The process of reward-based crowdfunding campaigns: different ways to succeed or fail

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Abstract:

Previous studies on reward-based crowdfunding have shown that a good start is an important predictor of campaigns' outcome: slow start leads to failure; quick start leads to success. We have opposite fates depending on campaign beginning. In this study, we go further drawing a campaigns' process typology based on a sequence analysis. Those ones are defined based on collect speed measured over tenth of campaign's duration. We identify five classes of process. The campaigns belonging to the more dynamic classes succeed more frequently and intensively. However, we still observe occasional success for campaigns belonging to less dynamic classes. For those ones, entrepreneurs' self-pledges, when they are more than two, have a positive impact on campaigns fate.

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One of the most well-established fact about reward-based crowdfunding is that the speed a campaign collect funds at its beginning is important for its future success (Colombo et al., 2015; Bouaiss et Vigneron, 2021). A quick beginning, the fact to reach an important pledged amount comparatively to the goal targeted one over the first days (a higher amount in proportion of the targeted goal than the proportion of time past), allows to generate a spillover effect which lead to more frequent and more important success. This show that the project has found its audience and that it has been certified by opinion leaders in its domain. Crowdfunding campaigns face two big difficulties. The first is related to the density of competitive offers. It is facilitated by the low cost of the online mediation of campaigns. This density generates congestion effects. Potential backers face to many choices. As a result, they have difficulties to even consider campaigns. The second is associated to asymmetric information problems affecting the relationship between backers and project/campaign carriers. Nothing guaranty that in fine those last will make the required efforts to fulfil they promises, or even that they are able to do it. The manifestations of an enthusiasm at the beginning of a campaign is the sign that at least part of these problems have been overcome.

This narrative has some limits. Considering only two types of campaign, the ones starting quickly and them succeed, and the ones starting slowly and them fail, it neglects a huge part of the underlining dynamics that can happen during the campaign's process. This last includes moments of slowing down and/or moments of acceleration which come after the initial impulsion. In order to add to the analysis, we build a typology of the campaigns based on the collecting speed measured over each tenth of their duration. Then, we identify determinants of campaign belonging to the different classes uncovered. Finally, we investigate the link between this belonging and campaigns' outcome. Here, we consider the use by the entrepreneur of a mechanism allowing her to support its own campaign: self pledges[2]. They make the threshold of the targeted goal less stiff. However, they are not allowed on every platform. We investigate their specific effect on campaign success for the different classes of process that we have identified.

The investigations are based on data from the French platform *Ulule*. We focus on campaigns launch in year 2015 and that last at least ten days. This allow us to work on 6025 projects submitted to get funds. The analysis is performed based the longest common sequence (LCS) and treated by hierarchical clustering analysis. Doing it we identify five characteristic

[2] The financial supports that the entrepreneur does to their own campaign.

processes. One of them, named **Speedy**, is what we can ideally expect of a successful campaign. Two others are associated with **U** shaped supports accumulation. They include an initial phase of acceleration, followed by a phase on stagnation or at least low progress, before a final acceleration. The two others process types are related to campaigns that do not really take off. We provide evidences that campaign with the process classified as belonging to the most dynamic categories success more frequently and more intensively. 44% of campaigns receive at least a self-pledge, 19% receive more than one. The specific analysis of this mechanism shows that it has a more positive effect on campaigns which do not belong to the category **Speedy**. However, the impact of self-pledges does not appear to be related to the campaigns' lake of dynamism. There are not able to make up for the short coming of the less well stated ones.

As far as we know, this study is the first to do this kind of typological work on campaigns process. It adds to the developing theoretical papers which try to model the dynamic of support accumulation (Kim et al., 2018; Ellman and Fabri, 2019; Kondor and Zawadowski, 2019; Deb et al., 2019). It also adds to empirical works focusing on campaigns' particular moments as their beginning (Colombo et al., 2015; Bouaiss and Vigneron, 2021) or when the target is close (Kuppuswamy and Bayus, 2017). Giving a structured vision of campaigns' process and of their diversity, the study calls for new works which go further than a binary vision of campaigns outcomes (success/failure). The goal is to get a better understanding of the in-between situations: the at the end of the time line success and the failures near the line. This give managerial perspectives both for the entrepreneurs using crowdfunding to get funds and for the platforms. It opens avenues for finding action levers to limit the negative effects of poorly implemented campaigns by identifying and characterizing them, and then by looking at self-contributions and their effects. We add to the rare works dealing with this mechanism (Crosseto and Regner, 2018; Regner and Crosseto, 2021). We show that they are only useful on a limit number of situations. They can even have a negative impact on the most dynamic campaigns. Others comparable mechanism have to be studied the same way.

The remaining of the paper is organized as follow. In section 1, we detail the literature on *reward-based crowdfunding* campaigns, the determinant of their success and their timing. This allows us to formulate hypothesis about the shape their process can take and its consequences on their outcome. In the section 2, we present the data and the methodology we use to build the typology and to test the consequences of the belonging to the defined categories. In the section 3, we present our results. We discussed them in section 4 before to conclude.

1. Literature and hypothesis

1.1. Theoretical background and previous works

Reward-based crowdfunding allows individuals interested by a project to financially support it and to obtain for that real (goods and/or services) or symbolic (a thank-you note) reward. They do it through payments mediated on the web site of the platform which broadcast the call for funding (Belleflamme et al., 2014). In its most frequent configuration, the "all or nothing" mode, funds are only payed to the entrepreneur at the end of the campaign which the duration is initially fixed, if the total amounts of supports obtained is at least equal to the targeted amount which is also initially fixed. If this condition is mate, the entrepreneur have to carry out the project and to provide the promised rewards. As a result, the *reward-based crowdfunding* is analyzed as a mechanism oscillating between conditional presales, if the rewards are real, and conditional gifts, if they are symbolic (Ryu et al., 2020). The condition here takes the form of a social validation by the crowd of the platform's users materialized by the total amount of supports obtained during the campaign which have to reach at least the targeted amount.

It is presented as financing method adapted for entrepreneurial venture aimed at launching new products (or service) involving an innovative[3] or creative dimension. It held to fulfil the gap, at least partially, left by classical methods: bank credit, trade credit, equity. Bankers, providers and shareholders do not support this type of projects because of the high degree of uncertainty affecting the existence of a demand, potential moral hazard problems and the different related information costs (Cosh et al., 2009). Strausz (2017) shows that the dual mechanism involving contracting with customers before starting the production and returning their payments at the end of the campaign reduces the difficulties and allows for the financing of good projects. Ellman and Hursken (2019a) point out that if it appears efficient to deal with ex ante asymmetric information problems, this is not always the case with ex post ones. Frauds cases, few in numbers, are presented as tolerable on the platforms insofar as the overall surplus generate remains positive. Ellman and Hursken (2019b) extend the reasoning and show that the fact that the campaigns involve limited prefunded production quantities (the rewards) reduces the importance of moral hazard.

[3] In the broad sense of the term, they are not limited to innovations with a strong technological dimension.

The *reward-based crowdfunding*, and then the other type of *crowdfunding* (*lending*, *equity*…), are part of the *continuum* of financing available to compagnies as they develop. This *continuum* modeled, before the emergence of crowdfunding, by Berger and Udell (1998) has been extended by Rossi (2014) to include it. It acts as both a (limited) seed fund and a test market whose results can be observed by third parties. A success will be interpreted as a proof of the existence of a demand for the goods (or services) offered (Fleming et al., 2016). In this way, it partially reduces the uncertainty that deterred ordinary funders (banks, suppliers, business angels, publishers…) from supporting the activity (Ryu et al., 2019). A series of studies provides evidences that entrepreneurs that have succeeded in a crowdfunding campaign find it easier to subsequently obtain the support of venture capital funds (Drover et al., 2017; Mödl, 2017; Sorenson et al., 2016). Vanacker et al. (2019) provide a survey of works focusing on the aftermath of successful campaigns that support this view.

The informational power attributed to crowdfunding relies on the postulated evaluation capacity of the crowd[4]. The online mediation of the calls for funding has drastically reduced the transaction costs associated with funding submitted projects. This allows less sophisticated individuals, non-professionals, to be involved in mass in their evaluation and express their positions through the explicit decision to support them or the implicit decision not to (Agrawal et al., 2014; Ahlers et al., 2015). Thus, for example, future readers can, through pre-purchases, substitute themselves, at least in part, for publishers in the start-up phase of literary projects. This also allows smaller projects to be offered for funding. Several studies show evidence of the effectiveness of crowdsourcing in evaluating projects and campaigns. Mollik and Kouppuswamy (2014) note that, in the video game field, 90% of the teams that succeeded in a campaign are still active two years later, compared to 60% of those that conducted a failed campaign. Mollik and Nanda (2015) show that, regarding projects in the field of theater, the crowd of contributors is as effective as experts in selecting viable projects.

Potential contributors are, in fact, faced with two sources of uncertainty. The classic question about the entrepreneur's ability and willingness to carry out the project and keep its commitments. Mollick (2017)[5] notes that nearly three-quarters of projects funded after a campaign in the "Design and Technology" area on Kickstarter are, as such, problematic.

[4] This is an old concept. It was first discussed by Sir Francis Galton. Since, it has been taken and developed by Surowiecki (2004). It is based on the observation that, on certain evaluation tasks of a measure, the average of the estimates made by a crowd of individuals interviewed independently of each other is a relatively close indicator of the true value. There are, of course, conditions for obtaining such effect.

[5] Over a sample of 381 campaigns.

Backers only end up delivering promised consideration with considerable delay, and in 3.6% of cases, they deliver nothing. The issue here is crucial for platforms that implement policies to avoid such situations, which damage their reputation and turn users away from them. They do this by selecting the campaigns they will host[6]. However, they do not go so far as to guarantee the delivery of the rewards or the reimbursement of contributions in the event of fraud. The second source of uncertainty concerns the campaign's ability to mobilize enough funds to reach the fundraising goal and thus put the entrepreneur in a position to carry out and keep its promises.

