crowdfunding-exploration

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1 10 Years of Crowdfunding on Kickstarter - Data Exploration

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3 1 Introduction

Crowdfunding on Kickstarter

This exploratory data analysis is dedicated to the 10th anniversary of the crowdfunding platform Kickstarter. Crowdfunding is a rather new form of finance to fund any projects and ventures. Typically small amounts of money are being raised by a large number of people. The world wide web streamlined the fundraising processes and allowed easy access to this form of finance to any project creators and private investors.

Kickstarter is one of the most popular crowdfunding websites in the Western world. It was launched in April 2009 in the USA. While there are many crowdfunding platforms online today, they may fundamentally differ in terms of investor audience, project characteristics and funding services. Kickstarter's focus is mainly creative. According to their website ***"Kickstarter helps artists, musicians, filmmakers, designers, and other creators find the resources and support they need to make their ideas a reality."***

Project ***creators*** choose a ***deadline*** and a funding ***goal*** and present their project on the platform to gather money from a public audience. People who back the project (***backers***) by ***pledging*** money are assured tangible rewards, depending on the amount they pledged. Unlike other opportunities of investment, Kickstarter does not allow to distribute shares of a venture to supporters; nor do they claim any ownership over the projects. If the goal was not met by the end of the deadline, the funding is not distributed. While Kickstarter is mainly open for project creators in the USA, Canada, UK, Australia, New Zealand, Mexico and parts of the EU, project support is allowed by people from all around the world.

https://www.kickstarter.com/

Kickstarter Data

The Kickstarter data set was gathered in July 2019 from an automated web scraping service called Web Robots. Since 2016, they have been publishing monthly updates on all ongoing and completed Kickstarter projects. Due to a lack of documentation provided by the source, I interpreted the data to the best of my belief. Insofar, I cannot guarantee for validity and completeness of the data and take no liability for misinterpretation of the results due to a lack of documentation. To better comprehend the data and rule out erroneous information, I collated the data set with Kickstarter's project archive, which is unrestrictedly accessible online. On the positive side, I did not encounter major inconsistencies during the wrangling and analysis processes.

During the wrangling processes only a few project observations were removed due to tidiness issues. Consequently, the following analysis of Kickstarter does not represent the full data set, but a major part. Please refer to the data crowdfund-wrangling notebook to gain more information on the wrangling process.

https://webrobots.io/kickstarter-datasets/

Throughout the course of this notebook I will have these two questions in mind. Based on the aforementioned data:

- Is it still worthwhile financing your project on Kickstarter, now that crowdfunding has become mainstream?

- What determines the success of a crowdfunding campaign on Kickstarter?

To get started, let's import our libraries and set plots to be embedded inline.

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns

        %matplotlib inline

        # uncomment the below settings to avoid collapsing of dataframes
        # from IPython.display import Markdown
        pd.set_option('display.max_rows', 2500)
        pd.set_option('display.max_columns', 100)
        pd.set_option('display.max_colwidth', -1)
        pd.options.display.float_format = '{:,}'.format # display execution times
        sns.set_style("whitegrid")
```

4 2 Preliminary Wrangling

To begin, I import my data from multiple files and combine them into a single data frame. Subsequently, I assess the dataset to clean it from remaining issues. At the end of this section, I will identify our main variables and explain the terminology around aspects of our main variables.

```
In [2]: # read in 4 files and concatinate the data into a single data frame
        file_name =  './data/kickstarter_master{}.csv'
        master_df = pd.concat([pd.read_csv(file_name.format(i)) for i in range(1,5)])
        master_df.reset_index(drop=True, inplace=True)
```

4.1 Assessing and Cleaning the Data

```
In [3]: # show amount of rows and features
        master_df.shape
```

```
Out[3]: (184909, 32)
```

```
In [4]: # inspect features, null values and data types
        master_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 184909 entries, 0 to 184908
Data columns (total 32 columns):
project_id                184909 non-null int64
project_name              184909 non-null object
url                       184909 non-null object
blurb                     184909 non-null object
category                  184909 non-null object
subcategory               184909 non-null object
image                     184909 non-null object
slug                      184909 non-null object
created_at                184909 non-null object
launched_at               184909 non-null object
deadline                  184909 non-null object
state_changed_at          184909 non-null object
last_update_at            184909 non-null object
status                    184909 non-null object
creator_id                184909 non-null int64
creator_name              184908 non-null object
country                   184900 non-null object
city                      184909 non-null object
state                     184856 non-null object
displ_loc                 184909 non-null object
loc_type                  184909 non-null object
backers_count             184909 non-null int64
featured                  184909 non-null object
currency                  184909 non-null object
goal_real                 184909 non-null float64
goal_current_usd          184909 non-null float64
goal_hist_usd             184909 non-null float64
pledged_real              184909 non-null float64
pledged_current_usd       184909 non-null float64
pledged_hist_usd          184909 non-null float64
current_fx_rate(usd)      184909 non-null float64
```

```
hist_exchange_rate(usd)    184909 non-null float64
dtypes: float64(8), int64(3), object(21)
memory usage: 45.1+ MB
```

In [5]:
```
# inspect 10 examples of the data in the dataset
master_df.sample(10)
```

Out[5]:
```
        project_id                                                project_name  \
91415   2408644     Bring the White Oak of Johnston to the Stage (Canceled)
129264  1629134     HERE WE ARE
47424   3179584     Let's Hangout: The Best Shared Events App!!
95798   2338396     Naheed's Gourmet Cuisine
81896   2591681     R.I.P. RaShawn
37521   3264703     Tha Wicked Kitchen - The First Juggalo Cookbook
91539   2405492     Trinity Lesions - A fantasy/thriller short
158509  923455      Mammoth Ski & Racquet Clubő T-Shirt (Canceled)
153941  1023900     American Nature (Canceled)
73150   2731499     Portal Kidnapped: Portal Origins Story


91415   https://www.kickstarter.com/projects/thewhiteoak/the-white-oak-of-johnston-a-ne
129264  https://www.kickstarter.com/projects/lonelygiant/here-we-are
47424   https://www.kickstarter.com/projects/weblinesolutions/lets-hangout-the-best-sha
95798   https://www.kickstarter.com/projects/1627713051/naheeds-gourmet-cuisine
81896   https://www.kickstarter.com/projects/530081902/rip-rashawn
37521   https://www.kickstarter.com/projects/1558256176/tha-wicked-kitchen-the-first-ju
91539   https://www.kickstarter.com/projects/578730237/trinity-lesions-a-fantasy-thril
158509  https://www.kickstarter.com/projects/1230168064/mammoth-ski-and-racquet-club-t-
153941  https://www.kickstarter.com/projects/430919248/american-nature
73150   https://www.kickstarter.com/projects/1507100940/portal-kidnapped-portal-origins


91415   Bring our play to the stage: The White Oak of Johnston
129264  An unambitious young writer attempts to escape his slacker surroundings for the
47424   Let's Hangout is a versatile and innovative application that will make it easie
95798   I want to open a restaurant. I have my own Home-Made, gourmet recipe book. Reci
81896   The officer-involved shooting of 18-year-old RaShawn wrecks his brother Jeremey
37521   A dope cookbook full of comedy, great tips and all that wicked s**t we come to
91539   A Senator funds a contingency plan called The "Shtriga Contagion" a virus capal
158509  Due to lack of interest from the owners at Mammoth Ski & Racquet Club, this can
153941  Showing the world the current state of the American Natural Treasures jewel by
73150   The film is about the origins story of what happened in aperture laboratories l

            category    subcategory  \
91415   Theater       Plays
129264  Film & Video  Narrative Film
47424   Technology    Apps
```

```
95798   Food          Restaurants
81896   Comics        Graphic Novels
37521   Publishing    Comedy
91539   Film & Video  Fantasy
158509  Design        Graphic Design
153941  Photography   Nature
73150   Film & Video  Action


91415   https://ksr-ugc.imgix.net/assets/012/398/589/ab669f7bb9d4e57cda38961f83ab8c00_
129264  https://ksr-ugc.imgix.net/assets/011/999/424/120549638f30900741a25165d1edbc19_
47424   https://ksr-ugc.imgix.net/assets/018/939/217/0a5d0a604df32a9b88f13d7f8b1c2b40_
95798   https://ksr-ugc.imgix.net/assets/012/362/580/8ea9156fcd2fbfdcb877245b234a8cda_
81896   https://ksr-ugc.imgix.net/assets/012/992/256/00247437636b4a12af72278a0a64783a_
37521   https://ksr-ugc.imgix.net/assets/019/751/771/faef47b9ed55abe55104dd4f203a9b80_
91539   https://ksr-ugc.imgix.net/assets/012/396/975/45ac776c9c9150daa8911070c6ad9b92_
158509  https://ksr-ugc.imgix.net/assets/011/664/503/ccb21dedc3eaf4c8ff9241a5c6461d0b_
153941  https://ksr-ugc.imgix.net/assets/011/705/848/f325257b3b7568528bd3610273d1ffce_
73150   https://ksr-ugc.imgix.net/assets/014/237/547/313fcd3fe48e986cd773474adc64558d_

                                                   slug          created_at  \
91415   the-white-oak-of-johnston-a-new-american-play  2016-03-05 22:28:19
129264  here-we-are                                    2015-01-13 21:33:58
47424   lets-hangout-the-best-shared-events-app        2017-10-11 15:32:22
95798   naheeds-gourmet-cuisine                        2016-01-24 21:25:10
81896   rip-rashawn                                    2016-07-08 00:32:56
37521   tha-wicked-kitchen-the-first-juggalo-cookbook  2018-01-03 04:24:12
91539   trinity-lesions-a-fantasy-thriller-short       2016-03-03 20:22:27
158509  mammoth-ski-and-racquet-club-t-shirt           2014-03-10 16:19:11
153941  american-nature                                2014-05-15 04:34:13
73150   portal-kidnapped-portal-origins-story          2016-10-24 11:26:08

                launched_at            deadline    state_changed_at  \
91415   2016-03-12 22:27:16  2016-05-11 21:27:16  2016-03-12 23:20:50
129264  2015-02-18 18:30:12  2015-03-20 17:30:12  2015-03-20 17:30:14
47424   2017-10-27 05:24:06  2017-12-26 06:24:06  2017-12-26 06:24:10
95798   2016-01-25 19:57:04  2016-02-24 19:57:04  2016-02-24 19:57:05
81896   2016-07-08 02:30:48  2016-08-07 02:30:48  2016-08-07 02:30:48
37521   2018-03-29 18:43:44  2018-05-13 18:43:44  2018-05-13 18:43:46
91539   2016-03-11 05:23:53  2016-04-10 04:23:53  2016-04-10 04:23:53
158509  2014-03-17 21:41:44  2014-04-26 21:41:44  2014-04-25 18:55:44
153941  2014-06-11 01:41:58  2014-07-31 01:41:58  2014-06-16 05:26:05
73150   2016-11-09 12:15:23  2016-12-09 12:15:23  2016-12-09 12:15:23

             last_update_at      status  creator_id         creator_name  \
91415   2016-03-05 22:28:19  canceled    2139680224  Thomas J. Morrissey
129264  2015-03-09 15:44:49  successful  1973179381  David Bellarosa
47424   2017-10-11 15:32:22  failed      648902740   WebLine Solutions
```

95798	2016-01-24 21:25:10	failed	1627713051	Naheed Syed
81896	2016-07-08 00:32:56	failed	530081902	Ronnie Sidney II
37521	2018-09-17 05:52:07	successful	1558256176	Brad Konsek-Valloni
91539	2016-03-03 20:22:27	failed	578730237	Stephanie Hyde
158509	2015-03-09 15:44:11	canceled	1230168064	Charles Engen
153941	2015-03-09 15:44:17	canceled	430919248	Marcus Lusky
73150	2016-10-24 11:26:08	failed	1507100940	Lars anda

	country	city	state	displ_loc \
91415	US	Armonk	NY	Armonk, NY
129264	US	Austin	TX	Austin, TX
47424	SV	San Salvador	San Salvador	San Salvador, El Salvador
95798	US	North Charleston	SC	North Charleston, SC
81896	US	Richmond	VA	Richmond, VA
37521	US	Seattle	WA	Seattle, WA
91539	US	Baltimore	MD	Baltimore, MD
158509	US	Mammoth Lakes	CA	Mammoth Lakes, CA
153941	US	Yosemite Village	CA	Yosemite Village, CA
73150	NO	Oslo	Oslo Fylke	Oslo, Norway

	loc_type	backers_count	featured	currency	goal_real \
91415	Town	1	no support	USD	50,000.0
129264	Town	312	full support	USD	26,000.0
47424	Town	0	no support	USD	13,000.0
95798	Town	0	no support	USD	100,000.0
81896	Town	2	no support	USD	3,500.0
37521	Town	63	spotlight	USD	1,500.0
91539	Town	3	no support	USD	1,100.0
158509	Town	4	no support	USD	420.0
153941	Town	2	no support	USD	1,000.0
73150	Town	0	no support	NOK	16,000.0

	goal_current_usd	goal_hist_usd	pledged_real \
91415	50,000.0	50,000.0	100.0
129264	26,000.0	26,000.0	30,410.0
47424	13,000.0	13,000.0	0.0
95798	100,000.0	100,000.0	0.0
81896	3,500.0	3,500.0	123.0
37521	1,500.0	1,500.0	2,755.0
91539	1,100.0	1,100.0	50.0
158509	420.0	420.0	80.0
153941	1,000.0	1,000.0	6.0
73150	1,798.1013611996004	1,881.231557259936	0.0

	pledged_current_usd	pledged_hist_usd	current_fx_rate(usd) \
91415	100.0	100.0	1.0
129264	30,410.0	30,410.0	1.0
47424	0.0	0.0	1.0

