefore,
$IC_\tau^i - AP_\tau^i = -(c+vl_p)\int_{t=\tau-l_s+l_p}^{\tau} f_i(t)\,dt = -(c+vl_p)\,D_i\,(l_s-l_p)$. When $l_s \leq l_p$, $AP_\tau^i = c\int_{t=\tau-l_s+l_p}^{\tau+l_p} f(t)\,dt + v\int_{t=\tau-l_s+l_p}^{\tau+l_p}(l_p-(t-\tau))\,f(t)\,dt$, so that $IC_\tau^i - AP_\tau^i = c\int_{t=\tau}^{\tau-l_s+l_p} f_i(t)\,dt + v\int_{t=\tau}^{\tau-l_s+l_p}(l_p-(t-\tau))\,f_i(t)\,dt = D_i\left[c\,(l_p-l_s) + v\int_{t=\tau}^{\tau-l_s+l_p}(l_p-(t-\tau))\,dt\right]$.

Case (i): For a constant demand function, the receivables, inventory cost and payables are equal regardless of the FYE location τ. That is, AR_τ^i, IC_τ^i and AP_τ^i equal $AR_{\tau+T}^i$, $IC_{\tau+T}^i$ and $AP_{\tau+T}^i$ respectively. Therefore, the average receivables, inventory cost and payables equal the corresponding values at time τ. The calculations for DSO, DIO and DPO change accordingly in section 3. $DSO_\tau^i = \frac{T\times AR_\tau^i}{rD_\tau^i} = \frac{T\times r\int_{t=\tau-l_c}^{\tau} f_i(t)dt}{r\int_{t=\tau-T}^{\tau} f_i(t)dt} = \frac{T\times rD_il_c}{rD_iT} = l_c$, $DIO_\tau^i = \frac{T\times IC_\tau^i}{(c+vl_p)D_\tau^i}$ and $DPO_\tau^i = \frac{T\times AP_\tau^i}{(c+vl_p)D_\tau^i}$, where $D_\tau^i = D_iT$ is the total demand. Substituting in the expression for CCC we get, $CCC_\tau^i = DSO_\tau^i + DIO_\tau^i - DPO_\tau^i = l_c + \frac{IC_\tau^i - AP_\tau^i}{(c+vl_p)D_i}$. Substituting for $IC_\tau^i - AP_\tau^i$ when $l_s > l_p$, we get $CCC_\tau^i = l_c + l_p - l_s$. Since the CCC is independent of the demand, and the credit policies of both firm types are same, $CCC_\tau^l = CCC_\tau^h$. Substituting for $IC_\tau^i - AP_\tau^i$ when $l_s \leq l_p$, we get $CCC_\tau^i = l_c + \frac{c(l_p-l_s)+v\int_{t=\tau}^{\tau-l_s+l_p}(l_p-(t-\tau))dt}{c+vl_p}$. Since the parameter values are the same for both demand forms, and the expression itself is independent of demand, $CCC_\tau^l = CCC_\tau^h$. As $CCC_\tau^l = CCC_\tau^h$ when $l_s > l_p$ as well as when $l_s \leq l_p$, Case (i) is established.

Case (ii) (a): $l_s > l_p$. From Section 3.3,
$AP_\tau^i = c\int_{t=\tau-l_s+l_p}^{\tau+l_p} f_i(t)\,dt + v\left[\int_t^{\tau+l_p}(l_p-(t-\tau))\,f_i(t)dt + l_p\int_{t=\tau+l_p-l_s}^{\tau} f_i(t)\,dt\right]$. Combining terms, $WC_\tau^i = rD_il_c - c\int_{t=\tau-l_s+l_p}^{\tau} f_i(t)\,dt - vl_p\int_{t=\tau+l_p-l_s}^{\tau} f_i(t)\,dt = rD_il_c - (c+vl_p)\,D_i\,(l_s-l_p)$. Thus, $WC_\tau^l = D_l\left[rl_c - (c+vl_p)(l_s-l_p)\right]$, and $WC_\tau^h = D_h\left[rl_c - (c+vl_p)(l_s-l_p)\right]$. Since $D_l < D_h$, $WC_\tau^l < WC_\tau^h$ if and only if $rl_c - (c+vl_p)(l_s-l_p) > 0$.