The platforms set up instruments and the entrepreneurs establish strategies to overcome the difficulties associated with these uncertainties. The goal is to attract contributions by creating a sufficient climate of confidence. Certain choices in the configuration of campaigns can thus be used by good quality entrepreneurs to signal themselves. They can, for example, do so by preferring the all or nothing (fixed) mode to the keep it all (flexible) mode, when the platform offers both (Chang, 2020; Cumming et al., 2020). They can also set the fundraising goal[7], the target, which conditions the payment of the promised funds, at a high level (Chakraborty and Swinney, 2021; Chemla and Tinn, 2020). Entrepreneurs also use the campaign to dialog with the community of potential buyers of their future production in order to adapt it to their expectation. Backers thus enter into a process of co-designing the project (Wachs and Vedres, 2021; Clauss et al., 2018), which facilitates its targeting (Hervé and Schwienbacher, 2018), information exchanges (Chaney, 2019) and creates an effect of commitment. The individual characteristics of the entrepreneur are also considered by the public to judge the project, which materializes in identified biases such as gender homophily (Greenberg and Mollick, 2017), unfavorable treatment of ethnic minorities (Younkin and Kuppuswamy, 2018), and a preference for geographic proximity[8].

The main success factor identified is associated with early campaign momentum. Herzentein et al. (2011) and Zang and Liu (2012) note trends toward mimetic behavior in crowdfunding (lending) markets. Burtch et al. (2015) emphasize the importance in this context of the visibility of the relationships established between entrepreneurs and current and past backers. Observed patterns can drive informational cascading and observational learning

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[6] They also implement filters to avoid promoting campaigns that would only be dirty money laundering schemes.

[7] In All or nothing mode.

[8] The likelihood of a platform user to support a campaign is greater if the entrepreneur is located nearby (Agrawal et al., 2015). Nevertheless, campaigns that, on average, attract further away backers succeed more frequently (Guo et al., 2018 ; Vigneron, 2022).

(Welch, 1992; Bikhchandi et al., 1992; Parker, 2014). The observed popularity acts as a certification that reassures potential backers and encourages them to get involved. The flow of new supports is then self-sustaining until the campaign succeed. An increasing number of studies highlight the conditions for the setting up of this type of virtuous process. The social capital of the entrepreneur, whether internal (Colombo et al., 2015) or external (Ordanni et al., 2011; Dai et al., 2017; Lagazio and Querci, 2018) to the platform, is presented there as a determining factor (Cai et al., 2021). The same is true of the ability of entrepreneurs to mobilize opinion leaders, whether they are recognized experts (Kim and Viswanathan, 2019) or central individuals within the communities of interest which use the platform (Bouaiss and Vigneron, 2021). In this study, we reexamine these dynamics to specify their forms by going beyond the primary observation that campaigns that manage to mobilize more broadly at their start succeed much more frequently than those that have a less brilliant start.

1.2. The campaigns' process

Early work on the subject (Ordanini et al., 2011; Agrawal et al., 2014) identifies a typical process for successful campaigns based on three successive phases: the friendly funding, when funds mainly come from the entrepreneur relatives and friends [Vigneron, 2022]; the involving of the crowd, when the backers' spectrum expand and when the informational cascade phenomenon as well as network effects engage (Belleflamme et al., 2021); the run to the target, when the main motivation to support the campaign is to allow it to meet the target to be finally successful (Kuppuswamy and Bayus, 2017). Kim et al. (2022) show that the progression of the cumulative number of contributions (the collection speed) is different in the three phases. It is slow in the first phase, faster in the second and very fast in the third. Campaigns that fail are not able to pass the first phase and see their collection speed stays slow till the end. This vision of campaigns' process with two opposite configuration seems to ignore the possibility to see things change for the best or for the worst during its course.

Theoretical models have been elaborated to understand those dynamic. They base their analysis on games of contributions to a public good, here the funded project. Alaei et al. (2021) differentiate potential backers based on whether they value the project highly or poorly. Regardless of this value, if they support the campaign and it fails, they incur an opportunity cost[9]. They chose to support the campaign or not based on the price of the supports and on the

[9] The amount of supports mode could have been used in another way between the time of the support and the end of the campaign.

probability of success of the campaign that they infer at the moment they discover it. The timing of this discovering follows a random process. As a result, the structure and final result of the process differ according to the price of the support and the size of the targeted amount. This give both campaigns doomed from the beginning because they have not convinced the individuals who value the project strongly that those who will follow them will support it, and successful campaigns that manage to convince them soon enough. In this case, the collection dynamic depends on the pace of their arrival. Zhang et al. (2022) take a close frame work. They also consider two types of individuals: the ordinary potential backers, which support the campaign independently from the others choice if they attach to its success enough value, and the followers, which support the campaign at its end if it is close to reach its target (and if there are interest by the funded project). The model is inspired by the diffusion dynamics formalized by Bass (1969). It allows to generate process where supports are distributed (over time) in L [10] when campaigns fail and in U [11] when campaigns succeed.

Hellman and Fabri (2019) propose the same type of model with the difference that potential contributors have *a priori* knowledge of the utility they would get if the campaign is successful and can revise this assessment by incurring a verification cost. They obtain then a correct evaluation of this utility. The a priori utility can either be positive (and correspond to the price asked) or be zero[12] with a given probability. Potential contributors discover the campaign with a uniform probability over its duration. When one of them does, she decides whether to pay the verification cost or not and then whether to support financially or not the campaign. Here, she will act on the basis of the amount of money that remains to be raised to reach the target and the time remaining to do so. Under the hypothesis of a constant verification cost, Hellman and Fabri show that the rate of contributions decreases with the progress of the campaign. We then have a more or less steep L-shaped curve. If the verification cost is low, successes are more frequent. If they are high, failures are more frequent. In both cases, the frequency depends on the beginning of the campaign and therefore on the common a priori value attributed by potential backers. Under the dual assumption of a verification cost structure involving low-cost[13] and high-cost potential backers, and the possibility of choosing their support, they show that the pace of contributions is first decreasing and then increasing. Low-cost potential backers support the campaign as soon as they discover it, while high-cost

[10] A start with an increase in supports accumulation followed by a drop (a slowdown) and then a stagnation.
[11] A start with an increase in supports accumulation followed by a fall (a slowdown) and then a rise.
[12] Individuals support the campaign only if the price is zero, which it is never the case.
[13] For example, the entrepreneur’s relatives.

potential backers postpone their support until success is assured. The contribution curve thus takes the shape of a more or less marked U.

Deb et al. (2019) propose a similar model. They consider two types of potential backers: customers, who chose between the good offered as reward and an alternative, and donators, who are motivated by the success of the campaign. The first ones discover the campaign with a random timing. Then they must decide whether or not they support it. If they do, they take the risk of not obtaining the desired good because of the campaign failure. Their choice depends on what they anticipate for what will happen to the campaign. The second ones discover the campaign at its beginning and can support it whenever they want. Their actions are observed by customers who are nevertheless unaware of their overall financial capacity. A coordination problem then emerges that materializes through different supports dynamics, including the L-Shaped and U-shaped ones. Ryu et al. (2020), in an empirical study carried out on an Asian platform, make observations that are consistent with this model. They use a questionnaire on the backer motivation and note that those with altruistic motives, the donators, intervene both more frequently and for larger amounts at the beginning of the campaign.

We draw from all these models, and the sequences they manage to predict, the basis of our typology. We expect to find three broad categories of sequences, ranging from a constant growth in the number of contributions from the beginning to the end of the campaign, to a concentration of supports at the beginning, followed by a stagnation (or a low growth), to sequences characterized by concentrations at the beginning and end of the campaign. Our first hypothesis is thus as follows:

Hypothesis 1: Typical campaign sequences can be divided into three broad classes

- One with a uniformly increasing trend
- One with a L-shaped patterns (a spike at the beginning followed by stagnation or very slow growth)
- One with a U-shaped patterns (more growth at the beginning and at the end)

We should observe variations within these categories with different slopes on the different sequences that characterize them. This will allow us to obtain a set of alternatives beyond the three main ones. They should be distinguished globally by the dynamism they reflect and, by consequence, lead to different campaign outcome.

Papers on the impact of the beginning of campaigns on their future are consistent with this. They show that those with fastest starts (marked by a proportion of funds raised relative to the goal that is greater than the proportion of campaign time that has elapsed) are also those that succeed most frequently and, when they do, exceed their goal the most (Colombo et al., 2015; Bouaiss and Vigneron, 2021). This early stage dynamic is interpreted as a mark that these campaigns were able to mobilize their entrepreneur's social capital early on so as to enter as soon as possible into the phase in which network effects and informational cascades come into play and the phase characterized by the goal race (Odanini et al., 2011; Agrawal et al., 2015; Kuppuswamy and Bayus, 2017). The mechanisms at work include reciprocity, reputation, and certification effects. Colombo et al. (2015) note that campaigns whose entrepreneurs have previously supported other campaigns receive more support at the beginning of their own one. Butticè et al. (2017) note that campaigns run by individuals who have previously run other campaigns succeed more frequently. Bouaiss and Vigneron (2021) note that attracting, at the beginning of a campaign, backers with tastes representative of the ones of a large community makes campaigns more successful.

A good start for a campaign should result in sequences in which a dynamic is imprinted: either with high levels of supports all along, with a constant growth of supports levels over time, or with a stagnating following the initial spike leading or not to a final spike (we can also image intermediary spikes). A bad start could either be prolonged in a dynamic of low level of contributions, or lead over time to a recovery of the situation with campaigns that take off late. In any case, the evolution of the number of contributions over each sub-period, which we characterize through our typical progressions, is a clear predictor of the future of campaigns. Campaigns with a positive dynamic should lead to more frequent and larger successes. Our second hypothesis is established on this basis.

Hypothesis 2: Campaigns with the most dynamic sequences are more frequently successful.

The campaigns that are described as more dynamic are those whose progressions reflect a series of increasing levels of contribution, in other words, those where stagnation is rare or non-existent. The least dynamic campaigns are those that experience the most stagnation.