```
95798   0.0                 0.0               1.0
81896   123.0               123.0             1.0
37521   2,755.0             2,755.0           1.0
91539   50.0                50.0              1.0
158509  80.0                80.0              1.0
153941  6.0                 6.0               1.0
73150   0.0                 0.0               8.8982747832

        hist_exchange_rate(usd)
91415   1.0
129264  1.0
47424   1.0
95798   1.0
81896   1.0
37521   1.0
91539   1.0
158509  1.0
153941  1.0
73150   8.5050667677
```

Null values & Duplicates

Notice one observation with an empty creator name. It shouldn't cause any problems in the analysis. Also missing states won't bother, since there are locations like New Zealand or Antarctica, where states as organisational territories don't exist.

However, there are empty values in *country* of some observations. The assessment shows, the country Namibia, short "NA" was interpreted as a null value after we read in our csv files. Let's correct that.

In [6]:
```
# there is one project without the name of creator
master_df[master_df.creator_name.isna()]
```

Out[6]:
```
       project_id            project_name  \
97701  2298709     Cannabis Colouring Book

                                                                     url  \
97701  https://www.kickstarter.com/projects/498969171/cannabis-colouring-book

                                                                  blurb  \
97701  A Cannabis Colouring Book, 20 black and white prints by a Fine Artist

      category     subcategory  \
97701  Art      Conceptual Art


97701  https://ksr-ugc.imgix.net/assets/012/342/732/d13264538144cbd88347a1b50579e6e4_o

                          slug           created_at          launched_at  \
97701  cannabis-colouring-book  2015-12-31 05:21:47  2015-12-31 18:31:24
```

```
                  deadline     state_changed_at       last_update_at  status  \
97701  2016-01-30 18:31:24  2016-01-30 18:31:24  2015-12-31 05:21:47  failed

       creator_id creator_name country     city state    displ_loc loc_type  \
97701  498969171   NaN          US      Chicago   IL    Chicago, IL  Town

       backers_count    featured currency  goal_real  goal_current_usd  \
97701  1              no support  USD     2,500.0    2,500.0

       goal_hist_usd  pledged_real  pledged_current_usd  pledged_hist_usd  \
97701 2,500.0        4.2           4.2                 4.2

       current_fx_rate(usd)  hist_exchange_rate(usd)
97701 1.0                  1.0
```

In [7]:
```
# assess null values in state
master_df[master_df.state.isna()][['state','country', 'displ_loc', 'city']].sample(5)
```

Out[7]:

	state	country	displ_loc	city
23778	NaN	AQ	Antarctica	Antarctica
140430	NaN	NZ	South Oamaru, NZ	South Oamaru
20067	NaN	NZ	Taupo, NZ	Taupo
3291	NaN	NZ	Taupo, NZ	Taupo
32104	NaN	XK	Pristina, Kosovo	Pristina

In [8]:
```
# several projects with missing country, which should be Namibia instead of NaN
master_df[master_df.country.isna()][['country', 'displ_loc']]
```

Out[8]:

	country	displ_loc
19347	NaN	Windhoek, Namibia
40976	NaN	Walvis Bay, Namibia
59198	NaN	Windhoek, Namibia
74927	NaN	Windhoek, Namibia
86451	NaN	Tsumkwe, Namibia
101130	NaN	Rundu, Namibia
101191	NaN	Okahandja, Namibia
105663	NaN	Windhoek, Namibia
183865	NaN	Walvis Bay, Namibia

In [9]:
```
# replace NaN by "NA"
master_df.country.fillna("NA", inplace=True)

# test
master_df[master_df.country.isna()][['country', 'displ_loc']]
```

Out[9]:
```
Empty DataFrame
Columns: [country, displ_loc]
Index: []
```

In [10]: # duplicates
```
master_df.duplicated().sum()
```

Out[10]: 0

Outliers

In [11]: # show descriptive statistics of each numeric variable
```
master_df.describe()
```

Out[11]:

	project_id	creator_id	backers_count
count	184,909.0	184,909.0	184,909.0
mean	2,195,092.092656388	1,074,463,036.5046158	133.61772547577456
std	1,085,587.0335574246	620,158,412.854741	873.6055966262201
min	19.0	3.0	0.0
25%	1,365,660.0	537,822,751.0	3.0
50%	2,329,722.0	1,073,670,955.0	23.0
75%	3,161,115.0	1,612,081,008.0	81.0
max	3,775,211.0	2,147,483,434.0	105,857.0

	goal_real	goal_current_usd	goal_hist_usd
count	184,909.0	184,909.0	184,909.0
mean	53,178.173466840446	43,125.31016430783	44,164.54284856914
std	1,251,484.5834085431	1,129,656.0699383984	1,165,270.6918196438
min	0.01	0.01	0.01
25%	1,500.0	1,500.0	1,500.0
50%	5,000.0	5,000.0	5,000.0
75%	15,000.0	13,104.902477181711	14,000.0
max	100,000,000.0	121,822,933.67875078	150,099,318.94817606

	pledged_real	pledged_current_usd	pledged_hist_usd
count	184,909.0	184,909.0	184,909.0
mean	16,481.028197978463	11,572.573042683343	11,739.976538271778
std	361,532.80395922204	89,427.97724549935	89,972.85909344895
min	0.0	0.0	0.0
25%	75.0	70.0	72.2348210697422
50%	1,275.0	1,228.0	1,259.9222798694514
75%	6,125.0	5,787.0	5,910.0
max	98,863,825.0	11,385,449.05	11,385,449.05

	current_fx_rate(usd)	hist_exchange_rate(usd)
count	184,909.0	184,909.0
mean	1.5133052788138077	1.486521775516778
std	4.758657265159066	4.868749652889349
min	0.8208635023	0.5826048629999999
25%	1.0	1.0
50%	1.0	1.0
75%	1.0	1.0
max	106.46285867520001	113.9401218152

The descriptive statistics above reveal an extreme range of values for the number backers, project goals and the pledged funding. For example, the collected funding of a campaign may vary between zero to more than USD 11mi (pledged_hist_usd). In the following analysis, I will need to pay extra attention to outliers and extreme values.

Time Variables and Project Duration

There are several time-related features to be converted to pandas date time format for analysis.

The funding period of is one of the features a creator has to decide on before launching a project. I suppose it may affect the success of the campaign. I will add the duration as a new feature to this data set.

```
In [12]: # convert time data to date time format
         master_df[['created_at', 'launched_at', 'state_changed_at', 'deadline', 'last_update_a
```

```
In [13]: # engineer variable to asses funding duration
         master_df['duration'] = master_df['deadline'] - master_df['launched_at']
         master_df[['launched_at', 'deadline', 'duration']].sample(5)
```

```
Out[13]:                launched_at            deadline          duration
         5996   2019-05-18 17:23:19 2019-06-17 17:23:19 30 days 00:00:00
         114612 2015-06-23 05:43:11 2015-07-23 05:43:11 30 days 00:00:00
         40619  2018-02-10 14:11:18 2018-03-12 13:11:18 29 days 23:00:00
         56651  2017-06-22 13:07:15 2017-07-06 11:06:00 13 days 21:58:45
         167626 2013-05-15 12:03:00 2013-07-01 03:59:00 46 days 15:56:00
```

```
In [14]: # convert duration time delta to float of days
         master_df['duration_days'] = (master_df['duration'].astype('timedelta64[h]') / 24)
```

```
In [15]: # the first project ever launched
         first_project_launched = master_df.sort_values(by='launched_at', ascending=True).iloc
         first_project_launched[['project_name', 'blurb', 'url', 'launched_at', 'deadline', 'du
```

```
Out[15]: project_name        New York Makes a Book!!
         blurb               Let's make the world's first crowd-funded book! \r\n\r\nNew York M
         url                 https://www.kickstarter.com/projects/nymab/new-york-makes-a-book
         launched_at         2009-04-28 11:55:41
         deadline            2009-05-16 09:59:00
         duration            17 days 22:03:19
         goal_hist_usd      3,000.0
         pledged_hist_usd   3,329.0
         city                New York
         Name: 184908, dtype: object
```

```
In [16]: # the first project ever funded
         first_project_funded = master_df.sort_values(by='deadline', ascending=True).iloc[0, :]
         first_project_funded[['project_name', 'blurb', 'url', 'launched_at', 'deadline', 'dura
```

```
Out[16]: project_name        New York Makes a Book!!
         blurb               Let's make the world's first crowd-funded book! \r\n\r\nNew York M
         url                 https://www.kickstarter.com/projects/nymab/new-york-makes-a-book
```

```
launched_at          2009-04-28 11:55:41
deadline             2009-05-16 09:59:00
duration             17 days 22:03:19
goal_hist_usd       3,000.0
pledged_hist_usd    3,329.0
city                 New York
status               successful
Name: 184908, dtype: object
```

In [17]:
```
# the latest launched project
latest_project = master_df.sort_values(by='launched_at', ascending=False).iloc[0, :]
latest_project[['project_name', 'blurb', 'url', 'launched_at', 'deadline', 'duration'
```

Out[17]:
```
project_name         Shirt and hat
blurb                I'm just going to say it, I'm not special. I'm pretty mediocre so
url                  https://www.kickstarter.com/projects/dima01/shirt-and-hat
launched_at          2019-07-18 05:04:48
deadline             2019-08-17 05:04:48
duration             30 days 00:00:00
goal_hist_usd       5,000.0
pledged_hist_usd    0.0
city                 Wasilla
Name: 0, dtype: object
```

Kickstarter's 10 year anniversary was 28th April 2019. The first project on Kickstarter was launched 28/04/2009, which was also the first project ever successfully funded. The latest project launched in this data set was by 18/07/2019.

As we would like to analyze 10 years of Kickstarter data, we are going to only include projects, that were funded between May 2009 and April 2019.

In [18]:
```
# filter by campaigns that ended before before May 2019
master_df = master_df[master_df.deadline < '05-01-2019']
```

In [19]:
```
# the latest funded project
latest_project_funded = master_df.sort_values(by='deadline', ascending=False).iloc[0,
latest_project_funded[['project_name', 'blurb', 'url', 'launched_at', 'deadline', 'du
```

Out[19]:
```
project_name         Divine Passerine II - The BIRDENING
blurb                A beautiful new collection of hard enamel bird pins
url                  https://www.kickstarter.com/projects/yseulta/divine-passerine-ii-
launched_at          2019-04-10 23:01:14
deadline             2019-04-30 23:01:14
duration             20 days 00:00:00
goal_hist_usd       392.6300000198906
pledged_hist_usd    1,371.9614000695035
city                 Dublin
Name: 9222, dtype: object
```

In [20]:
```
# the latest project that was launched
latest_project_launched = master_df.sort_values(by='launched_at', ascending=False).ilo
latest_project_launched[['project_name', 'blurb', 'url', 'launched_at', 'deadline', 'c
```

Out[20]:
```
project_name        Who Shot J.R.?
blurb               A component-free storytelling & memory game
url                 https://www.kickstarter.com/projects/1610277086/who-shot-jr
launched_at         2019-04-23 14:56:32
deadline            2019-04-30 14:56:32
duration            7 days 00:00:00
goal_hist_usd      10.0
pledged_hist_usd   321.0
city                Trenton
Name: 8319, dtype: object
```

Categories

In [21]:
```
# show example of subcategory with multiple parent categories
master_df[master_df.subcategory == 'Web'][['category', 'subcategory']].sample(5)
```

Out[21]:

	category	subcategory
59276	Technology	Web
75160	Technology	Web
55896	Technology	Web
141758	Journalism	Web
128890	Journalism	Web

There are project categories and subcategories in our dataset. The same subcategory may have different parent categories. For example, the subcategory "Web" may be refer to the parent category "Technology" or "Journalism". In order to be explicit about categories, I create a combined category for both category types for each project.

In [22]:
```
# create combined category
master_df['comb_cat'] = master_df['category'] + "/" + master_df['subcategory']
master_df[['category', 'subcategory','comb_cat']].sample(5)
```

Out[22]:

	category	subcategory	comb_cat
87546	Crafts	Crafts	Crafts/Crafts
70172	Film & Video	Drama	Film & Video/Drama
142365	Games	Mobile Games	Games/Mobile Games
39687	Music	Indie Rock	Music/Indie Rock
89927	Theater	Plays	Theater/Plays

Project status

In [23]:
```
# show possible state of projects
master_df.status.value_counts()
```

Out[23]:
```
successful     93006
failed         72446
canceled       8372
suspended      622
Name: status, dtype: int64
```

Most projects were successfully completed or failed by the end of the funding period. The project statuses show a relatively small amount of unfinished projects, which were either canceled or suspended. As I am mostly interested in identifying what makes campaigns successful, I will focus on completed projects only during this analysis.