Case (ii) (b): $l_s \leq l_p$. From Section 3.3,
$AP_\tau^i = c\int_{t=\tau-l_s+l_p}^{\tau+l_p} f_i(t)\,dt + v\left[\int_{t=\tau+l_p-l_s}^{\tau+l_p}(l_p-(t-\tau))\,f(t)\,dt\right]$. Combining terms, $WC_\tau^i = rD_il_c + cD_i(l_p-l_s) + v\int_{t=\tau}^{\tau+l_p-l_s}(l_p-(t-\tau))\,f_i(t)\,dt = rD_il_c + cD_i(l_p-l_s) + \frac{vD_i\left(l_p^2-l_s^2\right)}{2}$. Since

$l_p \geq l_s WC_\tau^l < WC_\tau^h$ always holds.

Summary for Constant Demand. A general merit of comparing CCC, therefore, is that it is scale free. In the above discussion, the WC needs of the two firms are different; the firm with the higher WC is not necessarily the firm with the higher demand. The WC values are different for the firms even when their efficiencies in converting purchases to cash are the same, as evidenced by equal CCCs. The discussion on Zone of Concern and Proposition 4.2 identifies the role of FYE, seasonality and growth rates that can confound interpretations of longitudinal CCC comparisons.

C.7.2.1 Effect of *FYE* on Working Capital and *CCC* for seasonal demand.

Recall from Sections 3.1-3.3, at time τ, the accounts receivables is $AR_\tau = r\int_{t=\tau-l_c}^{\tau} f(t)\,dt$, the inventory is $\mathrm{IC}_\tau = c\int_{t=\tau}^{\tau+l_p} f(t)\,dt + v\int_{t=\tau}^{\tau+l_p}(l_p-(t-\tau))\,f(t)\,dt$, and the accounts payable is $AP_\tau = c\int_{t=\tau-l_s+l_p}^{\tau+l_p} f(t)\,dt + v\left[\int_{t=\tau+max(l_p-l_s,0)}^{\tau+l_p}(l_p-(t-\tau))\,f(t)\,dt + l_p\int_{t=\tau+min(l_p-l_s,0)}^{\tau} f(t)\,dt\right]$. The working capital at τ is $WC_\tau = AR_\tau + IC_\tau - AP_\tau$.

Scenario 2A. $f(\tau+T) = f(\tau)$ and $l_s > l_p$. Because $l_s > l_p$, the accounts payable is $AP_\tau = c\int_{t=\tau-l_s+l_p}^{\tau+l_p} f(t)\,dt + v\left[\int_{t=\tau}^{\tau+l_p}(l_p-(t-\tau))\,f(t)\,dt + l_p\int_{t=\tau-l_s+l_p}^{\tau} f(t)\,dt\right]$. Substituting the expression for each of the constituents of working capital we get, $WC_\tau = r\int_{t=\tau-l_c}^{\tau} f(t)\,dt - (c+vl_p)\int_{t=\tau-l_s+l_p}^{\tau} f(t)\,dt$. In the paper, we show that the fiscal year end and seasonality interact to either increase the cash conversion or decrease it. To see the impact of a small change in the FYE on WC when the fiscal ending is at time τ, we determine $\frac{\partial WC_\tau}{\partial \tau} = r\{f(\tau) - f(\tau-l_c)\} - (c+vl_p)\{f(\tau) - f(\tau-l_s+l_p)\}$. Define the contribution margin, $\pi \equiv r - (c+vl_p)$ (Dechow et al. 2010). We can now rewrite the above expression as $\frac{\partial WC_\tau}{\partial \tau} = \pi\{f(\tau) - f(\tau-l_s+l_p)\} - r\{f(\tau-l_c) - f(\tau-l_s+l_p)\}$.

A small shift in the FYE increases the working capital if and only of the ratio $\frac{\pi}{r} > \frac{f(\tau-l_c)-f(\tau-l_s+l_p)}{f(\tau)-f(\tau-l_s+l_p)}$. This result also shows the role of the credit policies in affecting the sensitivity of WC to a change in FYE. As an example, suppose two firms have different credit policies (a potential source of heterogeneity among accrual determinants for firms in the same industry, see p. 390, Dopuch et al. (2012)) but are otherwise identical. Let l_s^i, l_p^i, and l_c^i for firm $i = \{1,2\}$ denote the supplier's credit period, the manufacturing lead time and the customer's credit period. If, for firm 1, $f(\tau) > f(\tau-l_{s_1}+l_{p_1}) > f(\tau-l_{c1})$, for all

$\pi > 0$, a positive shift in the FYE reduces working capital. However, for firm 2 suppose that the credit policies are such that both $f(\tau)$ and $f(\tau - l_{c2})$ exceed $f(\tau - l_{s_2} + l_{p_2})$. If $\frac{\pi}{r} < \frac{f(\tau - l_{c_2}) - f(\tau - l_{s2} + l_{p2})}{f(\tau) - f(\tau - l_{s2} + l_{p2})}$ a positive shift in the fiscal year end decreases the working capital.