On some platforms, entrepreneurs are allowed[14] to contribute to their own campaign. This is the case for the platform we are investigating (*Ulule*). This practice makes the barrier linked to the collection target less difficult to overcome. Some entrepreneurs can use the induced flexibility to catch up with a campaign that has not gone well and thus gain access to the funds pledged by the other backers. However, this is not without costs since the platform also takes its commission on these sums. Few works have focused in this practice[15]. Crosseto and Regner (2018) note that there are no significant differences between campaigns that received self-pledge and those that did not regarding the propensity of their entrepreneur to fulfill their rewards commitments. Regner and Crosseto (2021) do not find clear markers that self-pledges can generate a ripple effect that can put a not engaged campaign back on track. Nevertheless, even if they do not seem to produce information on the quality of the projects, or even contribute to the process of informational cascades, they still have a mechanical effect associated with the amounts they bring to the campaign. Therefore, we formalize Hypothesis 3, according to which self-pledges have a positive impact on the success of campaigns in general and especially on those facing unfavorable supports dynamics.

Hypothesis 3: the impact of self-pledges on campaign success is greatest for those with the least favorable sequences dynamic.

The campaigns that are not going well, those that are less dynamic, could be saved (at least some of them) when they are close to the limit, or even, in the worst case, be cancelled by the entrepreneurs, by one or more self-pledges. This mechanism makes the targeted amount that triggers the payment, apparently fixed since it is determined before the campaign is launched, flexible. Self-pledges can be mobilized strategically according to the cost/benefit ratio established as a result of the dynamics observed.

2. Data and methodology

2.1. The sample

The analyses are based on data from the reward-based crowdfunding platform *Ulule*[16]. We work on campaigns launched during 2015, limiting ourselves to those that received at least

[14] The US reward-based crowdfunding platform *Kickstarter* and the French *Kiss Kiss Bank Bank*, like many other platforms, prohibit self-contributions.

[15] The ones we were able to identify are preformed on the German platform *Startnext*.

[16] Whose address is https://fr.ulule.com. It is one of the most important crowdfunding platforms in France, with its direct competitor *Kiss Kiss Bank Bank*. It works on a model close to that of the American Kickstarter.

one support and whose duration is greater than or equal to 10 days. In the end, the sample includes 6,025 campaigns. Table 1 provides a brief description.

Table 1: sample description

The table present for the entire sample and for the sub-sample of campaigns that have failed and the ones that have succeed a series of statistics related to their characteristics. For qualitative ones, it gives the frequency (in number) and the relative frequency (in percent) of the designated modality. For the quantitative ones, it gives the mean followed by the median (after /) and, below under brackets, the standard deviation. The p-values of the performed tests are reported in the last column. They are related to Chi2 test of independency for qualitative variables and Wilcoxon-Mann-Withney test of difference in median for the quantitative ones.

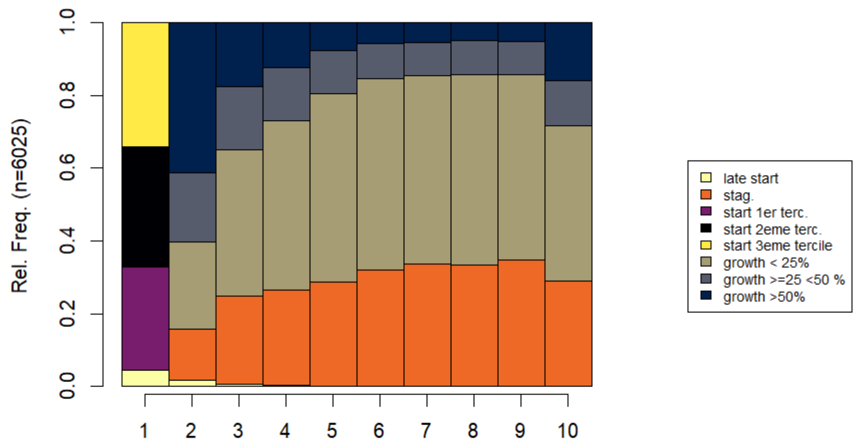
	Total	*Failure*	*Success*	*p-value*
Campaigns	6,025	1,888	4,137	
		31%	69%	
Final amount collected /	96/103	17/12	132/109	>0.001
target (in %)	(134)	(17)	(148)	
Project characteristics				
Entrepreneur type				0.035
Association	2,267	695	1,572	
		31%	69%	
Firm	582	210	372	
		36%	64%	
Individual	3,086	958	2,128	
		31%	69%	
Missing	90	25	65	
Domain				>0.001
Art	2,359	609	1,750	
		26%	74%	
Entrepreneurship	1,345	506	839	
		38%	62%	
Solidarity	1,800	565	1,235	
		31%	69%	
Other	521	208	313	
		40%	60%	
Campaign characteristics				
Target	4,211/2,160	5,945/3,000	3 419/2,000	>0.001
	(29,115)	(49,936)	(9,746)	
Duration	41.58/40	43.20/41	40.84/40	>0.001
	(16.47)	(17.22)	(16.07)	
Communications	5.45/3	2.40/1	6.84/5	>0.001
	(7.62)	(5.45)	(8.05)	

The success rate of the campaigns is 69%. Those that succeed collect, on average, 132% of their objective while those that fail collect, on average, only 17%. The majority of the campaigns in the sample are carried out by individuals (51.22%) and most often (39.5%) aim to finance artistic projects (video, music, performing arts or graphic arts). Campaigns in this field have a higher probability of success (74.18%) than those in other fields. The average size of the campaigns is 4,211 Euros (with a median of 2,160 Euros). They last around 42 days and are punctuated on average by 5.4 (6.8 for those that succeed) announcements by the entrepreneur on the platform. Successful campaigns have on average lower objectives than unsuccessful ones, last less time and are subject to more communications.

2.2. Campaigns' process typology

To establish our typology, we rely on two elements: the fraction of the target collected at the beginning of the campaign and the evolution of the amounts collected throughout the campaign. The whole is measured on the basis of a regular time interval corresponding to one tenth of the duration of the fundraising. For each of these tenths, we calculate the total amount of the support obtained as well as its accumulation. The first interval is used to characterize the beginning of the campaign. We consider here four possibilities: the case where the campaigns have not received any support (we will then speak of a late start[17]), and for those that have received some, we divide the sample on the basis of the terciles of the position reached with respect to the target. We thus have a slow-start group, which at the end of this first period has collected less than 6.52% of the target, a medium-start group, which at the end of this same period has collected between 6.52% and 20%, and a fast-start group, which has collected more than 20%. For the following intervals, we consider five possibilities: the case where the campaign has still not received any supports (still a late start), the case where the progression of the amounts collected is zero, which is qualified as stagnation, the case where the progression is less than 25%, a weak to average progression, the case where the progression is between 25% and 50%, a strong progression, and finally, the case where the progression is greater than 50%, a very strong progression. Figure 1 shows the distribution of the different states identified on each interval.

Figure 1: Chronogram of states of each tenth of campaign duration



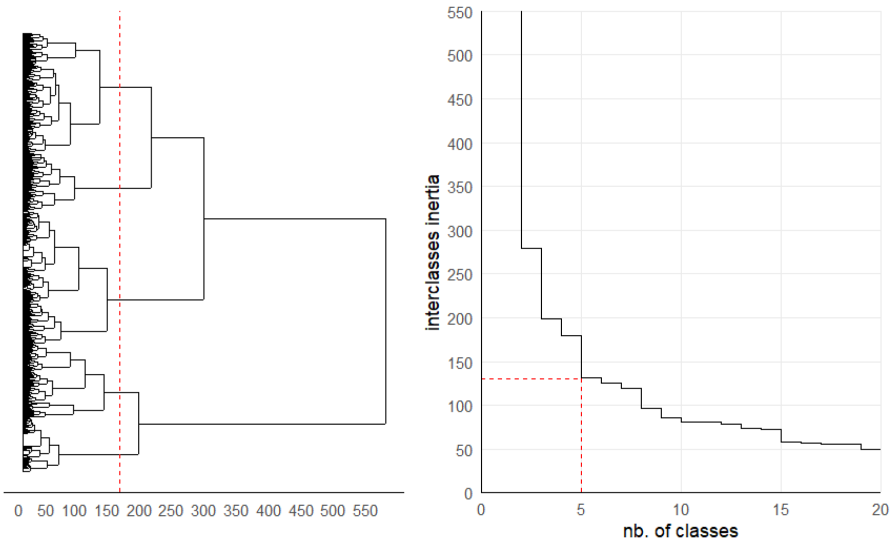
On the first interval, we note that the vast majority of the campaigns have received supports, only 4.5% have not received anything. 34% had a fast start. 33% had a medium-speed start and 28.5% a slow start. Over the following intervals, we see a gradual disappearance of

[17] It is termed "late" in that they will eventually receive it. The sample includes only campaigns that have received at least one support.

the campaigns that received nothing (in very pale yellow on the graph). The most frequent type of progression corresponds to a low to average evolution of the collected sums (in dark grey) followed by stagnation (in orange). The most rapid types of progression (in dark blue and blue grey) are less frequent overall. They are nevertheless more frequent at the beginning of the campaign and at the very end (in the last period).

Behind these global trends, there are 4,158 different sequences (sequences of states) that we need to group according to their degree of similarity in order to create relevant categories. To do this, we start by establishing a distance matrix between the different observed sequences on the basis of the longest common sequence (LCS)[18]. This matrix is used to initialize a hierarchical bottom-up classification algorithm using the Ward method (based on squared distances). Figure 2 shows the resulting dendrogram as well as the inter-group inertia curve corresponding to the different levels of classification proposed.