```
In [24]: # create a separate data frame for completed projects only
         ks_compl = master_df.query('(status == "successful") | (status == "failed")')
         ks_compl.reset_index(drop=True, inplace=True)
         ks_compl.status.value_counts()

Out[24]: successful    93006
         failed        72446
         Name: status, dtype: int64
```

Irrelevant features

```
In [25]: # remove columns that are irrelevant to our analysis to keep our dataframe neat
         ks_compl = ks_compl.drop(labels=['slug', 'created_at', 'last_update_at', 'state_change
                                          'goal_real', 'goal_current_usd','pledged_real', 'ple
                                          'current_fx_rate(usd)', 'hist_exchange_rate(usd)'], a
         ks_compl.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 165452 entries, 0 to 165451
Data columns (total 24 columns):
project_id          165452 non-null int64
project_name        165452 non-null object
url                 165452 non-null object
blurb               165452 non-null object
category            165452 non-null object
subcategory         165452 non-null object
image               165452 non-null object
launched_at         165452 non-null datetime64[ns]
deadline            165452 non-null datetime64[ns]
status              165452 non-null object
creator_id          165452 non-null int64
creator_name        165451 non-null object
country             165452 non-null object
city                165452 non-null object
state               165407 non-null object
loc_type            165452 non-null object
backers_count       165452 non-null int64
featured            165452 non-null object
currency            165452 non-null object
goal_hist_usd       165452 non-null float64
pledged_hist_usd    165452 non-null float64
duration            165452 non-null timedelta64[ns]
duration_days       165452 non-null float64
comb_cat            165452 non-null object
```

```
dtypes: datetime64[ns](2), float64(3), int64(3), object(15), timedelta64[ns](1)
memory usage: 30.3+ MB
```

The structure of the dataset

This cleaned dataset contains information on 10 years of Kickstarter projects; from Kickstarter's launch in late April 2009 to 30/04/2019. The main focus of my analysis are completed projects: projects that were either successfully funded or failed the funding. The dataset of completed projects is composed of 165,452 rows. Each row represents a project.

As for the features of this dataset, there are 24 variables that have been selected. We got quantitative variables like goal or pledged, several time-related variables and qualitative data, like project categories, names and project states.

Featured

are categorical values. It describes to what extent Kickstarter supported a campaign.

Kickstarter applies two different strategies to promote projects. One possibility is to award the badge "Projects We Love", meaning a project was recommended by staff. The badge will be shown on the project's description page.
The other possibility of promotional support is by *spotlighting* a project in some way in one of the sections on Kickstarter's landing page. According to Kickstarter's guide, they may also advertise projects in their newsletters or social media channels. However, the data set does not provide any information on how a project was spotlighted exactly. Obviously, projects can also be supported in both ways: being awarded the badge and being spotlighted on the landing page. The following variables describe Kickstarter's promotional efforts:

- *no support:* Kickstarter does not spotlight a project on their website, nor award the *Projects We Love* badge,
- *Projects We Love:* Kickstarter awards *Projects We Love* badge without any further spotlighting
- *spotlight:* Kickstarter spotlights a project on their landing page without awarding a badge
- *full support:* Kickstarter spotlights a project on their landing page and awards the *Projects We Love* badge

Currencies

To allow comparison of the project's financial features, I converted all project currencies to USD. Since the funding of a campaign is estimated best by their capital value at the time of the funding, I used historic exchange rates based on the date of the campaign deadline. Please refer to the wrangle notebook for further information.

Main feature of interest

The main feature that I will explore is the *status* of a project. It depicts whether the crowdfunding was **successful or failed**.

Supporting features

Undoubtedly, there are many different factors that may affect the success or failure of a crowdfunding campaign. In the course of this data set, I suspect the following factors to be most influential on a project:

- the amount of the initial funding goal: *goal hist usd*
- the amount pledged: *pledged hist usd*
- the number of backers: *backers count*
- the promotional support provided by Kickstarter: *featured*
- the project categories: *category, subcategory, comb cat*

- the dates of the project's launch and deadline: *launched at*, *deadline*
- the duration period of a funding: *duration*
- the location of a project: *country*, *loc type*.

5 3 Utilities

In this section, I set up commonly used variables and functions that come in handy for the analysis and help reduce repetition of code.

```
In [26]: # create separate data frames for successful and failed projects
         ks_compl_success = ks_compl[ks_compl.status == "successful"]
         ks_compl_failed = ks_compl[ks_compl.status == "failed"]
```

```
In [27]: # create dataframe containing yearly project counts
         ks_year_count = ks_compl.copy()
         ks_year_count = ks_year_count.groupby([ks_year_count.deadline.dt.year]).project_id.cou
         ks_year_count = ks_year_count.reset_index(name='count_year')

         # create dataframe containing monthly project counts
         ks_month_count = ks_compl.copy()
         ks_month_count = ks_month_count.groupby([ks_month_count.deadline.dt.month]).project_i
         ks_month_count = ks_month_count.reset_index(name='count_month')
         ks_month_count.head()

         # create dataframe containing monthly project counts for each year
         monthly_count = ks_compl.copy()
         monthly_count = monthly_count.groupby([monthly_count.deadline.dt.year,
                                               monthly_count.deadline.dt.month])\
                                               .project_id.count().values
         ks_monthly_counts = pd.DataFrame({'date':np.arange('2009-05', '2019-05', dtype='datet
                                          'count_monthly': monthly_count})

         ks_monthly_counts.sample(5)
```

Out[27]:

	date	count_monthly
57	2014-02-01	726
71	2015-04-01	3520
84	2016-05-01	2532
14	2010-07-01	106
26	2011-07-01	370

```
In [28]: # define commonly used colors
         cust_green = '#66cdaa'
         cust_red = '#f08080'
         cust_blue = '#43a2ca'
         status_colors = [cust_blue, cust_green, cust_red]
         cust_purple = sns.color_palette("Pastel1")[3]
         cust_blues = sns.color_palette("Blues_r")[3]
```

```
        feat_color = sns.color_palette("Set1")
        fill_red = '#fee0d2'
        fill_green = '#e0f3db'
        goal_color =  sns.color_palette("Blues_r")[0]
        pledged_color = "#c994c7"
        backers_color = '#a6611a'
        duration_color = '#5e3c99'
        category_colors = ['#a6cee3','#e5c494', '#1f78b4', '#33a02c', '#fb9a99', '#b3b3b3', '#
                           '#ff7f00', '#cab2d6', '#6a3d9a', '#b2df8a', '#984ea3', '#ffd92f',
        success_colors = ['#66a61e', '#1b9e77','#d95f02','#e41a1c']
```

```
In [29]: # utility to improve readability of large numbers
         def format_num(num):
             num = round(float(num))
             formatted_num = str(num)
             str_length = len(formatted_num)
             cursor = str_length % 3
             if str_length > 3 and cursor > 0:
                 formatted_num = formatted_num[0:cursor] + "," + formatted_num[cursor:]
                 cursor += 1
                 str_length = str_length - cursor
             while str_length > 3:
                 formatted_num = formatted_num[0:cursor+3] + "," + formatted_num[cursor+3:]
                 cursor += 4
                 str_length -= 3
             return formatted_num

         # utility to format yticks
         def format_yticks(maximum, step, minimum=0):
             ylocs = np.arange(minimum, maximum+step, step)
             ylabels = [format_num(yloc) for yloc in ylocs]
             plt.yticks(ylocs, ylabels)

         # utility to format xticks
         def format_xticks(maximum, step, minimum=0):
             xlocs = np.arange(minimum, maximum+step, step)
             xlabels = [format_num(xloc) for xloc in xlocs]
             plt.xticks(xlocs, xlabels)
```

```
In [30]: # utility to log transform data
         def log_trans(x, inverse = False):
             if not inverse:
                 return np.log10(x)
             else:
                 return np.power(10, x)
```

```
In [31]: # utility to create xticks for a timeline
         def timeline_ticks(df):
```

```
    x_labels = np.arange('2009-05', '2019-05', 7, dtype='datetime64[M]')
    x_ticks = np.arange(0,len(df), 7)
    plt.xticks(x_ticks,x_labels, rotation=45, ha='right')
    plt.xlabel("")
```

In [32]:
```
# frequently used variables
dates = np.arange('2009-05', '2019-05', dtype='datetime64[M]')
month_names = ["January", "February", "March", "April", "May", "June",
               "July", "August", "September","October", "November", "December"]
months = ["July", "August", "September",
          "October", "November", "December", "January",
          "February", "March", "April", "May", "June"]
```

6 4 Descriptive Statistics

To understand the characteristics of our main features, I'm going to start by computing descriptive statistics.

How many projects were completed by Kickstarter's 10th anniversary?

In [33]:
```
n_compl_projects = ks_compl.project_id.nunique()
format_num(n_compl_projects)
```

Out[33]: '165,452'

How many creators contributed by Kickstarter's 10th anniversary?

In [34]:
```
creators_unique = ks_compl.creator_id.nunique()
format_num(creators_unique)
```

Out[34]: '144,141'

What are the descriptive statistics of the numeric supporting features?

In [35]:
```
# descriptive statistics of numeric values
ks_compl[['backers_count', 'goal_hist_usd', 'pledged_hist_usd', 'duration']].describe
```

Out[35]:

	backers_count	goal_hist_usd	pledged_hist_usd \
count	165,452.0	165,452.0	165,452.0
mean	135.87277881198173	41,609.39954329339	11,829.218299924965
std	879.6782897111349	1,120,318.782513759	85,552.3359362955
min	0.0	0.01	0.0
25%	3.0	1,500.0	100.0
50%	25.0	5,000.0	1,454.0
75%	84.0	13,119.62814922761	6,221.100134982495
max	105,857.0	150,099,318.94817606	11,385,449.05

	duration
count	165452
mean	32 days 15:57:02.739894

```
std     11 days 18:03:37.653279
min      1 days 00:00:00
25%     29 days 23:00:00
50%     30 days 00:00:00
75%     34 days 04:24:19
max     93 days 02:32:04
```

Since Kickstarter's launch, USD {{format_num(ks_compl_success['pledged_hist_usd'].sum())}} successful funding dollars were collected.

Independent from a project's success, USD {{format_num(master_df['pledged_hist_usd'].sum())}} of funding was collected within 10 years. Apparently, only a relatively small percentage was not distributed due to Kickstarter all-or-nothing approach to funding.

How many backers have supported completed projects by Kickstarter's 10th anniversary?

```
In [36]: backers_sum = ks_compl.backers_count.sum()
         format_num(backers_sum)
```

```
Out[36]: '22,480,423'
```

What were the chances to complete projects successfully?
First, assess the success probabilities of all campaigns. Second, calculate the success probabilities for completed projects only.

```
In [37]: # calculate total counts of each status from the master data set
         n_success = len(master_df[master_df.status == "successful"])
         n_failed = len(master_df[master_df.status == "failed"])
         n_canceled = len(master_df[master_df.status == "canceled"])
         n_suspended = len(master_df[master_df.status == "suspended"])
         n_total = len(master_df)
         print(format_num(n_success), "projects were successfully funded.")
```

```
93,006 projects were successfully funded.
```

```
In [38]: # status probability of all projects
         p_success = n_success / n_total
         p_failed = n_failed / n_total
         p_canceled = n_canceled / n_total
         p_suspended = n_suspended / n_total
         print("Successful projects: {}%.".format(round(p_success*100,2)))
         print("Failed projects: {}%.".format(round(p_failed*100, 2)))
         print("Canceled projects: {}%.".format(round(p_canceled*100, 2)))
         print("Suspended projects: {}%.".format(round(p_suspended*100, 2)))
```

```
Successful projects: 53.32%.
Failed projects: 41.53%.
Canceled projects: 4.8%.
Suspended projects: 0.36%.
```

```
In [39]: # status probability of ordinarily completed projects
         n_compl_success = len(ks_compl[ks_compl.status == "successful"])
         n_compl_fail = len(ks_compl[ks_compl.status == "failed"])
         p_compl_success = n_compl_success / n_compl_projects
         p_compl_fail = n_compl_fail / n_compl_projects
         print("Success: {}%.".format(round(p_compl_success*100,2)))
         print("Failed: {}%.".format(round(p_compl_fail*100, 2)))
```

```
Success: 56.21%.
Failed: 43.79%.
```

How many projects do creators usually run?

```
In [40]: # number of unique project creators
         n_compl_creators_unique = ks_compl.creator_id.nunique()
         format_num(n_compl_creators_unique)
```

```
Out[40]: '144,141'
```

```
In [41]: # project counts per user
         power_users = (ks_compl['creator_id'].value_counts()
                 .reset_index()
                 .rename(index=str, columns={"creator_id": "project_count"})['project_count']
                 .value_counts()
                 .reset_index()
                 .rename(index=str, columns={"index": "project_count", "project_count": "creat
                 .sort_values(by='project_count', ascending=False))

         print(f"Proportion of users with 1 project: {round(power_users['creator_count'].values
         print(f"Proportion of users with 2 project: {round(power_users['creator_count'].values
         power_users
```

```
Proportion of users with 1 project: 91.0%
Proportion of users with 2 project: 6.0%
```

Out[41]:

	project_count	creator_count
31	68	1
24	54	1
30	35	1
29	34	1
28	33	1
27	32	1
26	31	1
23	30	2
25	27	1
19	24	5
21	23	3

```
20   21          3
18   20          7
22   19          2
16   18          7
13   17          9
15   16          8
14   15          9
17   14          7
12   13         17
11   12         21
9    11         33
10   10         30
8    9          44
7    8          62
6    7         101
5    6         188
4    5         345
3    4         689
2    3        1983
1    2        9157
0    1      131401
```

In [42]:
```
# What kind of projects did the most active user launch?
creators_ordered = ks_compl.creator_id.value_counts().index
print(f"username: {ks_compl[ks_compl.creator_id == creators_ordered[0]]['creator_name
ks_compl[ks_compl.creator_id == creators_ordered[0]]
```

```
username: Collectable Playing Cards
```

Out[42]:
```
       project_id  \
8581     3504998
12444    3372265
13725    3460006
15690    3455599
16952    3427450
21142    3393416
22518    3377666
24613    3354163
26866    3312725
28474    3300497
29819    3272726
30921    3238805
31631    3178449
32611    3220166
33779    3143358
34868    3156729
```

36045	3156701
37286	3141084
38096	3139736
40508	3101579
42769	3069811
43776	3040674
45192	3027536
46370	2930595
47207	2962784
48759	2941226
49922	2919809
51310	2876799
52476	2872774
53994	2864425
55055	2842165
57173	2795714
58251	2777007
59845	2750267
61724	2711161
62523	2657711
63583	2677562
64578	2532350
65694	2634233
66600	2622739
69662	2557085
74664	2455648
75423	2435733
79126	2357424
81866	2316696
83309	2280017
87582	2196328
89849	2149135
90875	2127895
95473	2035414
97270	1992818
102688	1900583
107223	1762421
112057	1637481
114555	1642708
115716	1642040
117551	1546121
118918	1547364
119822	1508905
122537	1459054
124416	1167048
128195	1294634
132727	1090862
135538	1026828