We now derive conditions under which the change in the CCC value is positive as the FYE undergoes a small shift. In the WC case, the demand at three points in time, along with the value of $\frac{\pi}{r}$, determines how changing the FYE will affect WC. For the CCC case, the total sales over the period T also affects the CCC. Dividing the receivables by the total sales, and the inventory cost and accounts payables by the cost of goods sold gives $CCC_\tau = \frac{\int_{t=\tau-l_c}^{\tau} f(t)dt - \int_{t=\tau-l_s+l_p}^{\tau} f(t)dt}{\int_{t=\tau}^{\tau+T} f(t)dt}$. By taking the partial derivative of CCC_τ with respect to the FYE we get, $\frac{\partial CCC_\tau}{\partial \tau} = \frac{1}{\left\{\int_{t=\tau}^{\tau+T} f(t)dt\right\}^2} \left[f(\tau - l_s + l_p) - f(\tau - l_c)\right]$. By our assumption $f(\tau + T) = f(\tau)$, which makes the differential simpler to analyse. Clearly, if $f(\tau - l_c) > f(\tau - l_s + l_p)$, $\frac{\partial CCC_\tau}{\partial \tau} < 0$. However, if $\frac{\pi}{r} \geq \frac{f(\tau - l_c) - f(\tau - l_s + l_p)}{f(\tau) + f(\tau - l_c) - f(\tau - l_s + l_p)}$, $\frac{\partial WC_\tau}{\partial \tau} \geq 0$. In this situation, we observe that the impact of a shift in the FYE could be different for CCC and WC.

Scenario 2B. $f(\tau + T) = f(\tau)$ and $l_s < l_p$. The accounts payable in this case is $AP_\tau = c\int_{t=\tau-l_s+l_p}^{\tau+l_p} f(t)\,dt + v\int_{t=\tau-l_s+l_p}^{\tau+l_p} (l_p - (t-\tau)) f(t)\,dt$. Using this expression, we get $WC_\tau = r\int_{t=\tau-l_c}^{\tau} f(t)\,dt + c\int_{t=\tau}^{\tau-l_s+l_p} f(t)\,dt + v\int_{t=\tau}^{\tau-l_s+l_p} (l_p - (t-\tau)) f(t)\,dt$. To study the sensitivity of the working capital to a change in FYE, we find the partial derivative of WC_τ with respect to FYE τ and obtain $\frac{\partial WC_\tau}{\partial \tau} = r\{f(\tau) - f(\tau - l_c)\} + c\{f(\tau - l_s + l_p) - f(\tau)\} + v\left\{l_s f(\tau - l_s + l_p) - l_p f(\tau) + \int_{t=\tau}^{\tau-l_s+l_p} f(t)\,dt\right\} = r\{f(\tau) - f(\tau - l_c)\} + (c + vl_s) f(\tau - l_s + l_p) - (c + vl_p) f(\tau) + v\int_{t=\tau}^{\tau-l_s+l_p} f(t)\,dt$. As earlier, setting the contribution margin $\pi = r - (c + vl_p)$, we can rewrite the above expression as:
$\frac{\partial WC_\tau}{\partial \tau} = (c + vl_p)\left[\frac{\pi}{c+vl_p} f(\tau) - \frac{r}{c+vl_p} f(\tau - l_c) + \frac{c+vl_s}{c+vl_p} f(\tau - l_s + l_p) + \frac{v}{c+vl_p}\int_{t=\tau}^{\tau-l_s+l_p} f(t)\,dt\right]$.