Figure 2. Dendrogram and inter-group inertia curves

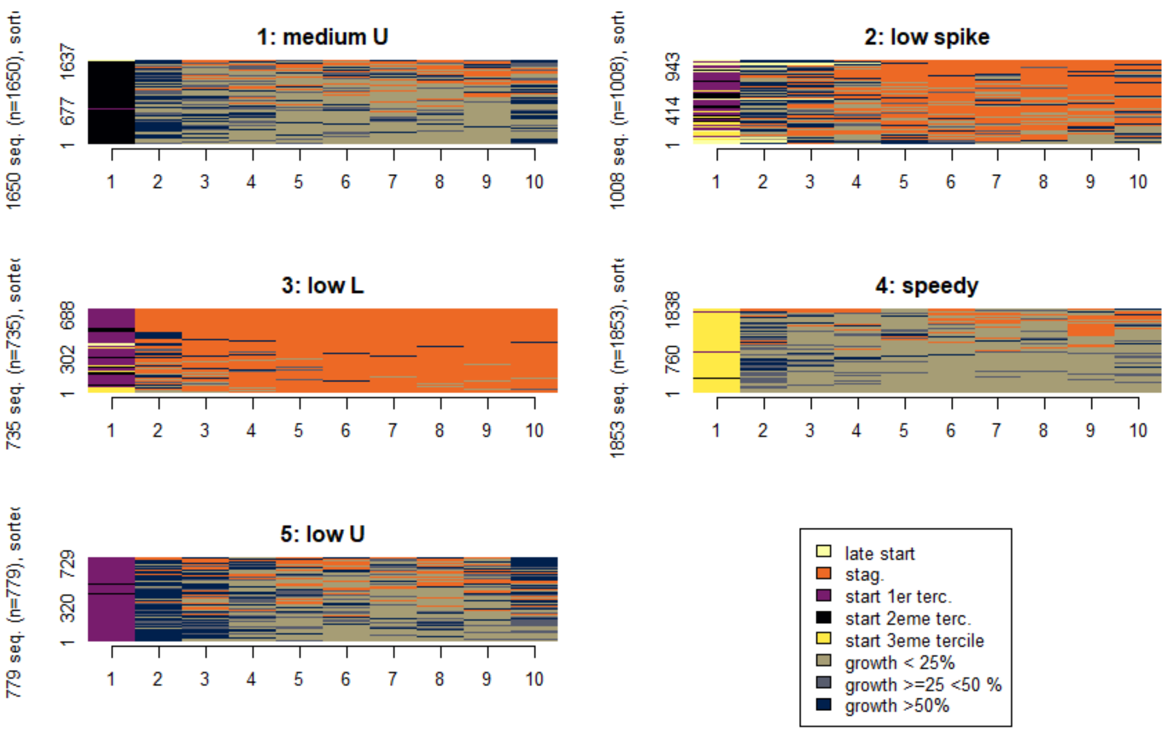


Based on this decomposition, we choose to retain five classes. This corresponds to the last big jump in inertia of the candidate classifications. It is a compromise between the detail of the information and the ease with which the typology can be used. Class 1 comprises 27.4% of the sample (1,650 campaigns), class 2 16.7% (1,008), class 3 12.2% (735), class 4 30.8% (1,853), and class 5 12.9% (779).

[18] The longest sequence of the same states over different intervals.

It remains to characterize the sequences that the typology group together in order to give it a meaning. To do this, we examine the index plots[19] of the campaigns attached to the different classes. They are shown in Figure 3[20]. The campaigns belonging to the **class 1** have an average start, followed by rapid progress in the immediately following intervals (2-3), then a weak to average progression over the rest of the campaign, with the exception of the very end where accelerations are frequent. We will qualify them as **medium U** campaigns. Those belonging to the **class 2** start very slowly, can experience a short acceleration and then stagnate. We will qualify them as **low spike** campaigns. Those belonging to the **class 3** start slowly and stagnate until the end. We will qualify them as **low L** campaigns. Those belonging to the **class 4** start very strong, accelerate at the beginning and then keep a medium growth until the end. We will qualify it as **speedy**. Those belonging to the **class 5** start slowly, accelerate strongly at the beginning, grow slowly in the middle of the campaign and then accelerate again at the end. We will call them **low U** campaigns.

Figure 3. Index plot



[19] The state sequences here on our ten intervals.

[20] A breakdown of possible classifications (including up to seven classes) with an overview of the index plot of the candidate classes is proposed in Appendix 1.

We thus have a class with sequences involving a constant growth of contributions (the **speedy** one), two others marking a U-shaped progression, thus with stronger progressions at the beginning and at the end, which are differentiated by the initial dynamics (**low U** and **medium U**) and two courses without any real progression beyond the start (**low L** and **low spike**). This is in line with hypothesis 1.

2.3. Variables and models

To analysis of these sequences, we mobilize three main categories of variables: those that allow us to characterize the configuration of the campaign (the target in Euros, the duration in days and the number of messages published by the entrepreneur on the platform), those that describe the nature of the project (the type of the entrepreneur and the domain of the funded activity) and those that concern the use of self-pledges. The variables in the first category are numerical and have asymmetric distributions[21]. In order to linearize the relationships, we add one[22] to them and log the result when they are used in our different models. The second ones are categorical. They are recoded as series of binary variables. The presence of self-pledges is considered through a single binary variable indicating whether or not the campaign has received self-pledges (at least two[23]).

The models used are of three types. The first type focuses on characterizing the classes of sequences identified on the basis of the configuration of the campaigns and the projects they seek to finance. These are *multinomial Logit* models whose basic specification is given in equation *(1)*. We estimate them using neural networks.

$$Sequence_i = \alpha + \beta_1 Camp.charac._i + \beta_2 Proj.charac._i + \varepsilon_i \tag{1}$$

The latter are used to examine the determinants of campaign success. Their general specification is given in equation *(2)*. Success is explained by the class of sequences the campaign belongs, the use of self-pledgs, the interaction between class of sequence and the use of self-pledges, as well as by a series of control variables associated with the campaign characteristics (target, duration, communication) and those of the projects they aim to finance (type of entrepreneur, project's domain). We consider here two measures of success that are alternately used as explained variables in our regressions. The first is the probability that a

[21] This is less clear for the duration of the campaigns.
[22] To avoid cases of log of 0, which happens for communications.
[23] We justify this choice later, when we analyze the models used to test our hypotheses.

campaign will raise enough money to reach its target. It takes a binary form with a value of one if the campaign succeeds and zero if it fails. We use it in a Logit specification estimated via maximum likelihood. The second corresponds to the intensity of the success or failure of the collection. It takes the form of the ratio of the total amount collected to the target. We use it in a linear specification estimated by ordinary least squares.

$$Success_i = \alpha + \beta_1(Sequences_i \times Selfpleges._i) + \beta_2 Camp.charac._i + \beta_3 Proj.charc_i + \varepsilon_i \qquad (2)$$

3. Results

3.1. Determinants of a campaign belonging to a class of sequences

Now that we have identified the classes of sequences, let's look at the characteristics of the campaigns that are related to them. Table 2 presents a series of statistics crossing different categories (sequences class versus type of entrepreneur and project’s domain) and indicates for each crossing the corresponding success rates. Not surprisingly, the campaigns belonging to the most dynamic sequences classes, the **speedy** and **medium U** ones, have very high success rates (95% and 85%). Nevertheless, it can be noted that even those belonging to the least dynamic sequences classes can sometimes reach their target. Those attached to the **low L** and **low spike** classes do so in 5.85% (43 out of 735) and 37% of cases respectively. As shown by the Chi-square test of independence, the variables sequences types and success are not independent. With a Cramer's V of 0.66, they present a medium degree of association (strong limit[24]).

The differences in the class of sequence according to the type of entrepreneur are negligible. Even if they appear statistically significant (Chi-square), the size of the variations in numbers is small (Cramer's V is very small). The same observation is made with regard to the differences in the type of sequence according to the project domain. In fact, it is on the success rates of the groups defined according to these elements that the differences appear. Campaigns driven by firms are less likely to reach their target than other campaigns, regardless of the sequence class they belong. The extent of this penalty varies, however, depending on it. The firms which have conducted a campaign classified as **medium U** or **low U** have a success rate of 10 points lower than the average of these classes, those having conducted a campaign in **low spike** have a success rate of 11 points lower, none of those in **low L** are successful.

[24] It is generally considered strong from 0.7. The maximum is 1.

Campaigns for entrepreneurial projects also succeed less often than others, especially when their sequence is classified as **medium U** (78% vs. 86%) or **low spike** (27% vs. 37%). The campaigns for projects in the field of solidarity with a **low spike** sequence succeed more frequently than the others 46% against 37% on average. The platform's public appears less interested in projects that are more oriented towards economic activity, whether because of their entrepreneur (firm) or their domain (entrepreneurial). Even if their campaigns do not necessarily have different sequences types from the others, within these sequences types they are less successful. Concerning the solidarity projects, they appear more frequently saved from an unfavorable course than the others.

Table 2: project characteristic of campaigns belonging to the different sequence classes

The table presents for each class of sequence the characteristic of project that campaigns offer to finance (entrepreneur type and activity domain – reduced to four). It displays in each box the number of campaigns in the designated groups and the proportion that the sequence class represents for the category, as well as the number of successful campaigns and the corresponding success rate in parentheses. The set is accompanied by Chi-square tests of independence and measures of association in the form of Cramer's V.