```
136439  1027487
138360  952804
139187  932083
141138  838197

                                             project_name  \
8581    Bicycle Stained Glass Leviathan Playing Cards
12444   BICYCLE MARBLE Playing Cards by Max
13725   Bicycle Limited Edition Bald Eagle Playing Cards
15690   Bicycle Explostar Playing Cards
16952   Bicycle Limited Edition Gyrfalcon Playing Cards
21142   Bicycle Antiques Playing Cards
22518   Bicycle Carnival Playing Cards & Stripper Deck Magic Trick
24613   Bicycle Okeanos Playing Cards
26866   Bicycle Stained Glass Phoenix Playing Cards
28474   Bicycle Open Season Playing Cards
29819   Bicycle Prism Gilded Limited Edition (Red) Playing Cards
30921   Bicycle Koi Playing Cards
31631   Bicycle Limited Edition CPC 100th Deck Design
32611   Bicycle Fireflies Playing Cards
33779   Bicycle MARBLE RIDER BACK Playing Cards by Max
34868   Bicycle Four Seasons Limited Edition (Summer) Playing Cards
36045   Bicycle Four Seasons Limited Edition (Spring) Playing Cards
37286   Bicycle Four Seasons Limited Edition (Winter) Playing Cards
38096   Bicycle Four Seasons Limited Edition (Autumn) Playing Cards
40508   Bicycle Human Evolution Playing Cards
42769   Bicycle Starlight Solar Playing Cards
43776   Bicycle Four Seasons Playing Cards
45192   Bicycle Vintage Classic Playing Cards
46370   Bicycle METAL RIDER BACK (BLUE EDITION) Playing Cards by Max
47207   Bicycle Natural Disasters "Blizzard" Playing Cards
48759   Bicycle Natural Disasters "Tsunami" Playing Cards
49922   Bicycle Natural Disasters "Hurricane" Playing Cards
51310   Bicycle Natural Disasters "Tornado" Playing Cards
52476   Bicycle Natural Disasters "Earthquake" Playing Cards
53994   Bicycle Natural Disasters "Wildfire" Playing Cards
55055   Bicycle Natural Disasters "Volcano" Playing Cards
57173   Bicycle NYX Playing Cards
58251   Bicycle Heir Playing Cards
59845   Bicycle Cinema Playing Cards
61724   Bicycle Denim Playing Cards
62523   Bicycle Nocturnal Playing Cards
63583   Bicycle Prism Gilded Limited Edition Playing Cards
64578   Bicycle WOOD RIDER BACK Playing Cards by Max
65694   Bicycle Old Parchment Playing Cards
66600   Gluttony Playing Cards
69662   Bicycle Frost Playing Cards
74664   Bicycle Starlight Lunar Playing Cards
```

```
75423   Bicycle Aurora Playing Cards
79126   Bicycle Starlight Shooting Star Playing Cards
81866   Bicycle Limited Edition Vincent's Royals Playing Cards
83309   Bicycle Mummies Playing Cards
87582   Bicycle Limited Edition Black Rose Playing Cards
89849   Bicycle Limited Edition Sistine Playing Cards
90875   Bicycle Gnomes Playing Cards
95473   Bicycle Bellezza Playing Cards
97270   Bicycle Elemental Earth, Wind & Fire Playing Cards
102688  Bicycle Stained Glass Playing Cards
107223  Bicycle Fireworks Playing Cards
112057  Bicycle Robotics Playing Cards
114555  Bicycle US Presidents Playing Cards
115716  Bicycle Starlight Black Hole Playing Cards
117551  Bicycle Ancient Machine Playing Cards
118918  Bicycle Redcore Playing Cards
119822  Bicycle Essence Playing Cards
122537  Bicycle Blue & White Collar Playing Cards
124416  Bicycle METAL RIDER BACK Playing Cards by Max
128195  Bicycle Panthera Playing Cards
132727  Bicycle Disruption Playing Cards
135538  Physique Playing Cards printed by USPCC
136439  Bicycle Starlight Playing Cards
138360  Bicycle Limited Edition Elegance Playing Cards
139187  Bicycle Killer Clowns Playing Cards
141138  Bicycle Old Masters Playing Cards
```

```
8581    https://www.kickstarter.com/projects/2104052526/bicycle-stained-glass-leviatha
12444   https://www.kickstarter.com/projects/2104052526/bicycle-marble-playing-cards-l
13725   https://www.kickstarter.com/projects/2104052526/bicycle-limited-edition-bald-e
15690   https://www.kickstarter.com/projects/2104052526/bicycle-cardistry-explostar-pl
16952   https://www.kickstarter.com/projects/2104052526/bicycle-limited-edition-gyrfal
21142   https://www.kickstarter.com/projects/2104052526/bicycle-antiques-playing-cards
22518   https://www.kickstarter.com/projects/2104052526/bicycle-carnival-playing-cards
24613   https://www.kickstarter.com/projects/2104052526/bicycle-okeanos-playing-cards
26866   https://www.kickstarter.com/projects/2104052526/bicycle-stained-glass-phoenix-
28474   https://www.kickstarter.com/projects/2104052526/bicycle-open-season-playing-ca
29819   https://www.kickstarter.com/projects/2104052526/bicycle-prism-gilded-limited-e
30921   https://www.kickstarter.com/projects/2104052526/bicycle-koi-playing-cards
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141138	https://www.kickstarter.com/projects/2104052526/bicycle-old-masters-playing-ca

8581 The Leviathan Sea Monster takes form as the 3rd edition in the Stained Glass S
12444 The NEW GENERATION of the TEXTURE SERIES by Max (Max Playing Cards)
13725 The emblem bird of the United States The Bald Eagle, is now a limited edition
15690 Collectable Playing Cards first Cardistry deck is ready and set to explode ont
16952 The largest falcon in the world now a limited edition Bicycle playing cards de
21142 Travel back in time with the Bicycle Antiques Deck
22518 Grab your popcorn and cotton candy The Bicycle Carnival deck is coming to town
24613 Hit the waters with The Bicycle Okeanos Playing Cards
26866 The Stained Glass Phoenix Playing Cards emerges from its ashes.
28474 Get your rifles and arrows ready for the Open Season Playing Cards!
29819 Print run of only 1000 numbered Bicycle Prism Gilded Limited Edition (Red) Pla
30921 It is time to relax with The Bicycle Koi Playing Cards
31631 The leader in custom designed playing cards celebrates their 100th deck!
32611 Collect as many as you can with The Bicycle Fireflies Deck!
33779 The LAST deck in the RIDER BACK TEXTURE SERIES by Max (Max Playing Cards)
34868 Enjoy all the seasons all year long with Bicycle Four Seasons Playing Cards
36045 Enjoy all the seasons all year long with Bicycle Four Seasons Playing Cards
37286 Enjoy all the seasons all year long with Bicycle Four Seasons Playing Cards
38096 Enjoy all the seasons all year long with Bicycle Four Seasons Playing Cards
40508 Motion Deck - Homo-sapiens evolve before your eyes as you flip through Bicycle
42769 The Bicycle Starlight Solar Playing Cards are a rare sight to see, don't miss
43776 Enjoy all the seasons all year long with Bicycle Four Seasons Playing Cards
45192 We've blown the dust off of Bicycle Vintage for you to display for all to see
46370 The new unlimited METAL DECK by Max (Max Playing Cards) in the TEXTURE SERIES
47207 Seventh Deck in a Seven Deck Natural Disaster Collector Series. GET THE ENTIRE
48759 Sixth Deck in a Seven Deck Natural Disaster Collector Series
49922 Fifth Deck in a Seven Deck Natural Disaster Collector Series
51310 Fourth Deck in a Seven Deck Natural Disaster Collector Series
52476 Third Deck in a Seven Deck Natural Disaster Collector Series
53994 Second Deck in a Seven Deck Natural Disaster Collector Series
55055 First Deck in a Seven Deck Natural Disaster Collector Series
57173 The Goddess of the Night's will watch over you in your darkest hour.
58251 The Heir deck shall be passed down for generations to come!
59845 See real live motion with The Bicycle Cinema Deck. Flip through the backs of t
61724 The Bicycle Denim Deck Is Forever In Blue Jeans
62523 The Nocturnal Deck will keep you company during those long sleepless nights.
63583 Collectable Playing Cards has partnered up with USPCC to release a Limited Edi
64578 The SECOND deck in the TEXTURE SERIES by MAX (Max Playing Cards)
65694 We have discovered Bicycle Old Parchment Playing Cards and we are bringing the
66600 Feast like a King with Gluttony Playing Cards
69662 Cool off during the hot summer months with the Bicycle Frost Deck
74664 Bicycle Starlight Lunar only comes around once in a lifetime
75423 Witness the golden gleam of the Aurora Playing Cards for yourself and be one o
79126 Look up! Bicycle Starlight Shooting Star is here!
81866 One of the most famous artists in the world gave us his art to admire, to insp
83309 The Mummies deck is here and they are hauntingly beautiful. Printed by USPCC a

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87582   The Bicycle Limited Edition Black Rose deck is a dark yet beautiful design wi
89849   Bicycle Branded Sistine Playing Cards - Limited to 1000 numbered decks.
90875   Bicycle Gnomes Playing Cards by Collectable Playing Cards bringing custom art
95473   Beautifully crafted Italian Bicycle design printed by USPCC.
97270   The Bicycle Elemental series is a 4 deck series with the first 3 decks (Earth
102688  The Bicycle Stained Glass Deck is so beautiful that it belongs in a museum!
107223  The Bicycle Fireworks deck. These beautiful explosions in the sky will leave
112057  The Robotics Deck by Collectable Playing Cards is taking you into the future!
114555  America, synonymous with liberty and young enough to fit all 44 of its leader
115716  This 2nd deck in the Starlight series displays a glorious abyss of glowing st
117551  One for the ages! This deck has the makings of a futuristic, yet olden day de
118918  An almost hypnotizing Bicycle Deck by Collectable Playing Cards
119822  The Bicycle Essence and Essence Lux Playing Cards are beautifully crafted to
122537  Limited Edition 100% Custom Bicycle Playing Cards Honoring the Blue & White C
124416  The METAL DECK is the very first deck on a series called TEXTURE SERIES by Ma
128195  You can almost hear the roar of the tiger in each one of Bicycle's hand drawn
132727  Get ready for the most fun you'll have with a playing deck ever with the Disr
135538  Johnny Whaam, the designer of Old Masters and Elegance deck brings to you his
136439  Catch a glimmer of the luminescent Bicycle Starlight Deck.
138360  The Bicycle Elegance deck is one of the highest quality decks ever created. P
139187  The Bicycle Killer Clowns Playing Cards introduces the most crazy, demonic an
141138  Old Masters playing cards - Johnny Whaam brings you a collection of the great

       category     subcategory  \
8581    Games    Playing Cards
12444   Games    Playing Cards
13725   Games    Playing Cards
15690   Games    Playing Cards
16952   Games    Playing Cards
21142   Games    Playing Cards
22518   Games    Playing Cards
24613   Games    Playing Cards
26866   Games    Playing Cards
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45192   Games    Playing Cards
46370   Games    Playing Cards
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47207	Games	Playing Cards
48759	Games	Playing Cards
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141138	Design	Graphic Design

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52476  2017-03-03 23:52:18 2017-04-02 22:52:18  successful  2104052526
53994  2017-02-10 18:34:01 2017-03-12 17:34:01  successful  2104052526
55055  2017-01-27 17:02:25 2017-02-26 17:02:25  successful  2104052526
57173  2016-12-21 17:46:05 2017-01-20 17:46:05  successful  2104052526
58251  2016-12-01 17:18:22 2016-12-31 17:18:22  successful  2104052526
59845  2016-11-10 17:19:08 2016-12-10 17:19:08  successful  2104052526
61724  2016-10-14 16:36:30 2016-11-13 17:36:30  successful  2104052526
62523  2016-10-03 18:07:18 2016-11-02 18:07:18  successful  2104052526
63583  2016-09-16 16:37:11 2016-10-17 16:37:11  successful  2104052526
64578  2016-09-01 17:00:05 2016-10-01 17:00:05  successful  2104052526
65694  2016-08-15 18:57:44 2016-09-14 18:57:44  successful  2104052526
66600  2016-08-01 19:13:19 2016-08-31 19:13:19  successful  2104052526
69662  2016-06-15 16:17:53 2016-07-15 16:17:53  successful  2104052526
74664  2016-04-12 18:26:49 2016-05-12 18:26:49  successful  2104052526
75423  2016-04-03 17:57:10 2016-05-03 17:57:10  successful  2104052526
79126  2016-02-18 19:27:50 2016-03-19 18:27:50  successful  2104052526
81866  2016-01-16 18:46:29 2016-02-21 18:46:29  successful  2104052526
83309  2015-12-22 17:13:10 2016-01-21 17:13:10  successful  2104052526
87582  2015-10-29 16:29:12 2015-11-28 17:29:12  successful  2104052526
89849  2015-10-02 16:17:13 2015-11-01 17:17:13  successful  2104052526
90875  2015-09-21 18:57:23 2015-10-21 18:57:23  successful  2104052526
95473  2015-07-29 15:02:00 2015-09-07 15:02:00  successful  2104052526
97270  2015-07-08 17:23:08 2015-08-17 17:23:08  successful  2104052526
102688 2015-05-15 16:07:04 2015-06-14 16:07:04  successful  2104052526
107223 2015-04-03 16:02:23 2015-05-03 16:02:23  successful  2104052526
112057 2015-02-21 17:25:56 2015-04-02 16:25:56  successful  2104052526
114555 2015-01-31 17:29:11 2015-03-08 16:29:11  successful  2104052526
115716 2015-01-21 16:31:32 2015-02-20 16:31:32  successful  2104052526
117551 2014-12-27 18:12:16 2015-01-26 18:12:16  successful  2104052526
118918 2014-12-02 21:12:11 2015-01-01 21:12:11  successful  2104052526
119822 2014-11-20 17:01:33 2014-12-25 17:01:33  successful  2104052526
122537 2014-10-22 17:13:34 2014-11-21 18:13:34  successful  2104052526
124416 2014-10-01 16:05:26 2014-11-10 17:05:26  successful  2104052526
128195 2014-08-18 17:20:35 2014-09-17 17:20:35  successful  2104052526
132727 2014-07-11 16:01:23 2014-08-10 16:01:23  successful  2104052526
135538 2014-06-06 15:50:10 2014-07-06 15:50:10  successful  2104052526
136439 2014-05-23 16:14:03 2014-06-22 16:14:03  successful  2104052526
138360 2014-04-18 19:19:51 2014-05-18 19:19:51  successful  2104052526
139187 2014-03-30 16:00:41 2014-04-29 16:00:41  successful  2104052526
141138 2014-01-31 13:30:29 2014-03-04 13:30:29  successful  2104052526