To find the expression for the CCC it is convenient to express the WC as: $WC_\tau = r\int_{t=\tau-l_c}^{\tau} f(t)\,dt + (c + vl_p)\int_{t=\tau}^{\tau-l_s+l_p} f(t)\,dt - v\int_{t=\tau}^{\tau-l_s+l_p} (t-\tau) f(t)\,dt$. The expression for CCC is $CCC_\tau = \frac{\int_{t=\tau-l_c}^{\tau} f(t)dt + \int_{t=\tau}^{\tau-l_s+l_p} f(t)dt}{\int_{t=\tau}^{\tau+T} f(t)dt} - \frac{v}{c+vl_p}\frac{\int_{t=\tau}^{\tau-l_s+l_p}(t-\tau)f(t)dt}{\int_{t=\tau}^{\tau+T} f(t)dt} = \frac{\int_{t=\tau-l_c}^{\tau-l_s+l_p} f(t)dt}{\int_{t=\tau}^{\tau+T} f(t)dt} - \frac{v}{c+vl_p}\frac{\int_{t=\tau}^{\tau-l_s+l_p}(t-\tau)f(t)dt}{\int_{t=\tau}^{\tau+T} f(t)dt}$.
To find the sensitivity of CCC to change in FYE, we differentiate the expression above to get $\frac{\partial CCC_\tau}{\partial \tau} = \frac{1}{\left\{\int_{t=\tau}^{\tau+T} f(t)dt\right\}^2}\left[f(\tau - l_s + l_p) - f(\tau - l_c) - \frac{v(l_p - l_s)}{c+vl_p} f(\tau - l_s + l_p) + \frac{v}{c+vl_p}\int_{t=\tau}^{\tau-l_s+l_p} f(t)\,dt\right]$
$= \frac{1}{\left\{\int_{t=\tau}^{\tau+T} f(t)dt\right\}^2}\left[\frac{c+vl_s}{c+vl_p} f(\tau - l_s + l_p) - f(\tau - l_c) + \frac{v}{c+vl_p}\int_{t=\tau}^{\tau-l_s+l_p} f(t)\,dt\right]$. Shifting the FYE reduces CCC if and only if $f(\tau - l_c) > \frac{c+vl_s}{c+vl_p} f(\tau - l_s + l_p) + \frac{v}{c+vl_p}\int_{t=\tau}^{\tau-l_s+l_p} f(t)\,dt$. Compar-

ing the sensitivities of CCC and WC to a change in the FYE shows that when the condition $\frac{c+vl_s}{c+vl_p} f(\tau - l_s + l_p) + \frac{v}{c+vl_p} \int_{t=\tau}^{\tau-l_s+l_p} f(t)\,dt < f(\tau - l_c) < \frac{\pi}{r} f(\tau) + \frac{c+vl_s}{r} f(\tau - l_s + l_p) + \frac{v}{r} \int_{t=\tau}^{\tau-l_s+l_p} f(t)\,dt$ holds, then a small change in the FYE causes the CCC to reduce while WC to increase.

Summary: Impact of Seasonality. The $f(.)$ values in the expressions above depend on the location of τ relative to the *Seasonality.* Therefore, the results for the above scenarios also show that the impact on CCC and WC of a shift in the FYE could be different. Note that we do not assume a specific functional form of demand which makes the analysis fairly robust.

C.7.2.2 Effect of changing FYE on Working Capital and CCC for demand with trend only.

Scenario 3A. $f(t) = \alpha + \beta t$ and $l_p < l_s$. When $l_p < l_s$, from Sections 3.1-3.3, $AR_\tau = \frac{1}{2} r l_c (2\alpha - \beta l_c + 2\beta\tau)$ and $IC_\tau - AP_\tau = \frac{1}{2}(l_s - l_p)(c + vl_p)\{-2\alpha + \beta(l_s - l_p - 2\tau)\}$. This gives $WC_\tau = \frac{1}{2} r l_c (2\alpha - \beta l_c + 2\beta\tau) + \frac{1}{2}(l_s - l_p)(c + vl_p)\{-2\alpha + \beta(l_s - l_p - 2\tau)\}$, so that $\frac{\partial WC_\tau}{\partial \tau} = \beta\{rl_c - (c + vl_p)(l_s - l_p)\} = \beta\{\pi(l_s - l_p) - r(l_c + l_p - l_s)\}$ where $\pi \equiv r - (c + vl_p)$. Therefore, for all $\beta > 0$ if $l_p < l_s \le l_c + l_p - l_s$, a positive shift in the FYE location increases WC otherwise $(l_s > l_c + l_p - l_s)$, a positive shift in FYE location reduces WC. Basically, for firms which have a FYE ahead of a benchmark, due to the higher sales, the payables increase more than the firm can produce (or move from its shelves) and collect from receivables when $l_s > l_c + l_p - l_s$. Therefore, the WC reduces.