Sequence classes	*Number*	*Entrepreneur type*			*Domain*			
		Association	*Firm*	*Individual*	*Arts*	*Entrepre-neurship*	*Solidarity*	*Others*
medium U	1,650-27% (1,418-86%)	650-29% (580-89%)	164-28% (125-76%)	808-26% (687-85%)	712-30% (636-89%)	304-23% (239-78%)	497-27% (429-86%)	137-26% (114-83%)
low spike	1,008-17% (373-37%)	390-17% (137-35%)	73-12% (12-16%)	530-17% (219-41%)	349-15% (133-38%)	224-16% (61-27%)	340-19% (155-46%)	95-18% (24-25%)
low L	735-12% (43-5.9%)	253-11% (16-6%)	56-10% (0-0%)	417-14% (27-6%)	216-9% (16-7%)	198-15% (8-4%)	231-13% (18-8%)	90-17% (1-1%)
speedy	1,853-31% (1,762-95%)	604-27% (576-95%)	196-34% (180-92%)	1 028-33% (983-96%)	771-33% (742-96%)	472-35% (437-93%)	466-26% (446-96%)	144-28% (137-95%)
low U	779-13% (541-69%)	370-16% (263-71%)	93-16% (55-59%)	303-10% (212-70%)	311-13% (223-72%)	147-11% (94-64%)	266-16% (187-70%)	55-11% (37-67%)
Khi2	2,647.8***	87.549***			103.64***			
Cramer's V	0.66	0.08			0.07			

*** significance level of 99%, ** of 95%, * of 90%.

The differences between the sequences are also reflected in the quantitative elements that can describe the campaigns (degrees of success or failure, size of the target, duration, number of communications). Table 3 describes them. It should be noted that the degree of final success of the campaigns appears strongly linked to the dynamism of their sequence. On average, the **speedy** ones meet a larger share of their target (151%), followed by the **medium U**, the **low U**, the **low L** and the **low spike**. The same pattern holds true for both campaigns that succeeded in meeting their target, with one notable exception, and for those that did not. Nevertheless, campaigns that succeed despite a **low spike** sequence have an average position relative to the target that is higher than expected. 4.8% of these campaigns collect at least twice their goal. The most successful campaign collected almost eight times its target[25].

[25] We are still far from the global maximum of collection which is achieved by a **speedy** class campaign that received 65 times its target. This last was relatively low (260 Euros).

Regarding more directly the configuration of the campaigns, we can see that those with the lowest objectives, the shortest durations and those that communicate the most intensely succeed more frequently, regardless of their sequence class. **Low U** campaigns have on average higher target and **low L** campaigns have the lowest target. There is no apparent relationship (dependency) between campaign sequence class and fundraising goal size or fundraising duration. However, it can be noted that campaigns that are successful despite a **low L** or **low spike** sequence are on average shorter than others. In contrast, the communication-dynamic link appears to be strong. The **speedy** types communicate more, followed by the **medium U**, **low U**, **low L** and **low spike**.

<u>Table 3:</u> characteristic of campaigns belonging to the different sequence

The table presents for each class of sequence the mean of the different variables defined in column. The mean is computed both for the full sample and for the subsample of the failed campaigns and of successful ones. Standard deviations are also computed. You can find them below under brackets. The set is completed by series of Student tests of difference in mean.

Sequence classes	*Final position regard to the target*			*Campaigns characteristics*								
				Target			*Duration*			*Communication*		
	Full sample	*Failure-Success*	*t-stat (p-value)*	*Full sample*	*Failure-Success*	*t-stat (p-value)*	*Full sample*	*Failure-Success*	*t-stat (p-value)*	*Full sample*	*Failure-Success*	*t-stat (p-value)*
medium U	101.1	35.31-111.86	61.51***	3,901	4,803-3,753	3.250***	43.6	47.69-42.98	61.51***	6.9	5.10-7.22	61.51***
	(34.4)	(16.61-22.57)	(0.000)	(5,161)	(4,437-5,257)	(0.001)	(16.5)	(18.20-16.09)	(0.000)	(7.4)	(5.66-7.61)	(0.000)
low spike	55.6	15.61-123.63	39.45***	4,162	5,995-1,042	2.042**	39,8	42.87-34.60	39.45***	1.8	1.65-2.20	39.453***
	(61.9)	(13.68-51.83)	(0.000)	(48,549)	(61,103-1,277)	(0.042)	(17,3)	(16,36-17,62)	(0.000)	(3.0)	(3.09-2.88)	(0.000)
low L	13.9	7.70-113.89	34.81***	2,856	2,980-862	10.671***	40,8	41.27-33.95	34.82***	0.9	0.83-1.30	34.817***
	(26.9)	(9.18-19.87)	(0.000)	(3,488)	(3,551-955)	(0.000)	(17.8)	(17.89-15.36)	(0.000)	(1.7)	(1.72-1.99)	(0.000)
speedy	151.0	38.05-156.88	20.9***	4,579	28,166-3,361	1.496	40.2	44.14-40.04	20.9***	7.8	6.80-7.90	20.9***
	(217.1)	(20.47-221.02)	(0.000)	(35,954)	(158,116-7,178)	(0.138)	(15.2)	(15.78-15.15)	(0.000)	(9.1)	(8.98-9.15)	(0.000)
low U	82.9	23.22-109.09	59.56***	5,331	7,047-4,576	2.167**	43.4	45.0-42.72	59.56***	5.6	4.67-6.04	59.556***
	(45.3)	(15.29-24.35)	(0.000)	(19,084)	(9,921-21,901)	(0.031)	(16.3)	(16.1-16.42)	(0.000)	(8.0)	(10.58-6.60)	(0.000)
Total	95.8	17.17-131.75	49.26***	4,210.7	5,945-3,419	2.179**	41.6	43.2-40.8	5.037***	5.5	2.39-6.84	25.05***
	(133.7)	(16.63-147.57)	(0.000)	(29 115)	(49,936-9,746)	(0.029)	(16.5)	(17.22-16.07)	(0.000)	(7.6)	(5.45-8.05)	(0.000)

*** significance level of 99%, ** of 95%, * of 90%.

Let us complete these elements through a multinomial Logit regression analysis which allows us to better control the links between the variables. The specification used is the one defined in equation *(1)*. It is a matter of characterizing the campaigns that are attached to the different sequence classes without taking into consideration their success, which will be examined later. The reference value of the explained variable is the attachment to the **speedy** class. This one corresponds best to the ideal campaign with both a very high success rate (95%) and collections that often go well beyond the targeted amount (on average 150% of the target collected). Concerning the categorical variables, type of entrepreneur and domain of the project, we chose for reference the associations and the projects in the Arts. The model estimates are shown in Table 4. The first part uses the specification based on a division into four domains, while the second part considers a broader division (15 domains). The latter will be used in the analysis of the success of the campaigns. We use it here only as a robustness test.

All the results obtained are presented in the form of odds ratios. A value of 1 corresponds to a probability of encountering the modality of the explanatory variable on the group designated by the explained variable equal to that prevailing on our reference group, the belong to the **speedy** class of sequence. A lower value corresponds to a lower probability. A higher value corresponds to a higher probability. Thus, all other things being equal, the higher the target of a campaign is, the more likely it is to have a **low U**, **low L** or **medium U** type of sequence, rather than a **speedy** one. There are no significant differences on this basis between campaigns belonging to the **speedy** and **low spike** classes. As for their duration, the longer it is, the greater the probability of having a **low L**, **low spike** or **medium U** type of sequence rather than a **speedy** one. Things are simpler for the communication. We can see the same trend as before. The less a campaign communicates, the more likely it is to have a less dynamic sequence. The hierarchy of estimates is clear.

Table 4: Multinomial regression

The table presents estimates of two specifications of a multinomial regression explaining the belonging to the different class of sequence that we have identified. The reference for the variable is the belonging to the speedy class. The first specification to deal with the domain of the project consider four different categories (arts, entrepreneurship, solidarity and other). The second consider fifteen categories. The associated estimates are not reported to keep the table simple. The elements indicated are the odds ratio associated with the variable considered for the class considered and, in brackets, the standard error of the regression coefficient.

	medium U	*low spike*	*Low L*	*Low U*	*medium U*	*low spike*	*Low L*	*Low U*
Intercept	0.050***	0.661	0.048	0.016	0.046***	0.796	0.043***	0.011***
	(0.385)	(0.445)	(0.519)	(0.495)	(0.410)	(0.479)	(0.563)	(0.536)
Target (log)	1.325***	1.009	1.355***	1.628***	1.317***	0.976	1.327***	1.610***
	(0.043)	(0.052)	(0.059)	(0.054)	(0.044)	(0.052)	(0.060)	(0.055)
Duration (log)	1.398***	1.376***	1.461***	1.165	1.449***	1.458***	1.612***	1.243
	(0.104)	(0.122)	(0.141)	(0.131)	(0.105)	(0.124)	(0.143)	(0.133)
Communication (log)	0.811***	0.275***	0.129***	0.614***	0.836***	0.278***	0.131***	0.631***
	(0.041)	(0.053)	(0.074)	(0.051)	(0.042)	(0.054)	(0.075)	(0.052)
Entrepreneur type (ref. Association)								
Firm	0.751**	1.034	1.056	0.745*	0.728**	0.921	0.970	0.683**
	(0.131)	(0.175)	(0.207)	(0.158)	(0.136)	(0.183)	(0.214)	(0.165)
Individual	0.842**	0.919	1.213*	0.583***	0.838**	0.884	1.123	0.545***
	(0.077)	(0.094)	(0.110)	(0.097)	(0.080)	(0.099)	(0.115)	(0.102)
Domains (ref. Arts)								
Entrepreneurship	0.691***	1.396***	2.004***	0.776**	no	no	no	no
	(0.094)	(0.115)	(0.133)	(0.122)				
Solidarity	1.111	1.265**	1.441***	1.233*	no	no	no	no
	(0.086)	(0.106)	(0.126)	(0.107)				
Other	1.034	1.742***	2.499***	0.916	no	no	no	no
	(0.134)	(0.163)	(0.182)	(0.180)				
Domains (étendus à 15)	no	no	no	no	yes	yes	yes	yes
AIC	16,193.9				16,259.8			
% bons classements	38.97				38.83			
Pseudo *R2 Mc Fadden*	0.120				0.113			
Nb. obs.	5,927				5,935			

*** significance level of 99%, ** of 95%, * of 90%.

Campaigns run by firms are much less likely than those run by associations to have a **U-shaped** course rather than a **speedy** one (or **low spike** or **low L**). For them, when we control for the other factors, there is, on average, no intermediary, either the campaigns follow the ideal (**speedy**) sequence, or they follow one of the less dynamic ones. The same thing is true for those carried out by individuals[26]. The campaigns destined to finance entrepreneurial projects (whoever the entrepreneur is) have even more chances than those destined to finance projects in the field of art to follow a very low dynamic sequence, **L low** and especially **low spikes** (twice as much chance). They are also less likely to have a U-shaped path. Campaigns in the field of solidarity are more likely than those supporting an artistic project to have a **low L**, **low spike** or **low U** path rather than a **speedy** one.