                     creator_name country       city state loc_type  \
8581    Collectable Playing Cards  US      Lexington  KY    Town
12444   Collectable Playing Cards  US      Lexington  KY    Town
13725   Collectable Playing Cards  US      Lexington  KY    Town
15690   Collectable Playing Cards  US      Lexington  KY    Town
16952   Collectable Playing Cards  US      Lexington  KY    Town
21142   Collectable Playing Cards  US      Lexington  KY    Town
```

22518	Collectable Playing Cards	US	Lexington	KY	Town
24613	Collectable Playing Cards	US	Lexington	KY	Town
26866	Collectable Playing Cards	US	Lexington	KY	Town
28474	Collectable Playing Cards	US	Lexington	KY	Town
29819	Collectable Playing Cards	US	Lexington	KY	Town
30921	Collectable Playing Cards	US	Lexington	KY	Town
31631	Collectable Playing Cards	US	Lexington	KY	Town
32611	Collectable Playing Cards	US	Lexington	KY	Town
33779	Collectable Playing Cards	US	Lexington	KY	Town
34868	Collectable Playing Cards	US	Lexington	KY	Town
36045	Collectable Playing Cards	US	Lexington	KY	Town
37286	Collectable Playing Cards	US	Lexington	KY	Town
38096	Collectable Playing Cards	US	Lexington	KY	Town
40508	Collectable Playing Cards	US	Lexington	KY	Town
42769	Collectable Playing Cards	US	Lexington	KY	Town
43776	Collectable Playing Cards	US	Lexington	KY	Town
45192	Collectable Playing Cards	US	Lexington	KY	Town
46370	Collectable Playing Cards	US	Lexington	KY	Town
47207	Collectable Playing Cards	US	Lexington	KY	Town
48759	Collectable Playing Cards	US	Lexington	KY	Town
49922	Collectable Playing Cards	US	Lexington	KY	Town
51310	Collectable Playing Cards	US	Lexington	KY	Town
52476	Collectable Playing Cards	US	Huntley	IL	Town
53994	Collectable Playing Cards	US	Huntley	IL	Town
55055	Collectable Playing Cards	US	Huntley	IL	Town
57173	Collectable Playing Cards	US	Huntley	IL	Town
58251	Collectable Playing Cards	US	Huntley	IL	Town
59845	Collectable Playing Cards	US	Huntley	IL	Town
61724	Collectable Playing Cards	US	Huntley	IL	Town
62523	Collectable Playing Cards	US	Huntley	IL	Town
63583	Collectable Playing Cards	US	Huntley	IL	Town
64578	Collectable Playing Cards	US	Huntley	IL	Town
65694	Collectable Playing Cards	US	Huntley	IL	Town
66600	Collectable Playing Cards	US	Huntley	IL	Town
69662	Collectable Playing Cards	US	Huntley	IL	Town
74664	Collectable Playing Cards	US	Huntley	IL	Town
75423	Collectable Playing Cards	US	Huntley	IL	Town
79126	Collectable Playing Cards	US	Huntley	IL	Town
81866	Collectable Playing Cards	US	Huntley	IL	Town
83309	Collectable Playing Cards	US	Huntley	IL	Town
87582	Collectable Playing Cards	US	Huntley	IL	Town
89849	Collectable Playing Cards	US	Huntley	IL	Town
90875	Collectable Playing Cards	US	Huntley	IL	Town
95473	Collectable Playing Cards	US	Huntley	IL	Town
97270	Collectable Playing Cards	US	Huntley	IL	Town
102688	Collectable Playing Cards	US	Huntley	IL	Town
107223	Collectable Playing Cards	US	Huntley	IL	Town
112057	Collectable Playing Cards	US	Huntley	IL	Town

114555	Collectable Playing Cards	US	Huntley	IL	Town
115716	Collectable Playing Cards	US	Huntley	IL	Town
117551	Collectable Playing Cards	US	Huntley	IL	Town
118918	Collectable Playing Cards	US	Huntley	IL	Town
119822	Collectable Playing Cards	US	Huntley	IL	Town
122537	Collectable Playing Cards	US	Huntley	IL	Town
124416	Collectable Playing Cards	US	Huntley	IL	Town
128195	Collectable Playing Cards	US	Huntley	IL	Town
132727	Collectable Playing Cards	US	Huntley	IL	Town
135538	Collectable Playing Cards	US	Huntley	IL	Town
136439	Collectable Playing Cards	US	Huntley	IL	Town
138360	Collectable Playing Cards	US	Huntley	IL	Town
139187	Collectable Playing Cards	US	Huntley	IL	Town
141138	Collectable Playing Cards	US	Huntley	IL	Town

	backers_count	featured	currency	goal_hist_usd	pledged_hist_usd \
8581	634	spotlight	USD	4,000.0	13,687.0
12444	305	no support	USD	13,000.0	10,612.0
13725	111	spotlight	USD	3,000.0	3,523.0
15690	205	spotlight	USD	4,000.0	4,755.0
16952	325	spotlight	USD	2,500.0	9,533.0
21142	107	no support	USD	5,000.0	2,305.0
22518	209	spotlight	USD	5,000.0	5,414.0
24613	129	no support	USD	6,000.0	2,462.0
26866	495	spotlight	USD	4,000.0	10,543.0
28474	95	no support	USD	4,000.0	2,340.0
29819	122	no support	USD	15,000.0	12,189.0
30921	211	spotlight	USD	4,000.0	4,863.0
31631	494	spotlight	USD	4,000.0	19,572.0
32611	239	spotlight	USD	4,000.0	4,899.0
33779	306	no support	USD	18,000.0	12,863.0
34868	149	spotlight	USD	2,000.0	3,756.0
36045	158	spotlight	USD	2,000.0	3,883.0
37286	169	spotlight	USD	2,000.0	4,192.0
38096	170	spotlight	USD	2,000.0	4,355.0
40508	98	no support	USD	4,000.0	2,080.0
42769	400	spotlight	USD	4,000.0	8,877.0
43776	169	no support	USD	15,000.0	9,473.0
45192	296	spotlight	USD	4,000.0	7,015.0
46370	615	spotlight	USD	12,000.0	18,866.0
47207	330	spotlight	USD	4,000.0	14,651.0
48759	256	spotlight	USD	4,000.0	5,487.0
49922	247	spotlight	USD	4,000.0	5,771.0
51310	254	spotlight	USD	4,000.0	5,683.0
52476	232	spotlight	USD	4,000.0	4,963.0
53994	248	spotlight	USD	4,000.0	5,352.0
55055	298	spotlight	USD	4,000.0	6,489.0
57173	236	spotlight	USD	4,000.0	4,886.0

58251	177	spotlight	USD	4,000.0	4,124.0
59845	268	spotlight	USD	5,000.0	6,046.0
61724	236	spotlight	USD	5,000.0	5,929.0
62523	400	spotlight	USD	4,000.0	9,036.0
63583	270	spotlight	USD	15,000.0	22,483.0
64578	559	spotlight	USD	12,000.0	17,521.0
65694	583	spotlight	USD	4,000.0	12,698.52
66600	135	spotlight	USD	4,000.0	4,097.0
69662	233	spotlight	USD	3,000.0	4,803.0
74664	418	spotlight	USD	5,000.0	9,057.0
75423	397	spotlight	USD	5,000.0	11,302.0
79126	307	spotlight	USD	5,000.0	8,416.0
81866	249	spotlight	USD	4,000.0	7,091.0
83309	186	spotlight	USD	3,500.0	3,822.0
87582	227	spotlight	USD	5,000.0	5,418.0
89849	197	spotlight	USD	4,000.0	5,405.0
90875	229	spotlight	USD	5,000.0	5,239.0
95473	266	spotlight	USD	5,000.0	5,371.0
97270	240	spotlight	USD	15,000.0	16,008.0
102688	404	spotlight	USD	4,000.0	8,010.0
107223	209	spotlight	USD	3,500.0	3,939.0
112057	304	spotlight	USD	3,500.0	6,409.0
114555	518	spotlight	USD	15,000.0	19,587.0
115716	603	spotlight	USD	5,000.0	15,357.0
117551	255	spotlight	USD	2,500.0	5,424.0
118918	335	spotlight	USD	2,500.0	7,156.0
119822	263	spotlight	USD	7,500.0	9,777.0
122537	201	spotlight	USD	2,500.0	5,749.01
124416	1042	spotlight	USD	7,500.0	29,305.0
128195	164	spotlight	USD	2,500.0	4,979.0
132727	219	spotlight	USD	5,000.0	7,215.0
135538	317	spotlight	USD	8,000.0	9,569.0
136439	589	spotlight	USD	7,500.0	13,832.0
138360	861	spotlight	USD	10,000.0	31,285.0
139187	449	spotlight	USD	7,500.0	11,617.0
141138	619	spotlight	USD	15,000.0	18,095.0

	duration	duration_days	comb_cat
8581	30 days 00:00:00	30.0	Games/Playing Cards
12444	30 days 01:00:00	30.041666666666668	Games/Playing Cards
13725	30 days 00:00:00	30.0	Games/Playing Cards
15690	30 days 00:00:00	30.0	Games/Playing Cards
16952	30 days 00:00:00	30.0	Games/Playing Cards
21142	30 days 00:00:00	30.0	Games/Playing Cards
22518	30 days 00:00:00	30.0	Games/Playing Cards
24613	30 days 00:00:00	30.0	Games/Playing Cards
26866	30 days 00:00:00	30.0	Games/Playing Cards
28474	29 days 23:00:00	29.958333333333332	Games/Playing Cards

29819	30 days 00:00:00	30.0	Games/Playing Cards
30921	30 days 00:00:00	30.0	Games/Playing Cards
31631	30 days 00:00:00	30.0	Games/Playing Cards
32611	30 days 00:00:00	30.0	Games/Playing Cards
33779	30 days 00:00:00	30.0	Games/Playing Cards
34868	30 days 01:00:00	30.041666666666668	Games/Playing Cards
36045	30 days 01:00:00	30.041666666666668	Games/Playing Cards
37286	30 days 00:00:00	30.0	Games/Playing Cards
38096	30 days 00:00:00	30.0	Games/Playing Cards
40508	30 days 00:00:00	30.0	Games/Playing Cards
42769	30 days 00:00:00	30.0	Games/Playing Cards
43776	30 days 00:00:00	30.0	Games/Playing Cards
45192	30 days 00:00:00	30.0	Games/Playing Cards
46370	30 days 00:00:00	30.0	Games/Playing Cards
47207	30 days 00:00:00	30.0	Games/Playing Cards
48759	30 days 00:00:00	30.0	Games/Playing Cards
49922	30 days 00:00:00	30.0	Games/Playing Cards
51310	30 days 00:00:00	30.0	Games/Playing Cards
52476	29 days 23:00:00	29.958333333333332	Games/Playing Cards
53994	29 days 23:00:00	29.958333333333332	Games/Playing Cards
55055	30 days 00:00:00	30.0	Games/Playing Cards
57173	30 days 00:00:00	30.0	Games/Playing Cards
58251	30 days 00:00:00	30.0	Games/Playing Cards
59845	30 days 00:00:00	30.0	Games/Playing Cards
61724	30 days 01:00:00	30.041666666666668	Games/Playing Cards
62523	30 days 00:00:00	30.0	Games/Playing Cards
63583	31 days 00:00:00	31.0	Games/Playing Cards
64578	30 days 00:00:00	30.0	Games/Playing Cards
65694	30 days 00:00:00	30.0	Games/Playing Cards
66600	30 days 00:00:00	30.0	Games/Playing Cards
69662	30 days 00:00:00	30.0	Games/Playing Cards
74664	30 days 00:00:00	30.0	Games/Playing Cards
75423	30 days 00:00:00	30.0	Games/Playing Cards
79126	29 days 23:00:00	29.958333333333332	Games/Playing Cards
81866	36 days 00:00:00	36.0	Games/Playing Cards
83309	30 days 00:00:00	30.0	Games/Playing Cards
87582	30 days 01:00:00	30.041666666666668	Games/Playing Cards
89849	30 days 01:00:00	30.041666666666668	Games/Playing Cards
90875	30 days 00:00:00	30.0	Games/Playing Cards
95473	40 days 00:00:00	40.0	Games/Playing Cards
97270	40 days 00:00:00	40.0	Games/Playing Cards
102688	30 days 00:00:00	30.0	Games/Playing Cards
107223	30 days 00:00:00	30.0	Games/Playing Cards
112057	39 days 23:00:00	39.958333333333336	Games/Playing Cards
114555	35 days 23:00:00	35.958333333333336	Games/Playing Cards
115716	30 days 00:00:00	30.0	Games/Playing Cards
117551	30 days 00:00:00	30.0	Games/Playing Cards
118918	30 days 00:00:00	30.0	Games/Playing Cards

```
119822 35 days 00:00:00 35.0               Games/Playing Cards
122537 30 days 01:00:00 30.041666666666668  Games/Playing Cards
124416 40 days 01:00:00 40.041666666666664  Games/Playing Cards
128195 30 days 00:00:00 30.0               Games/Playing Cards
132727 30 days 00:00:00 30.0               Games/Playing Cards
135538 30 days 00:00:00 30.0               Games/Playing Cards
136439 30 days 00:00:00 30.0               Games/Playing Cards
138360 30 days 00:00:00 30.0               Games/Playing Cards
139187 30 days 00:00:00 30.0               Games/Playing Cards
141138 32 days 00:00:00 32.0               Design/Graphic Design
```

While the vast majority of users launched one project, the creator with the name "Collectable Playing Cards" stands out. They launched 70 campaigns to finance different bicycle-themed playing cards.

What are the projects with the highest goals?

In [43]:
```
# highest goal
highest_goal =  ks_compl.sort_values('goal_hist_usd')['goal_hist_usd'].values[-1]
ks_compl[ks_compl.goal_hist_usd == highest_goal]
```

Out[43]:
```
      project_id       project_name  \
85834  2200338     A Celtic Lovestory


                                                                   url  \
85834  https://www.kickstarter.com/projects/245190432/a-celtic-lovestory



85834  A 2000 year old "Romeo & Juliet" love story, set amidst the dramatic changes tl

          category subcategory  \
85834  Film & Video  Drama



85834  https://ksr-ugc.imgix.net/assets/012/292/886/67f8879c113e174e1f41465297cdd035_

             launched_at            deadline  status  creator_id  \
85834 2015-11-16 23:47:15 2015-11-30 22:01:00  failed  245190432

      creator_name country    city    state loc_type  backers_count  \
85834  Joe          GB      Dorset  England  County   0

         featured currency        goal_hist_usd  pledged_hist_usd  \
85834  no support  GBP     150,099,318.94817606 0.0

             duration      duration_days            comb_cat
85834 13 days 22:13:45 13.916666666666666  Film & Video/Drama
```

About USD 150mi was the highest funding ever asked for. However, the funding of the drama film "A Celtic Lovestory" failed miserably in November 2015 with not one single backer.