From the proof of Proposition 4.1 Appendix C, when $l_p < l_s$, we know that the expression for CCC is $CCC_{\tau+T} = -\frac{(l_c - l_s + l_p)(-2\alpha + \beta(l_c + l_s - l_p - T - 2\tau))}{2\alpha + \beta(T + 2\tau)}$. We can find the sensitivity of CCC to a change in the FYE (τ) by differentiating the above expression w.r.t. τ, $\frac{\partial CCC_{\tau+T}}{\partial \tau} = -\frac{-2\beta\{2\alpha + \beta(T+2\tau)\}(l_c - l_s + l_p) - 2\beta(l_c - l_s + l_p)\{-2\alpha + \beta(l_c + l_s - l_p - T - 2\tau)\}}{\{2\alpha + \beta(T + 2\tau)\}^2}$ which simplifies to $\frac{\partial CCC_{\tau+T}}{\partial \tau} = \frac{2\beta^2\left\{l_c^2 - (l_s - l_p)^2\right\}}{\{2\alpha + \beta(T + 2\tau)\}^2}$. Therefore, $\frac{\partial CCC_{\tau+T}}{\partial \tau} < 0$ if $l_c < l_s - l_p$, otherwise $\frac{\partial CCC_{\tau+T}}{\partial \tau} \ge 0$.

Scenario 3B. $f(t) = \alpha + \beta t$ and $l_p \ge l_s$. When $l_p \ge l_s$, substituting the expressions of receivable, payable and inventory cost from Appendix C and Scenario 2B, we know that $\frac{\partial WC_\tau}{\partial \tau} = r\{f(\tau) - f(\tau - l_c)\} + c\{f(\tau - l_s + l_p) - f(\tau)\} + v\left\{l_s f(\tau - l_s + l_p) - l_p f(\tau) + \int_{t=\tau}^{\tau-l_s+l_p} f(t)\,dt\right\}$. Substituting $f(t) = \alpha + \beta t$, we get, $\frac{\partial WC_\tau}{\partial \tau} = \beta\left[rl_c + (l_p - l_s)\left(c - v\frac{l_p - l_s}{2}\right)\right]$. Therefore, $\frac{\partial WC_\tau}{\partial \tau} < 0 if v > 2\left(r\frac{l_c}{(l_p - l_s)^2} + \frac{c}{l_p - l_s}\right) otherwise \frac{\partial WC_\tau}{\partial \tau} \ge 0$.

The expression for CCC when $l_p \geq l_s$ is $CCC_{\tau+T} = \frac{6c(l_c-l_s+l_p)\{2\alpha+\beta(l_p-l_c-l_s+T+2\tau)\}+v\left[4l_s^3\beta-3l_s^2\{2\alpha+\beta(2l_p+T+2\tau)\}+l_p\left\{12\alpha l_c+6\alpha l_p-6\beta l_c^2+6\beta l_c(T+2\tau)+\beta l_p(2l_p+3T+6\tau)\right\}\right]}{6(c+vl_p)(2\alpha+\beta(T+2\tau))}$

To find the impact of a shift in the FYE location we differentiate the expression with respect to τ. We get, $\frac{\partial CCC_{\tau+T}}{\partial\tau} = -\frac{\beta^2\left[6c\left\{l_c^2-(l_p-l_s)^2\right\}+v\left[4l_s^3-6l_s^2l_p+l_p\left\{-6l_c^2+2l_p^2\right\}\right]\right]}{3(c+vl_p)(2\alpha+\beta(T+2\tau))^2}$. Hence, $\frac{\partial CCC_{\tau+T}}{\partial\tau} < 0$ if $\frac{c}{v} > \frac{6l_p\left(l_s^2+l_c^2\right)-2\left(2l_s^3+l_p^3\right)}{l_c^2-(l_p-l_s)^2}, otherwise \frac{\partial CCC_{\tau+T}}{\partial\tau} \geq 0$. The expression $\frac{6l_p\left(l_s^2+l_c^2\right)-2\left(2l_s^3+l_p^3\right)}{l_c^2-(l_p-l_s)^2}$ is non-monotonic in all the three arguments. Therefore, depending on the procurement cost c, processing cost v and the specific threshold given by the existing credit policies of the firm, shifting the FYE location may either increase or decrease the CCC value. Notice that if $l_s = l_p$, then $\frac{\partial CCC_{\tau+T}}{\partial\tau} < 0$ if $\frac{c}{v} > 6l_p \Rightarrow vl_p < \frac{c}{6}$. What this establishes is firms that have a low processing cost relative to direct procurement cost benefit from a (positive) shift of the FYE location.

Summary: Impact of Trend. Shifting the FYE can either increase or decrease the WC and the CCC depending on a firm's Operating Policy and r, c, and v. The thresholds defining this change are not the same for WC and CCC. Therefore, comparisons and analysis that hold true for longitudinal comparisons of WC may not hold true for CCC.

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