The use of a breakdown of project areas into fifteen activity domains rather than four does not change these conclusions.

3.2 Sequence groups and campaigns success

Before going into the details of the analysis of the success of the campaigns and evaluating the associated hypotheses (2 and 3), let's examine the distribution of self-pledges by considering the set as well as the typical sequences we have identified. First, we note that 56% of the campaigns receive none, 25% receive one, and 19% receive at least two. Table 5 goes into more detail by highlighting the potential link between campaign success and the number of self-contributions.

<u>Table 5:</u> number of self-pledges for the different identified classes of sequences

The table present the repartition od self-pledges for the campaigns belonging to the five sequences classes identified differentiating between successful campaigns and failed ones. Each box displays the number of campaigns in the defined group and the percentage that it represents in the related subsample (it sums 100% over the column). The set is accompanied by Chi-square tests of independence and measures of association in the form of Cramer's V.

Nb. Of self-pledges	*Full sample*		*Medium U*		*Low spike*		*Low L*		*speedy*		*Low U*	
	Success	*Failure*	*Success*	*Failure*	*Success*	*Failure*	*Success*	*Failure*	*Success*	*Failure*	*Success*	*Failure*
0	2,276	1,126	702	136	212	386	25	416	1 097	55	240	133
	55%	60%	50%	59%	57%	61%	58%	60%	62%	60%	44%	56%
1	998	531	358	67	91	177	10	202	419	14	120	71
	24%	28%	25%	29%	24%	28%	23%	29%	24%	15%	22%	30%
2 and more	863	231	358	29	70	72	8	74	246	22	181	34
	21%	12%	25%	12%	19%	11%	19%	11%	14%	24%	33%	14%
Khi2	66.2***		18.09***		10.89***		2.79		8.89**		30.53***	
Cramer's V	0.10		0.10		0.10		0.06		0.07		0.19	

*** significance level of 99%, ** of 95%, * of 90%.

[26] They have a higher probability of experiencing a **low L** sequence rather than a **speedy** sequence in the specification where the activity domain breakdown selected is four groups (nevertheless with a p-value close to 10%). The relationship is not significant for the fifteen domains specification.

The tests carried out show the absence of independence between the number of self-pledges and the success of the campaign. The only exception concerns the **low L** campaigns which present too few successful campaigns (43 for 692 failures). In all cases, as shown by Cramer's V, the degree of association measured is very low. We note that among the successful campaigns, the proportion of campaigns that received at least two self-pledges is higher than among those that failed. Two elements follow from these facts. On the one hand, for the campaigns that most closely correspond to the ideal type sequence (speedy), self-pledges appear to play a different role than for those that are farther from it. They are relatively rarer and have less of an impact on success. On the other hand, the differences that have been identified do not seem to lie in the presence or absence of self-contributions but in the fact of receiving more than one. It is therefore this level that we will use to test the hypotheses concerning their role in the success of the campaign following the different typical sequences that we have identified.

Table 6 shows the estimates of the *logit* used to test our hypotheses. The specifications used are based on equation *(2)*. The elements are introduced progressively in order to uncover indirect effects. We start by only considering the impact of the sequence class the campaign belongs on its success without including the control variables, and then we introduce them. We continue with the self-pledges alone (2 and more), then with the control variables (without the sequence classes). We finish by considering on the same model the two variables of interest (the sequence classes and presence of at least two self-pledges) and their interactions. Concerning the sequence, we have retained the ideal sequence type, speedy, as a reference category. The first regression shows significant differences between the success probabilities of the campaigns according to the type of sequence followed. The hierarchy is similar to that revealed in the descriptive statistics. The speedy ones are far above with an estimated probability of 95%, then come the medium U (86%) and low U (69%) campaigns. The low type campaigns have the lowest predicted probabilities of success: low spike (37%) and low L (6%). The introduction of the control variables does not change this order. The most dynamic campaigns have a higher probability of success. These findings are consistent with our hypothesis 2.

Table 6: Logit regression of campaign probability of success

The table presents the estimates obtained using maximum likelihood of series of *Logit* type models for which the explained variable is the campaign probability of success. Reported information are odd-ratios and below under brackets coefficient standard errors.

	Campaign probability of success					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Intercept	19.363***	32340.925***	1.976***	346.067***	21.971***	45063.412***
	(0.107)	(0.530)	(0.030)	(0.394)	(0.123)	(0.539)
2 or more self-pledges			1.891***	1.905***	0.509***	0.724
			(0.080)	(0.094)	(0.254)	(0.293)
Sequence (ref. speedy)						
medium U	0.316***	0.320***			0.238***	0.255***
	(0.129)	(0.140)			(0.145)	(0.154)
low spike	0.030***	0.022***			0.024***	0.019***
	(0.126)	(0.153)			(0.142)	(0.167)
low L	0.003***	0.002***			0.003***	0.002***
	(0.190)	(0.222)			(0.213)	(0.243)
low U	0.117***	0.130***			0.080***	0.097***
	(0.133)	(0.148)			(0.151)	(0.166)
Sequence x self-pledge						
medium U x self-pledge					4.645***	3.543***
					(0.328)	(0.364)
low spike x self-pledge					3.550***	2.399**
					(0.313)	(0.363)
low L x self-pledge					3.751***	3.923**
					(0.483)	(0.546)
low U x self-pledge					5.927***	3.745***
					(0.328)	(0.368)
Target (log)		0.336***		0.460***		0.334***
		(0.055)		(0.043)		(0.056)
Duration (log)		0.932		0.793**		0.889
		(0.122)		(0.096)		(0.123)
Communication (log)		2.177***		3.842***		2.131***
		(0.052)		(0.043)		(0.052)
Entrepreneur type (ref. association)						
Firm		0,978		0,959		1,011
		(0,158)		(0,131)		(0,160)
Individual		0,850*		0,881*		0,845*
		(0,096)		(0,076)		(0,097)
Domain (extended to 15)	no	yes	no	yes	no	yes
AIC	4,690.912	3,863.934	7,427.492	5,708.781	4628.638	3,818.328
% of good classements	0.8378	0.8726	0.6866	0.7745	0.8378	0.8712
Mc Fadden Pseudo *R2*	0.3752	0.4825	0.0091	0.2315	0.3848	0.4900
Nb. of obs.	6,025	5,927	6,025	5,927	6,025	5,927

*** significance level of 99%, ** of 95%, * of 90%.

In the third regression, we consider only the presence or not of more than one self-pledge (2 and more). The variable has a positive effect, the associated odds ratio is greater than 1, and is statistically significant. The fact that a campaign received at least two self-pledges increases its probability of success from 66.4% to 78.9%, an increase of 12.5 points (+18.8%). When the control variables are introduced, the difference is slightly reduced. We go from a success rate of 72.1% for the reference, a campaign in the field of "arts and photography" launched by an association and using no more than one self-pledge, to a rate of 83.1%, an increase of 11 points (+15.25%) with self-pledge. When the sequence classes are introduced as well as the associated interactions, we note that the use of self-pledges is negatively associated with the success of **speedy** campaigns but positively with the other classes of sequence. The **speedy** have a probability of success of 95.64%, if they receive less than two self-pledges, 91.79% otherwise, a drop of 3.92 points (-4%). **Medium U** campaigns see their probability of success increase by 8.58 points (+10.22%), **low spike** by 14.41 (+40.9%), **low L** by 4.39 (+161%) and **low U** by 20.36 (21%). These findings are confirmed in principle by the model including the control variables. However, the effects are weaker with the exception of the **low L**. We have respectively in the order defined above: -1.33 (**speedy**); 7.77 (**medium U**); 13.06 (**low spike**); 7.68 (**low L**); 15.55 (**low U**) percentage points (-4%; +8.6%; +39.87%; +161%; +21.66%). In all cases, these findings are consistent with our hypothesis 3. Self-pledges contribute to the success of campaigns with less dynamic sequences.

With Table 7, we extend the analysis by considering a continuous spectrum of degrees of success. The explained variable takes the continuous form of the ratio of the final amount of contributions collected to the set collection target. It has a pivotal value of 1 (100%). Above this value, the campaign is successful. Below that, it is a failure. The specifications used are the same as those proposed for the *logit* models. In the first models, we find the typical patterns that were identified. The effects identified are such that, all other things being equal (model 2, including the control variables), **speedy** campaigns achieve on average 138.58% of their objective, **medium U** campaigns 99.74%, **low U** campaigns 88.29%, **low spike** campaigns 62.14%, and **low L** 33.2%. This is again consistent with our hypothesis 2.

The effect of self-pledges (two or more) on the ratio is less clear. The associated coefficient is not statistically significant in either the simple model or the one including the control variables. The situation changes with the introduction of the sequence classes and the associated interaction effects. This reveal differentiated impacts of self-pledges according to the dynamics of the campaign (their sequence), comparable to those found in the analysis of the probability of success of campaigns. Their presence is associated with less success, a lower ratio of total collections to target, for **speedy** campaigns. However, these remain high on average, all other things being equal (with control variables), 142% for those who did not use self-pledges, compared to 118.2% for those who did. That is a negative difference of 16.76% (-23.8 points). On the other hand, they improve the success of campaigns with another type of sequence. The campaigns that benefit most from self-pledges are those with a **low L** course, which see their ratio increase on average by 26.7% if they benefit from it (from 40.8% to 32.2% on average), **low U** (14% from 84.9% to 96.8%), **medium U** (4.04% from 98.8% to 102.8%) and then **low spike** (3.9% from 61.4% to 66.8%).

Table 7: linear model of the final result of the campaign repress in percent of the target

The table presents estimates obtain using ordinary least scare of linear model explaining the ratio of the total amount of euros obtain at the end of the campaign over the targeted amount. Reported information are regression coefficient associated to the explanatory variables and below under-brackets standard errors.