```
In [44]: # highest successful goals
         highest_goal_s =  ks_compl_success.sort_values('goal_hist_usd')['goal_hist_usd'].value
         ks_compl_success[ks_compl_success.goal_hist_usd == highest_goal_s]
```

```
Out[44]:        project_id                            project_name  \
        86447   2193016    Bring Back MYSTERY SCIENCE THEATER 3000
        99511   1935067    Shenmue 3
        149217  541556     WISH I WAS HERE
        150464  57628      The Veronica Mars Movie Project

                                                                                  url
        86447   https://www.kickstarter.com/projects/mst3k/bringbackmst3k
        99511   https://www.kickstarter.com/projects/ysnet/shenmue-3
        149217  https://www.kickstarter.com/projects/1869987317/wish-i-was-here-1
        150464  https://www.kickstarter.com/projects/559914737/the-veronica-mars-movie-projec


        86447   Almost there! MYSTERY SCIENCE THEATER 3000 will return... and if we can get to
        99511   Yu Suzuki presents the long awaited third installment in the Shenmue series.
        149217  "Hell, there are no rules here - we're trying to accomplish something." - Thor
        150464  UPDATED: This is it. We're making a Veronica Mars movie! Now the only questior

                    category    subcategory  \
        86447   Film & Video  Television
        99511   Games         Video Games
        149217  Film & Video  Narrative Film
        150464  Film & Video  Narrative Film


        86447   https://ksr-ugc.imgix.net/assets/012/289/124/ae6179e0455878652460b3f70d7550d0
        99511   https://ksr-ugc.imgix.net/assets/012/155/905/cc709c4441634e62db1d28d44ad6d8a8
        149217  https://ksr-ugc.imgix.net/assets/011/511/086/80b9bd751c8ab25337c418512a70bfc6
        150464  https://ksr-ugc.imgix.net/assets/011/303/414/9e0a1fd046b781883cc111d25165670e

                      launched_at            deadline      status  creator_id  \
        86447  2015-11-10 15:49:32 2015-12-12 06:00:00  successful  1587892087
        99511  2015-06-16 01:51:04 2015-07-18 01:51:04  successful  1569150382
        149217 2013-04-24 09:57:04 2013-05-24 19:00:00  successful  1869987317
        150464 2013-03-13 14:42:22 2013-04-13 03:00:00  successful  559914737

                creator_name country         city             state loc_type  \
        86447   Joel Hodgson  US      Minneapolis  MN                Town
        99511   Ys Net        JP      Tokyo        Tokyo Prefecture  Town
        149217  Zach Braff    US      Los Angeles  CA                Town
        150464  Rob Thomas    US      San Diego    CA                Town

                backers_count      featured currency  goal_hist_usd  pledged_hist_usd  \
        86447   48270          full support  USD     2,000,000.0    5,764,229.38
```

```
99511   69320          full support  USD     2,000,000.0    6,333,295.77
149217  46520          full support  USD     2,000,000.0    3,105,473.1
150464  91585          full support  USD     2,000,000.0    5,702,153.38

                  duration      duration_days                    comb_cat
86447   31 days 14:10:28 31.583333333333332  Film & Video/Television
99511   32 days 00:00:00 32.0                Games/Video Games
149217  30 days 09:02:56 30.375              Film & Video/Narrative Film
150464  30 days 12:17:38 30.5                Film & Video/Narrative Film
```

3 Film & Video projects and one video games realized the highest successful funding goal of USD 2mi.

The first time USD 2mi were successfully raised was in May 2013. The popular actor and director Zach Braff successfully funded the narrative film "WISH I WAS HERE". By the end of the funding period, he had realized 3,1mi from 46,5k supporters.

The Japanese video game "Shenmue 3" even realized USD 6.3mi in July 2015.

Which project collected the highest funding?

In [45]:
```
highest_pledge =  ks_compl.sort_values('pledged_hist_usd')['pledged_hist_usd'].index[-
ks_compl.iloc[[highest_pledge]]
```

Out[45]:
```
      project_id                                              project_name  \
2084  3665306     Critical Role: The Legend of Vox Machina Animated Special


2084  https://www.kickstarter.com/projects/criticalrole/critical-role-the-legend-of-vo


2084  Critical Role's The Legend of Vox Machina reunites your favorite heroes for a pr

          category subcategory  \
2084  Film & Video  Animation


2084  https://ksr-ugc.imgix.net/assets/024/180/681/20b0b3846c5175714b0cf75822d46e00_or

              launched_at            deadline      status   creator_id  \
2084 2019-03-04 17:54:29 2019-04-19 06:59:00  successful  1007835190

       creator_name country         city state loc_type  backers_count  \
2084  Critical Role  US      Los Angeles  CA    Town     88887

          featured currency  goal_hist_usd  pledged_hist_usd         duration  \
2084  full support  USD     750,000.0      11,385,449.05     45 days 13:04:31

          duration_days                comb_cat
2084 45.541666666666664  Film & Video/Animation
```

Shortly before Kickstarter's 10th anniversary, the creators of the animated film project "Critical Role: The Legend of Vox Machina Animated Special" celebrated the highest fundraising ever on

Kickstarter. On 19/04/2019 A September 2012, they successfully collected funding of almost USD 11.4mi at an initial goal of 750k.

Which project convinced the highest number of backers?

```
In [46]: most_backers =  ks_compl.sort_values('backers_count')['backers_count'].index[-1]
         ks_compl.iloc[[most_backers]]
```

```
Out[46]:        project_id                                             project_name  \
        136233  988854      Bring Reading Rainbow Back for Every Child, Everywhere!


        136233  https://www.kickstarter.com/projects/readingrainbow/bring-reading-rainbow-bac


        136233  Bring Reading Rainbows library of interactive books & video field trips to mo

                  category subcategory  \
        136233  Technology  Web


        136233  https://ksr-ugc.imgix.net/assets/011/690/614/fcbacbc0924942075477a04a01adb20a

                         launched_at            deadline      status   creator_id  \
        136233 2014-05-28 13:05:45 2014-07-02 19:00:00  successful  1038554387

                                   creator_name country         city state loc_type  \
        136233  LeVar Burton & Reading Rainbow  US      Los Angeles  CA    Town

                backers_count      featured currency  goal_hist_usd  pledged_hist_usd  \
        136233  105857         full support  USD     1,000,000.0    5,408,916.95

                         duration      duration_days        comb_cat
        136233 35 days 05:54:15 35.208333333333336  Technology/Web
```

In July 2014 the web project “Bring Reading Rainbow Back for Every Child, Everywhere!” collected funding from {{format_num(most_backers)}} supporters. While they initially asked for USD 1mi, they had realized USD 5.4mi by the end of their campaign.

Where are Kickstarter campaigns being launched?

```
In [47]: # globally
         ks_compl.country.value_counts()
```

```
Out[47]: US     115795
         GB     17015
         CA     7300
         AU     3576
         DE     2544
         FR     2083
         IT     1877
```

MX	1860
ES	1512
NL	1317
SE	1056
NZ	761
DK	693
HK	666
JP	544
CH	505
IE	495
SG	441
BE	398
NO	380
AT	374
CN	273
IN	166
KR	129
PL	128
PR	120
TH	116
UA	113
IL	107
CO	105
BR	99
ZA	96
RU	89
CZ	88
GR	86
TW	83
ID	83
PE	77
KE	73
AR	72
HU	60
TR	60
PH	60
IS	58
GH	54
CR	50
NP	49
VN	48
EC	48
RO	48
PT	46
SI	45
LT	44
FI	44
LU	42

BG	42
RS	42
CL	42
GT	41
UG	39
CU	38
KH	32
EG	29
HT	29
BA	29
MY	28
NI	28
TZ	27
MA	26
LV	26
AE	26
EE	25
AF	24
HR	23
NG	23
BO	22
SN	21
LB	21
JM	21
MN	20
SJ	20
DO	19
ET	19
RW	19
BZ	17
PA	16
VE	16
AQ	16
LK	15
JO	15
VI	15
HN	14
SK	14
PS	14
BY	13
SV	13
PK	13
GE	13
MT	12
IQ	11
CM	10
GU	10
ML	10

CD	10
UY	10
MM	10
SL	10
CY	10
ZW	10
AM	9
LR	9
MK	9
NA	9
ZM	8
BT	8
BS	8
MD	7
MG	7
TN	7
MW	7
GP	6
BD	6
IR	6
TT	6
BF	6
GL	5
SR	5
NE	5
PG	5
GN	5
CI	5
VU	4
BB	4
LY	4
KZ	4
PF	4
KG	4
FO	4
TO	4
KP	4
LA	3
BW	3
GY	3
CG	3
MU	3
SY	3
YE	3
GM	3
WS	3
PY	3
DM	3

```
DZ    3
MZ    3
FJ    3
VC    2
KW    2
AL    2
CW    2
NC    2
CK    2
SS    2
AX    2
MV    2
XK    2
FM    2
SX    2
MC    2
AG    2
TC    2
SO    2
LC    1
MO    1
GQ    1
PN    1
AZ    1
SZ    1
BJ    1
KY    1
SC    1
MQ    1
CV    1
VA    1
SA    1
TL    1
GA    1
QA    1
LS    1
SD    1
KI    1
KN    1
DJ    1
MR    1
TJ    1
GI    1
TD    1
Name: country, dtype: int64
```

In [48]:
```
# proportion of project countries - top 3
for i in range(3):
```

```
            print(ks_compl.country.value_counts().index[i],  ks_compl.country.value_counts().v
```

```
US 0.6998706573507725
GB 0.10283949423397723
CA 0.0441215579140778
```

In [49]:
```
# states of the USA
ks_usa_compl = ks_compl[ks_compl.country == "US"]
ks_usa_compl.state.value_counts()
```

Out[49]:
```
CA    21685
NY    13710
TX     6857
FL     5639
IL     4480
WA     3896
PA     3737
MA     3358
GA     3086
OH     3058
OR     2955
CO     2770
MI     2684
NC     2673
TN     2382
VA     2300
MN     2171
AZ     2156
UT     1875
NJ     1864
MO     1765
MD     1652
NV     1579
WI     1522
IN     1369
DC     1221
CT     1040
LA     1035
SC      927
KY      859
OK      804
AL      741
NM      705
IA      618
ME      613
ID      565
KS      561
```

```
HI    529
VT    513
NH    492
AR    486
RI    440
MT    429
NE    380
AK    330
MS    319
WV    285
DE    251
SD    148
ND    141
WY    140
Name: state, dtype: int64
```

In [50]:
```
# proportion of project US federal states - top 3
for i in range(3):
    print(ks_usa_compl.state.value_counts().index[i],  ks_compl.state.value_counts().v
```