	Amount collected over amount targeted ratio					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Intercept	151.046***	309.441***	96.094***	281.645***	155.464***	312.251***
	(2.92)	(18.4)	(1.90)	(18.9)	(3.16)	(18.5)
2 or more self-pledges			-1.351	-2.453	-30.547***	-23.819***
			(4.47)	(4.32)	(8.30)	(8.22)
Sequence (ref. speedy)						
medium U	-49.951***	-38.842***			-54.822***	-43.294***
	(4.26)	(4.25)			(4.74)	(4.72)
low spike	-95.463***	-76.439***			-101.13***	-80.704***
	(4.92)	(5.21)			(5.31)	(5.58)
low L	-137.138***	-105.383***			-141.861***	-109.908***
	(5.48)	(6.00)			(5.84)	(6.31)
low U	-68.194***	-50.289***			-76.77***	-57.087***
	(5.37)	(5.41)			(6.16)	(6.19)
Sequence x self-pledge						
medium U x self-pledge					32.482***	27.893**
					(11.1)	(10.9)
low spike x self-pledge					39.415***	29.205**
					(14.1)	(14.0)
low L x self-pledge					33.287**	32.445*
					(16.9)	(16.7)
low U x self-pledge					45.615***	35.623***
					(13.0)	(12.9)
Target (log)		-23.32***		-25.678***		-23.108***
		(1.94)		(1.98)		(1.94)
Duration (log)		-9.236*		-14.134***		-9.39**
		(4.72)		(4.86)		(4.72)
Communication (log)		22.912***		39.669***		22.793***
		(1.97)		(1.79)		(1.97)
Type of entrepreneur (ref. association)						
Firm		25.128***		25.883***		25.219***
		(6.36)		(6.56)		(6.36)
Individual		0.286		1.087		0.094
		(3.68)		(3.78)		(3.68)
Domain (extended to 15)	no	yes	no	yes	no	yes
Fisher	195.8***	52.7***	0.0915	39.3***	89.0***	43.7***
adj. R2	0.1146	0.1673	-0.0002	0.1145	0.1162	0.1681
Nb. of obs.	6025	5927	6025	5927	6025	5927

*** significance level of 99%, ** of 95%, * of 90%.

We find the same type of pattern as for the probability of success. The campaigns with the least dynamic sequence benefit the most from self-pledges (if they are two or more). This finding is consistent with hypothesis 3. Note, however, that this concerns the entire group of campaigns that do not have a **speedy** type of course and that within this group the benefit is not proportional to the weakness of the dynamism. It does not follow the order **low spike**, **low L**, **low U**, **medium U**, but **low L**, **low U**, **medium U** and **low spike**. The **low L** and **low spike** campaigns appear to be so poorly committed that even the self-pledges do not manage to rectify their situation. For the **medium U**, they correspond to cases of necessary help to pass the bar allowing to reach the success of the campaigns when this one is close to the objective. For the **low U**, the boost is generally not sufficient.

4. Discussion

In this study, we have explored the different forms that reward-based crowdfunding campaigns process can take through a sequence analysis. The sequences were defined on the basis of the rate of accumulation of supports observed over each tenth of the campaign duration. This allows us to establish a typology of sequences that goes beyond what suggested by the previous literature. It includes five classes qualified as: **speedy**, **medium U**, **low U**, **low L** and **low spike**. We then highlighted a number of determinants of the attachment of campaigns to one of these classes. The campaigns with the lowest target and the shortest duration, as well as those that communicate the most, are more likely to be attached to the **speedy** class of sequence which can be viewed as the ideal one. The campaigns driven by firms have more chance, than the ones driven by association, to follow one of the U shape sequence than a **speedy** one. The ones driven individuals have more chance to follow a **low spike** sequence. Campaigns in the entrepreneurial or solidarity domain have more chance to follow the one of less dynamic sequence (**low spike** or **low L**) than a **speedy** one, than campaigns funding artistic project. We also provide evidences that the more dynamic is the class the campaigns are attached to, the more frequently and intensively they succeed. At last, we explore the impact of the use of self-pledges on the campaigns' outcome according to the sequence class they belong to. This allow us to make two statements. First, the campaigns attached to the **speedy** sequence class which receive self-pledges succeed less than the ones which don't. Second, for campaigns attached to the others classes of sequence, the impact of reserving self-pledges is positive. It increases their probability of success and the quantity of funds they collect regarding their target. The link between the importance of this improvement and the lack of dynamism of the campaigns sequence does not appear to be linear. It also adopts different patterns following the measure of success used.

Those observations are globally in line with the research hypothesis that we have developed. First, the typology of sequences obtained include sequences with shape that can be predict by the theoretical models developed by literature L shaped and U shaped (Deb et al., 2019; Hellman et al., 2019; Alaei et al., 2021; Zang et al., 2022). It however provides more diversity than expected. For each characteristic shape, we have found groups of sequence that differentiate themselves from the others mainly considering their opening dynamic (the proportion of the target collected over the first tenth of the campaign duration). As a result, we identify the **medium U** and **low U** sequences classes, **low L** and **low spike** (which is basically a L-shaped sequence with late start). This diversity offers a broader view of the diversity of campaigns' progression that helps to apprehend more efficiently the complexity of the situations.

It pleads for new research both empirical and theoretical to determine what can explain the belonging of campaigns to this less expected classes of sequence. It also open new avenues for studying campaigns' outcomes. Previous works have largely explored the question of the factors that explain success or failure of campaigns. It is time to go further and investigate more precisely the determinants of the diversity of campaigns' outcome and of their progression. This is for us the main contribution of the paper. We open the path using an original methodology in the domain. Sequence analysis based on optimal matching algorithm was initially, in its modern configuration, developed in the 80's by the sociologist Andrew Abbott. It is now widely used in social sciences. It can be useful to implement it in fields where sequence of events or of state are relevant to understand like here in entrepreneurial finance.

Our typology however presents some limits. Even if we can think that the same type of decomposition could be found in another context (on another platform and/or over another period of time) this is not guaranteed. Investigation on the same model has to be performed in other context in order to have a broader view on its relevancy. We can image to find different classes of sequences or the same classes in different proportions on another crowdfunding platform. If it is the case, we can ask what are the determinants of those differences. They can be driven by the nature of the platform audience, its organization, its maturity, or the nature of projects financed through it. Many determinants can be considered especially if we consider other forms of crowdfunding (debt or equity). Beyond the context, the choice made to define the different state used to build the sequence can be discussed. Even if we have performed tests of their impact on the results and include control variables to deal with the consequences of these choices. Defining a state composing a sequence as lasting a tenth of campaign duration can be seen as arbitrary. This remain a compromise between accuracy and operationality. Each time we transform a continuous variable like time into a discrete one, we face this type of difficulties. In order to deal with the possible problems generated, we include campaign duration as control in the regression analysis. We can also question the way we characterize the resulting states using heterogenous progression limits (stagnation, late start, terciles…). Once again, these choices are the result of a compromise which is commanded by the complexity of the data. Many solutions have been tested to qualify effectively the progression of the collection among the different periods that we chose to consider (the tenth of the campaign duration). It doesn't change fundamentally the nature of the classes obtained.

Based on our typology, we show that the campaign attached to the classes presenting the most dynamic progression succeed more frequently and intensively. This is in line with previous literature (Colombo et al., 2018; Bouaiss and Vigneron, 2021) which has provided evidences that the initial dynamic of a campaign is an important determinant of its future success. Campaigns that starts quickly, collecting a high proportion of their target during its first moments (a proportion higher than the proportion of its duration lasted), succeed more frequently. At the opposite campaign, that start slowly, collecting a low proportion of their target at their beginning, fail more frequently. We offer here a framework that allows to consider more divers ways for campaigns to eventually succeed. The different classes of sequence characterizing the campaign dynamic offer a better understanding of the cases when funds collection reach the target despite of a start not as quick as expected (slow). Even if it is less frequent, some campaign with poor start can finally meet their target. It would be interesting to go further to understand the mechanisms that help not well engaged campaigns to get back on track. We have started the work here considering the support that entrepreneurs can make to their own campaigns (self-pledges). This practice is not allowed by every platform. So, the examination of others mechanisms is required. We call here for future research. We can consider in this context events like a new communication, change in the strategy used to promote the campaign, certification obtained through for example the support of an important backer, an opinion leader, among platform users, the concomitant success of a campaign in the same domain… Here, many elements can be in action more theoretical reflections are required.

We also add to the short literature on the use of self-pledges in reward-based crowdfunding campaigns. Previous works (Crosetto and Regner, 2018; Regner and Crosetto, 2021) do not find a specific impact of the type of entrepreneur intervention on campaign course other than the mechanical effect (the rise of the amount collected of the amount of the self-pledges). Our investigation shows that they are useful for not so well engaged campaigns and they affect negatively the well engaged ones (those belonging to the **speedy** class). These results show that their impact is more complex than expected. Once again, this plead for further investigations. Even if they are not allowed on many platforms (*Kickstarter*, *Kiss kiss bank bank*…), we cannot exclude that they also exist on them. On these platforms, the entrepreneur can do self-pledges using friend or relative as intermediary. She gives them the money corresponding to the supports that they want them to bring to their campaign and so they do it.

These hidden self-pledges cannot be identified by the platform which cannot prohibit them. This type of actions is hard to treat empirically. So, it is an opportunity to deal with a platform that allows self-pledges in order to approach, even imperfectly, the phenomenon and its impact. About self-pledges, it is important to keep in mind that they are costly and that they make the targeted amount threshold flexible. As for supports from other types of backers, self-pledges generate platform fees. The generated flexibility can question the credibility of the signal given through the campaign collection targeted amount. It also makes the information about actual level of collected fund more complex to interpret for potential backers. As a result, its impact on future success of the campaign is less easy to interpret. It raises the question of what is due to the crowd involvement and what is due the simple proximity of the target. Further investigations are required.