```
CA 0.13106520320092838
NY 0.09116843555834925
TX 0.0828639121920557
```

In [51]:
```
# projects from how many countries were lauched?
ks_compl.country.nunique()
```

Out[51]:
```
195
```

In [52]:
```
# evalutate location type
ks_compl.loc_type.value_counts()
```

Out[52]:
```
Town             153405
County           6254
Suburb           4201
LocalAdmin       951
Zip              400
Island           207
Country          16
Miscellaneous    14
Estate           4
Name: loc_type, dtype: int64
```

In [53]:
```
# proportion most common location type
ks_compl.loc_type.value_counts().values[0] / n_compl_projects
```

Out[53]:
```
0.927187341343713
```

There are projects from 195 countries from all around the world. With 70%, by far the most projects launched in the USA. To be more specific, 13% of all completed US projects were from California and 9% from the state of New York.

Globally, Great Britain follows the US with 10% of projects. Canada ranked third with 4.4% of all projects. The data is not only heavily biased towards US projects but also towards location type. 93% of all campaigns were launched in towns. As the overall majority of projects is happening in US towns and there are insufficient projects in other locations, I decided to not further consider the location as a predictor for this analysis.

What are common project categories?

In [54]:
```
# values categories
ks_compl.category.value_counts()
```

Out[54]:
```
Music            24200
Film & Video     23622
Art              17647
Technology       17355
Publishing       16755
Food             13283
Games             9935
Fashion           8466
Comics            6167
Photography       5689
Design            5526
Crafts            5464
Theater           4689
Journalism        3677
Dance             2977
Name: category, dtype: int64
```

In [55]:
```
# category count
ks_compl.category.nunique()
```

Out[55]:
```
15
```

In [56]:
```
# values subcategories
ks_compl.subcategory.value_counts()
```

Out[56]:
```
Web                    3548
Comedy                 2573
Public Art             2360
Mobile Games           2346
Classical Music        2341
Narrative Film         2339
Indie Rock             2337
Rock                   2334
Painting               2333
Pop                    2326
Webseries              2326
```

Hip-Hop	2322
Hardware	2320
Country & Folk	2319
Animation	2316
Software	2315
Mixed Media	2314
Art Books	2305
Drinks	2303
Restaurants	2300
Drama	2284
Shorts	2281
Nonfiction	2281
Fiction	2276
Graphic Novels	2238
Gadgets	2231
Documentary	2219
Children's Books	2209
Playing Cards	2197
Video Games	2186
Illustration	2162
Comic Books	2131
Apps	2114
World Music	2106
Electronic Music	2102
Performance Art	2094
Apparel	2084
Graphic Design	2070
Accessories	2025
Jazz	1911
Small Batch	1904
Food Trucks	1803
Sculpture	1802
Photobooks	1743
Product Design	1721
Digital Art	1508
Tabletop Games	1506
Plays	1491
Dance	1426
Poetry	1415
Jewelry	1366
Horror	1331
Woodworking	1236
Periodicals	1235
Farms	1199
DIY	1190
Wearables	1174
Faith	1167
Crafts	1143

Performances	1099
People	1087
Anthologies	1029
Conceptual Art	1021
Live Games	1020
Footwear	1018
Television	1002
Experimental	986
Radio & Podcasts	982
DIY Electronics	975
Musical	955
Academic	933
Ready-to-wear	921
Spaces	880
Festivals	878
Young Adult	835
Events	824
Webcomics	802
Fine Art	788
Science Fiction	785
Thrillers	779
Metal	750
Architecture	745
Action	735
Print	728
Sound	725
Vegan	707
Places	700
Music Videos	698
Journalism	683
3D Printing	678
Art	643
Robots	573
Photography	560
Cookbooks	556
Music	556
Nature	554
Installations	542
Theater	509
Childrenswear	506
Food	494
R&B	486
Zines	476
Candles	467
Camera Equipment	449
Audio	435
Farmer's Markets	430
Video	414

Interactive Design	398
Gaming Hardware	394
Flight	375
Immersive	372
Calendars	369
Fantasy	365
Family	346
Ceramics	339
Space Exploration	325
Movie Theaters	324
Textiles	322
Punk	322
Civic Design	303
Literary Journals	298
Kids	293
Technology	288
Community Gardens	285
Blues	285
Comics	284
Couture	266
Fabrication Tools	258
Animals	257
Puzzles	251
Stationery	244
Makerspaces	237
Printing	230
Publishing	218
Video Art	207
Romance	201
Knitting	195
Photo	187
Bacon	186
Film & Video	178
Crochet	176
Workshops	166
Latin	164
Translations	162
Design	162
Fashion	143
Glass	139
Pet Fashion	137
Pottery	130
Typography	127
Embroidery	124
Weaving	97
Quilts	83
Literary Spaces	83
Residencies	79

```
Letterpress            58
Chiptune               39
Games                  35
Taxidermy              10
Name: subcategory, dtype: int64
```

In [57]:
```
# subcategory count
ks_compl.subcategory.nunique()
```

Out[57]:
```
159
```

In [58]:
```
# values combined categories
ks_compl.comb_cat.value_counts()
```

Out[58]:
```
Art/Public Art                    2360
Games/Mobile Games                2346
Music/Classical Music             2341
Film & Video/Narrative Film       2339
Music/Indie Rock                  2337
Music/Rock                        2334
Art/Painting                      2333
Music/Pop                         2326
Film & Video/Webseries            2326
Music/Hip-Hop                     2322
Technology/Hardware               2320
Music/Country & Folk              2319
Technology/Web                    2318
Film & Video/Animation            2316
Technology/Software               2315
Art/Mixed Media                   2314
Publishing/Art Books              2305
Food/Drinks                       2303
Food/Restaurants                  2300
Film & Video/Drama                2284
Film & Video/Shorts               2281
Publishing/Nonfiction             2281
Publishing/Fiction                2276
Comics/Graphic Novels             2238
Technology/Gadgets                2231
Film & Video/Comedy               2228
Film & Video/Documentary          2219
Publishing/Children's Books       2209
Games/Playing Cards               2197
Games/Video Games                 2186
Art/Illustration                  2162
Comics/Comic Books                2131
Technology/Apps                   2114
Music/World Music                 2106
Music/Electronic Music            2102
```

Art/Performance Art	2094
Fashion/Apparel	2084
Design/Graphic Design	2070
Fashion/Accessories	2025
Music/Jazz	1911
Food/Small Batch	1904
Food/Food Trucks	1803
Art/Sculpture	1802
Photography/Photobooks	1743
Design/Product Design	1721
Art/Digital Art	1508
Games/Tabletop Games	1506
Theater/Plays	1491
Dance/Dance	1426
Publishing/Poetry	1415
Fashion/Jewelry	1366
Film & Video/Horror	1331
Crafts/Woodworking	1236
Publishing/Periodicals	1235
Journalism/Web	1230
Food/Farms	1199
Crafts/DIY	1190
Technology/Wearables	1174
Music/Faith	1167
Crafts/Crafts	1143
Dance/Performances	1099
Photography/People	1087
Art/Conceptual Art	1021
Games/Live Games	1020
Fashion/Footwear	1018
Film & Video/Television	1002
Publishing/Radio & Podcasts	982
Technology/DIY Electronics	975
Theater/Musical	955
Publishing/Academic	933
Fashion/Ready-to-wear	921
Publishing/Young Adult	835
Comics/Webcomics	802
Photography/Fine Art	788
Film & Video/Science Fiction	785
Film & Video/Thrillers	779
Music/Metal	750
Design/Architecture	745
Film & Video/Action	735
Journalism/Print	728
Technology/Sound	725
Food/Vegan	707
Photography/Places	700

Film & Video/Music Videos	698
Journalism/Journalism	683
Technology/3D Printing	678
Food/Events	651
Art/Art	643
Film & Video/Experimental	578
Technology/Robots	573
Theater/Festivals	571
Photography/Photography	560
Food/Cookbooks	556
Music/Music	556
Photography/Nature	554
Art/Installations	542
Comics/Anthologies	539
Theater/Theater	509
Fashion/Childrenswear	506
Food/Food	494
Publishing/Anthologies	490
Music/R&B	486
Publishing/Zines	476
Crafts/Candles	467
Food/Spaces	465
Technology/Camera Equipment	449
Journalism/Audio	435
Food/Farmer's Markets	430
Journalism/Video	414
Theater/Experimental	408
Design/Interactive Design	398
Games/Gaming Hardware	394
Technology/Flight	375
Theater/Immersive	372
Publishing/Calendars	369
Film & Video/Fantasy	365
Film & Video/Family	346
Art/Ceramics	339
Technology/Space Exploration	325
Film & Video/Movie Theaters	324
Music/Punk	322
Art/Textiles	322
Film & Video/Festivals	307
Design/Civic Design	303
Publishing/Literary Journals	298
Music/Kids	293
Technology/Technology	288
Music/Blues	285
Food/Community Gardens	285
Comics/Comics	284
Fashion/Couture	266

```
Technology/Fabrication Tools     258
Photography/Animals              257
Games/Puzzles                    251
Crafts/Stationery                244
Technology/Makerspaces           237
Crafts/Printing                  230
Publishing/Publishing            218
Theater/Spaces                   208
Art/Video Art                    207
Dance/Spaces                     207
Film & Video/Romance             201
Crafts/Knitting                  195
Journalism/Photo                 187
Food/Bacon                       186
Film & Video/Film & Video        178
Crafts/Crochet                   176
Theater/Comedy                   175
Comics/Events                    173
Dance/Workshops                  166
Music/Latin                      164
Design/Design                    162
Publishing/Translations          162
Fashion/Fashion                  143
Crafts/Glass                     139
Fashion/Pet Fashion              137
Crafts/Pottery                   130
Publishing/Comedy                130
Design/Typography                127
Crafts/Embroidery                124
Crafts/Weaving                   97
Crafts/Quilts                    83
Publishing/Literary Spaces       83
Dance/Residencies                79
Publishing/Letterpress           58
Music/Comedy                     40
Music/Chiptune                   39
Games/Games                      35
Crafts/Taxidermy                 10
Name: comb_cat, dtype: int64
```

In [59]:
```
# comb category count
ks_compl.comb_cat.nunique()
```

Out[59]:
```
169
```

Music, Film & Video and Art were most common among the 15 main project categories. Looking at subcategories, we found Web, Comedy and Public Art among the top 3. We increased the number of subcategories by 10 when we combined parent and subcategory. The most common combined categories were Public Art, Classical Music and Mobile Games.

There isn't any category dominating over other categories. In fact, there are many categories at the top of the ranking with similar project counts of plus 2k.

Rather unusual projects were of types Music/Comedy, Music/Chiptune and Crafts/Taxidermy.

What is the usual project duration of completed projects?

```
In [60]: # show descriptive statistics
         ks_compl.duration.describe()
```

```
Out[60]: count    165452
         mean     32 days 15:57:02.739894
         std      11 days 18:03:37.653279
         min      1 days 00:00:00
         25%      29 days 23:00:00
         50%      30 days 00:00:00
         75%      34 days 04:24:19
         max      93 days 02:32:04
         Name: duration, dtype: object
```

The project duration typically ranges around 30 days. The interquartile range was between 29 to 34 days. The minimum funding period only lasted one day and the longest period was 93 days.

6.0.1 Numeric Variables and Outliers

As aforementioned, we find extreme values in goals, pledged and backers counts. To evaluate how to deal with outliers, I will take a more detailed look on quantiles of each data point.

Goals

```
In [61]: # get quantiles of goals, converted to USD
         goal_min = 0
         goal_25 = ks_compl.goal_hist_usd.quantile(q=0.25)
         goal_50 = ks_compl.goal_hist_usd.quantile(q=0.5)
         goal_75 = ks_compl.goal_hist_usd.quantile(q=0.75)
         goal_95 = ks_compl.goal_hist_usd.quantile(q=0.95)
         goal_975 = ks_compl.goal_hist_usd.quantile(q=0.975)
         goal_outliers = ks_compl.goal_hist_usd.quantile(q=0.9999)
         goal_max = ks_compl.goal_hist_usd.max()

         print(f"\
             GOALS: \n\
             - Min. goal: {goal_min} USD,\n\
             - 25% quantile - low goals: < {format_num(goal_25)} USD,\n\
             - 50% quantile - medium goals: < {format_num(goal_50)} USD,\n\
             - 75% quantile - moderately high goals: < {format_num(goal_75)} USD,\n\
             - 95% quantile - high goals < {format_num(goal_95)} USD,\n\
             - 97.5% quantile - very high goals: < {format_num(goal_975)} USD,\n\
             - 99.99% quantile - extreme goals: < {format_num(goal_outliers)} USD,\n\
             - Max.goal <= {format_num(goal_max)} USD")
```

```
GOALS:
- Min. goal: 0 USD,
- 25% quantile - low goals: < 1,500 USD,
- 50% quantile - medium goals: < 5,000 USD,
- 75% quantile - moderately high goals: < 13,120 USD,
- 95% quantile - high goals < 65,282 USD,
- 97.5% quantile - very high goals: < 114,346 USD,
- 99.99% quantile - extreme goals: < 57,274,500 USD,
- Max.goal <= 150,099,319 USD
```

Goals range between USD 0, up to USD {{format_num(goal_max)}}. The large dimension of goals will likely obstruct our visualization and average estimations.

By using quantiles of 25%, 50%, 75%, 95%, 97.5%, 99.99%, I sectioned my data into categories of low, medium, moderately high goals, high goals, very high goals, extreme goals and outliers.

95% of projects stay below goals of USD {{format_num(goal_95)}}. Funding goals jump up into the range of millions beyond the 97.5% quantile. But, only a very few projects rocket very high in the range of several millions.

The median goal is recorded at USD 5k, whereas the mean computes to USD {{format_num(ks_compl.goal_hist_usd.mean())}}. In the light of the vast majority of projects never seeking this goal, the median appears to be the better estimator for averages.

Pledged

```
In [62]: # get quantiles of pledged amounts
         pledged_min = ks_compl.pledged_hist_usd.min()
         pledged_25 = ks_compl.pledged_hist_usd.quantile(q=0.25)
         pledged_50 = ks_compl.pledged_hist_usd.quantile(q=0.5)
         pledged_75 = ks_compl.pledged_hist_usd.quantile(q=0.75)
         pledged_95 = ks_compl.pledged_hist_usd.quantile(q=0.95)
         pledged_975 = ks_compl.pledged_hist_usd.quantile(q=0.975)
         pledged_outliers = ks_compl.pledged_hist_usd.quantile(q=0.9999)
         pledged_max = ks_compl.pledged_hist_usd.max()

         print(f"\
             PLEDGED AMOUNT: \n\
             - Min. pledged: {pledged_min} USD,\n\
             - 25% quantile - low amount pledged: < {format_num(pledged_25)} USD,\n\
             - 50% quantile - medium amount pledged: < {format_num(pledged_50)} USD,\n\
             - 75% quantile - moderately high amount pledged: < {format_num(pledged_75)} USD,\n
             - 95% quantile - high amount pledgeds < {format_num(pledged_95)} USD,\n\
             - 97.5% quantile - very high amount pledged: < {format_num(pledged_975)} USD,\n\
             - 99.99% quantile - extreme amount pledged: < {format_num(pledged_outliers)} USD,\
             - Max. pledged {format_num(pledged_max)} USD")
```