Our results are interesting both for the platforms and for the entrepreneurs which are driving crowdfunding campaigns. To know more about campaigns that do not follow the ideal path appears important. In our sample, only 31% of the campaign can be attached to the most desirable class of sequence: the **speedy** class. Even if these campaigns collect on average more than the others, they represent only a fraction of the total activity of the platform we study and as a result of the potential income that campaigns can generate for it. Hence, it can be interesting to identify campaigns for which success is less obvious but still possible, the ones attached to a *U*-shaped sequences class, in order to create conditions that promote their final success. At the opposite, it can be interesting to identify ex ante campaign with very low probability of success, the ones attached to a *L-shaped* class of sequence in order to reduce their number. This can make the platform more attractive. The more a platform shows that it can intermediate successful campaigns, the more it is interesting for entrepreneurs to drive their campaigns on it.

Our results can also raise awareness of the platforms about the use by entrepreneurs of self-pledges, and for those that do not allow them by extension about hidden self-pledges. If this kind of intervention can help some campaigns to finally succeed, it not always the case. The platform could find interesting to discourage inefficient self-pledges: the ones bring to a speedy type campaigns, which are not useful and have a negative impact on their probability of success; the ones on L-shape campaigns that do not really helps them to succeed. They are mostly useful in the U-shape campaigns context. Moreover, in every context, self-pledges can distort the information given to potential backers on the actual amount collected at a point of time. They can make a campaign seem more popular than its. We suggest two of improving the self-pledges management. First, platforms can charge different fees on self-pledges. They can charge unconditional fees to the campaign success on it. They charge more on self-pledges used to discard discretely a campaign or offer a possibility to pay a fix amount in order to discard a not well engaged campaign. They can also charge more on self-pledges that occur when the collection is close to the target. It would discourage the entrepreneur to reduce artificially the threshold when the limit is nearby. Second, platforms can inform potential backers more extensively about the entrepreneur use of self-pledges. They can present self-pledges as reduction of the target, or as entrepreneur's financial implication on the funding of the project. The information can be modulated whether the initial target has been reached or not. They could for example be presented as a target reduction before and as implication of the entrepreneur in the funding in the project after.

We can also recommend to the entrepreneurs using reward-based crowdfunding platform to modulate their communication strategy and their use of self-pledges following the type of path their campaign is actually engaged on. If the path appears more probably to be a **speedy** one, the best one, the entrepreneur must change nothing. If the path appears more probably to be a L-shaped one, they could reduce their effort and prepare them and their backers to the incoming failure. Here, an honorable exit has to be sought. If the path appears to be more probably a U-shaped one, the entrepreneur must increase its effort to promote the campaign, eventually make evolve its strategy, seek new backers through new canal and, may be, use the self-pledge. All these moves and, others that the entrepreneur can engaged in, have to be done to promote the campaign success. New researches both theoretical and empirical can help to identify all the action leverage that can be used in such a context.

Conclusion

Reward-based crowdfunding campaigns become a more and more used way to get fund for entrepreneurial and creative project. Their specific configuration that include in the "All or nothing" context a threshold of engagement of future clients before starting the production help to deal with, at least partially, asymmetric information problems. Research on the determinants of the success of individual campaigns has show that the dynamic of supports observed at their beginning are a major factor that lead the campaign to succeed (Colombo et al., 2018). This paper extends this literature considering not only the beginning of the campaign its entire path. We classify using sequence analysis based on longest common sequence algorithm the different plat that a campaign can follow. It allows us to observe more complex features. We identify five categories of path that we call: speedy, medium U, low U, low L and low spike. Each typical path has its own dynamic which can be associated with different campaign outcome. These dynamics are close to the ones predicted in the different theorical papers that try to model campaigns path (Deb et al., 2019; Hellman et al., 2019; Alaei et al., 2021; Zang et al., 2022).

This approach allows to kwon more about campaigns that do not follows the stereotypical path (good start leads to success; bad start lead to failure). We identify class of campaigns that succeed even their start is not so good. They get on track even if the initial dynamic is not the best ones. These campaigns belong to the U-shaped classes that we characterize in our sequence analysis. We provide evidences that the campaigns success is positively related with the global dynamic of the class of path they can be attached to. We also show that campaigns not belonging to the most dynamic one the speedy one the probability of success and its intensity can be improved by using self-pledges, financial support that the entrepreneurs bring to their own campaigns. The effect is more important for campaigns associated with U-shaped classes (medium U and low U).

This is a second originality of the paper self-pledges are not widely studied. In fact, they are not allowed on the most studied platform liked Kickstarter. Preview papers on them (Crosetto and Regner, 2018; Regner and Crosetto, 2021) do not show that they affect campaigns with other thing that their mechanical effect. We find that the things can be more complex. This pleads for new investigation on the subject. Our study is the first, as best as we know, to use sequence analysis in this context and to put the focus through it on campaigns that are at limit the ones that barely succeed or fail. We examine extensively one of the mechanisms that can help these campaigns to be finally successful, the use of self-pledges. We provide evidences that they are more useful for these campaigns, the one that follow a U-shape path. This open avenues for future researches. These new investigations can use our typology to have a better understanding of reward-based crowdfunding features. They also can use the sequence analysis methodology in other related context (others platforms, others period of time, other type of crowdfunding – debt or equity…) in order to see the different classes, that we have identified can be observed. They also can examine other mechanisms than self-pledges that can help campaigns with a not so good start to get back on track.

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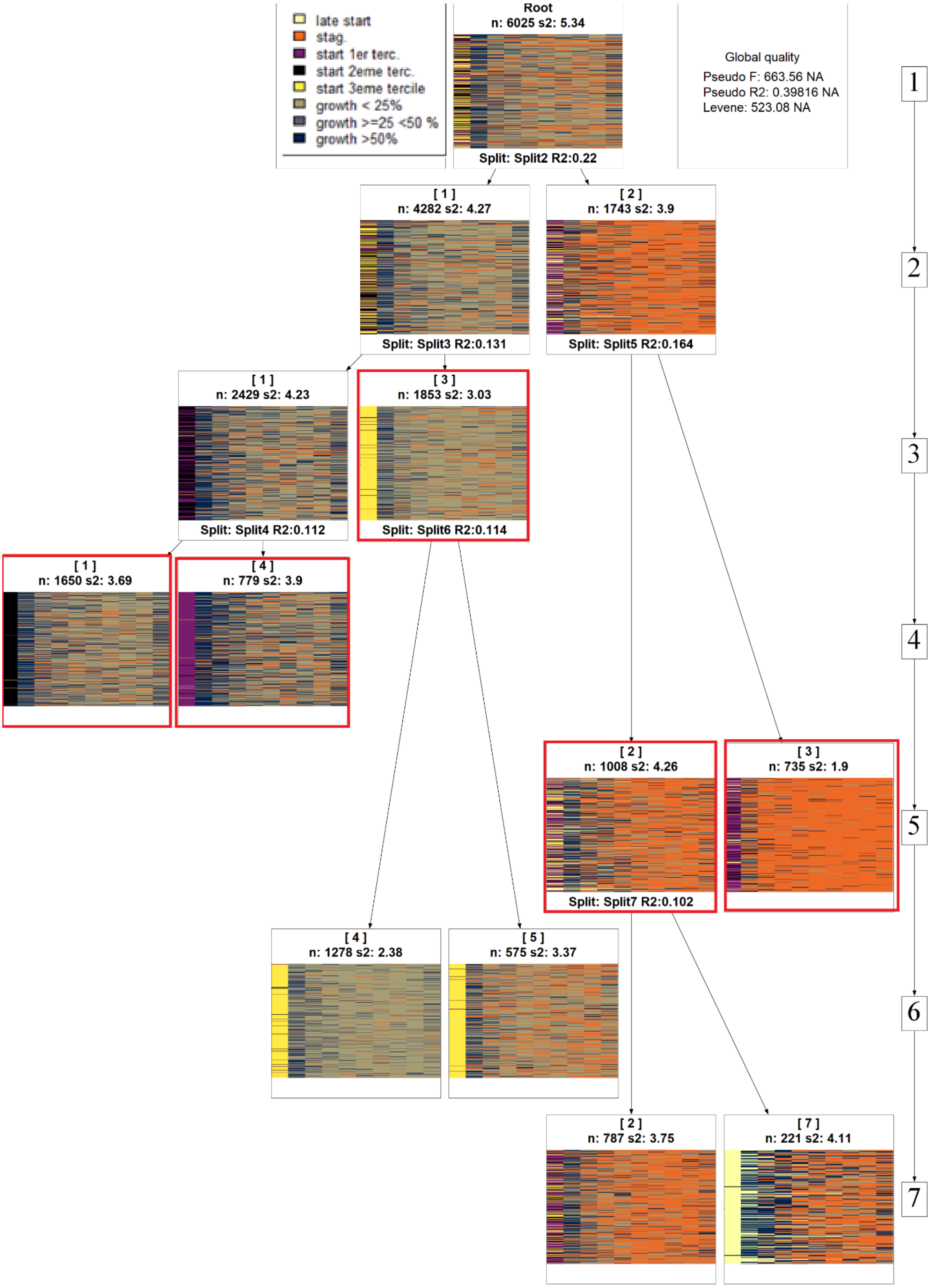
Annexe 1.



late start
stag.
start 1er terc.
start 2eme terc.
start 3eme tercile
growth < 25%
growth >=25 <50 %
growth >50%
Root
n: 6025 s2: 5.34
Split: Split2 R2:0.22
Global quality
Pseudo F: 663.56 NA
Pseudo R2: 0.39816 NA
Levene: 523.08 NA
[1]
n: 4282 s2: 4.27
Split: Split3 R2:0.131
[2]
n: 1743 s2: 3.9
Split: Split5 R2:0.164
[1]
n: 2429 s2: 4.23
Split: Split4 R2:0.112
[3]
n: 1853 s2: 3.03
Split: Split6 R2:0.114
[1]
n: 1650 s2: 3.69
[4]
n: 779 s2: 3.9
[2]
n: 1008 s2: 4.26
Split: Split7 R2:0.102
[3]
n: 735 s2: 1.9
[4]
n: 1278 s2: 2.38
[5]
n: 575 s2: 3.37
[2]
n: 787 s2: 3.75
[7]
n: 221 s2: 4.11
1
2
3
4
5
6
7