```
PLEDGED AMOUNT:
- Min. pledged: 0.0 USD,
- 25% quantile - low amount pledged: < 100 USD,
- 50% quantile - medium amount pledged: < 1,454 USD,
```

```
- 75% quantile - moderately high amount pledged: < 6,221 USD,
- 95% quantile - high amount pledgeds < 37,571 USD,
- 97.5% quantile - very high amount pledged: < 72,913 USD,
- 99.99% quantile - extreme amount pledged: < 3,231,067 USD,
- Max. pledged 11,385,449 USD
```

The amount pledged by supporters range between USD 0 and USD {{format_num(pledged_max)[:-5]}}mi. Similarly to goals, there are extreme outliers, albeit not as severe. For the pledged investments, I inspected 25%, 50%, 75%, 95%, 97.5%, 99.99% quantiles. I sectioned my data into categories of low, medium, moderately high, high, very high, extreme and outlier pledges.

The median funding per project was USD {{format_num(pledged_50)}}. This is less than a third of the median goal of USD {{format_num(goal_50)}} asked by creators. It may indicate either a high number of failed projects or a tendency for successful projects seeking very low funding goals.

Extremely high investments were very unlikely. Only a small number of projects of under 0.1% successfully realized more than USD 1mi.

Backers

In [63]:
```
# get quantiles of backers
backers_min = ks_compl.backers_count.min()
backers_25 = ks_compl.backers_count.quantile(q=0.25)
backers_50 = ks_compl.backers_count.quantile(q=0.5)
backers_75 = ks_compl.backers_count.quantile(q=0.75)
backers_95 = ks_compl.backers_count.quantile(q=0.95)
backers_975 = ks_compl.backers_count.quantile(q=0.975)
backers_outliers = ks_compl.backers_count.quantile(q=0.9999)
backers_max = ks_compl.backers_count.max()

print(f"\
    BACKERS: \n\
    - Min. backers: {backers_min},\n\
    - 25% quantile - low amount backers: < {format_num(backers_25)},\n\
    - 50% quantile - medium amount backers: < {format_num(backers_50)},\n\
    - 75% quantile - moderately high amount backers: < {format_num(backers_75)},\n\
    - 95% quantile - high amount backers < {format_num(backers_95)},\n\
    - 97.5% quantile - very high amount backers: < {format_num(backers_975)},\n\
    - 99.99% quantile - extreme amount backers: < {format_num(backers_outliers)},\n\
    - Max. backers {format_num(backers_max)}")
```

```
BACKERS:
- Min. backers: 0,
- 25% quantile - low amount backers: < 3,
- 50% quantile - medium amount backers: < 25,
- 75% quantile - moderately high amount backers: < 84,
- 95% quantile - high amount backers < 448,
- 97.5% quantile - very high amount backers: < 864,
```

```
- 99.99% quantile - extreme amount backers: < 35,460,
- Max. backers 105,857
```

Just as *goals* and the *pledged* funding, I calculated the quantiles of the number of backers per project. Similarly, the distribution of backers is heavily skewed. A quarter of all projects were completed with 3 or less backers. The median number of backers per project was {{backers_50}}.

Only 5% of projects ended with more than {{backers_95}} backers. Likewise *goals* and *pledged*, the number of project supporters sharply increased above the 97.5% quantile and ultimately peaked in a maximum of {{format_num(backers_max)}} backers.

As a consequence of the wide range of goals, pledges and backers counts, I will need to apply additional techniques to make visualization of those data points possible. The above analysis shows that observation with numeric values below the 95% quantile may provide a more realistic impression on Kickstarter crowdfunding campaigns.

Thus, I will treat values beyond the 95% interval like outliers. Eliminating very high values in backers, goals and pledged will improve the readability of the plots. In preparation for the visual analysis, I'm going to filter our data by choosing only the 95% interval of goals, pledgeds and backers counts.

```
In [64]: # remove outliers
         ks_compl_95 = ks_compl.copy()
         print("Projects completed : ", format_num(len(ks_compl_95)))

         # collect all projects that stay below the 95% quantiles in goal, pledged and backers
         ks_compl_95 = ks_compl_95.query('(goal_hist_usd < @goal_95) & \
                                          (pledged_hist_usd < @pledged_95) & \
                                          (backers_count < @backers_95)')

         ks_compl_95.reset_index(drop=True, inplace=True)
         print("After removal of outliers: ", format_num(len(ks_compl_95)))

         # create separate data frames with outliers removed for each, successful and failed p
         ks_success_95 = ks_compl_95[ks_compl_95.status == 'successful']
         ks_fail_95= ks_compl_95[ks_compl_95.status == 'failed']
         print("No. success projects 95%.: ", format_num(len(ks_success_95)) , \
               "\nNo. failed projects 95%.:", format_num(len(ks_fail_95)))
```

```
Projects completed :  165,452
After removal of outliers:  147,964
No. success projects 95%.:  82,388
No. failed projects 95%.: 65,576
```

6.1 4.1 Summary Descriptive Statistics

On Kickstarter's 10th anniversary, there were {{format_num(n_compl_projects)}} completed projects initiated by {{format_num(n_compl_creators_unique)}} unique creators. If we disregard canceled or suspended project, {{round(p_compl_success*100, 1)}}% of campaigns were finished successfully. {{format_num(ks_compl_success['backers_count'].sum())}} times supporters actively pledged for successful projects.

91% of users have not returned to funding after launching a project. Another 6% of users created 2 projects.

Although we found projects from 195 countries from all around the world, 70% were of the projects were launched in the USA. To be more specific, 13% of all completed projects are from California and 9% from the state of New York. Globally, Great Britain follows the US with 10% of projects. Canada ranks third with 4.4 % of all projects. Projects are typically launched in towns (93%). I suppose the uneven proportion of locations may not result in meaningful conclusions. Therefore, I'm going to prioritize the remaining data points to evaluate Kickstarter's success.

Music, *Film & Video* and *Art* are most common among the 15 main project categories. Out of 169 subcategories, we found *Public Art*, *Classical Music* and *Games/Mobile Games* were most popular. However, among subcategories the popularity was distributed relatively closely together, so that we cannot assume specific project types to be dominant.

Duration

The funding duration is typically around 30 days. The interquartile ranges between 29 to 34 days. The minimum funding period only lasted one day and the longest period was 93 days.

Goals

Funding goals range between USD 0 to USD {{format_num(goal_max)}}. However, the median goal was only USD 5k. 95% of projects sought funding below USD {{format_num(goal_95)}}. Only a very few projects realize very high in the range of several million.

Pledged

The contributed financing ranged between zero to USD 8.6 mi per project. Compared to the wide dimension of funding opportunity, the median pledged per project may seem disappointing. Only USD {{format_num(pledged_50)}} were collected on average. Only a very small number of projects of under 0.1% of projects successfully realized more than USD 1 mi. Compared to the median goal of USD {{format_num(goal_50)}}, this indicates either a high number of failed projects or the tendency of success of projects with very low funding goals.

Backers

A quarter of all projects were completed with 3 or less backers. The median number of backers was {{backers_50}}. Only 5% of all completed projects had more than {{goal_95}} supporters. Similar to goals and pledges, the number of backers increased sharply only after passing the 97.5% quantile. The maximum count of supporters in Kickstarter's history was {{format_num(backers_max)}} backers.

Highlights

- **The highest number of campaigns launched by the same creator: 68**

The creator with the name *Collectable Playing Cards* stands out. All 68 projects were started to fundraise bicycle-themed playing cards.

e.g. https://www.kickstarter.com/projects/2104052526/bicycle-stained-glass-leviathan-playing-cards

- **The project with highest funding goal ever sought for: USD 150 mi.**

The venture was created to finance a drama movie production: *A Celtic Lovestory*. The goal of USD 150 mi. was the highest ever sought for. However, it failed miserably in November 2015 with not one single backer.

https://www.kickstarter.com/projects/245190432/a-celtic-lovestory

- **The highest successful funding goal: USD 2 mi.**

3 Film & Video projects and one video games realized the highest successful funding goal of USD 2mi.

May 2013 was the first time USD 2mi was successfully raised. The popular actor and director Zach Braff successfully funded the narrative film "WISH I WAS HERE". By the end of the funding period, he had realized 3,1mi from 46,5k supporters.

https://www.kickstarter.com/projects/1869987317/wish-i-was-here-1

The Japanese video game "Shenmue 3" even realized USD 6.3mi in July 2015.

https://www.kickstarter.com/projects/ysnet/shenmue-3

- **The highest number of supporters: 105,857**

In July 2014 the project *Bring Reading Rainbow Back for Every Child, Everywhere!*, a web tech project, won 105,857 supporters. While they initially asked for USD 1 mi., they eventually sourced 5.4 mi. by the end of their campaign.

https://www.kickstarter.com/projects/readingrainbow/bring-reading-rainbow-back-for-every-child-everywh

- **The highest amount pledged: USD 11.4 mi.**

Shortly before Kickstarter's 10th anniversary, the creators of the animated film project "Critical Role: The Legend of Vox Machina Animated Special" celebrated the highest fundraising ever on Kickstarter. On 19/04/2019 A September 2012, they successfully collected funding of almost USD 11.4mi at an initial goal of 750k.

https://www.kickstarter.com/projects/criticalrole/critical-role-the-legend-of-vox-machina-animated-s

Outliers

The above campaign highlights mostly fall under the category extreme. They do not represent the average crowdfunding campaign on Kickstarter. The descriptive statistics reveal extreme outlier projects in regard to their goal, amount pledged and backers count. Thus, to keep plots readable and to not further distort our data, I'm going to focus on projects fitting the lower 95% quantile of aforementioned values. According to the statistics, I expect even within the 95% quantiles an extremely long right tail. In order to best reflect the measures of mean, I'm going to apply the median instead of the average whenever necessary.

7 5 Univariate Exploration

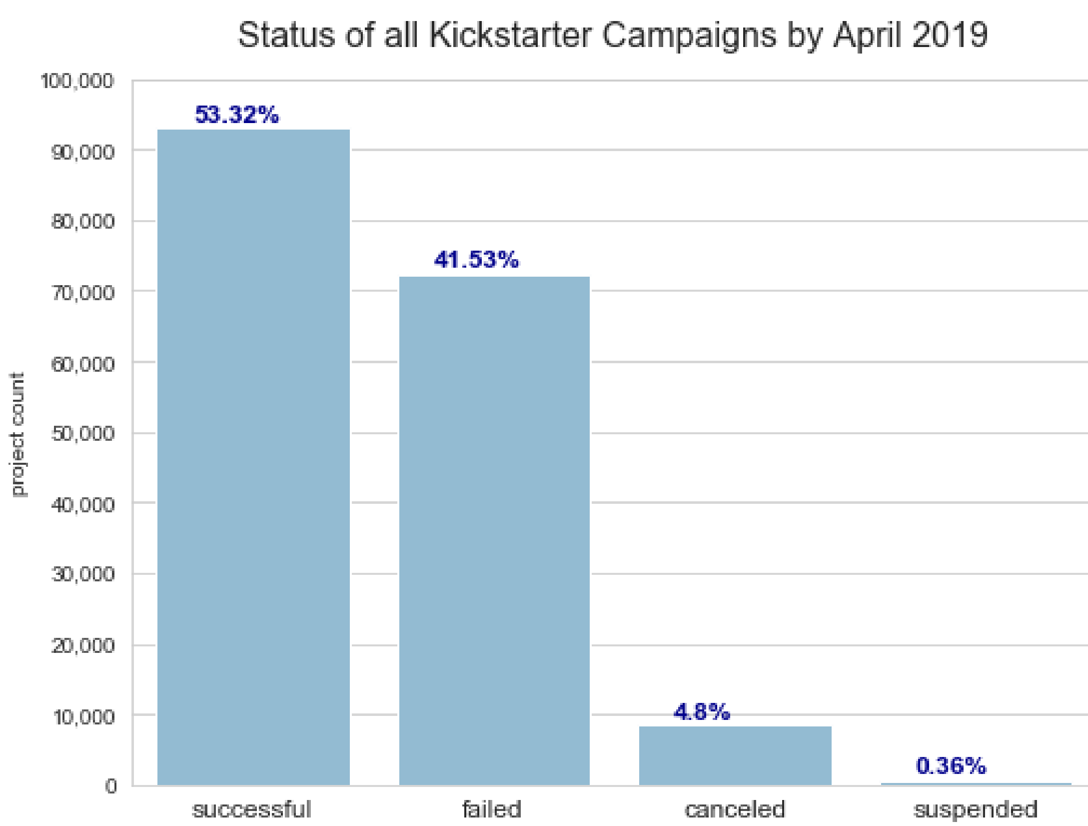
In this section, we explore the relevant features one by one visually. Univariate plots will allow a general understanding about the potential predictors of what it takes to launch a campaign successfully on Kickstarter.

Let's start our exploration by looking at the main domain of interest: status.

7.0.1 Project Status

What was the status of all campaigns on Kickstarter's anniversary?

```
In [65]: # style
         plt.figure(figsize=[8,6])

         # create ordering
         order = master_df.status.value_counts().index

         # plot bar chart for catergorical data
         ax = sns.countplot(data=master_df, x='status', color=cust_blues, order=order);

         # annotate proportions
         for p in ax.patches:
             ax.text(p.get_x()+0.15,
                     p.get_height()+1000,
                     str(round((p.get_height() / len(master_df))*100,2)) + '%',
                     fontsize=12, color='darkblue', weight='bold')

         # labels and ticks
         plt.title("Status of all Kickstarter Campaigns by April 2019", fontsize=16, pad=15)
         plt.xticks(fontsize=12)
         plt.xlabel(" ")
         format_yticks(master_df.status.value_counts().values.max(), 10000)
         plt.ylabel("project count")
         plt.show()
```

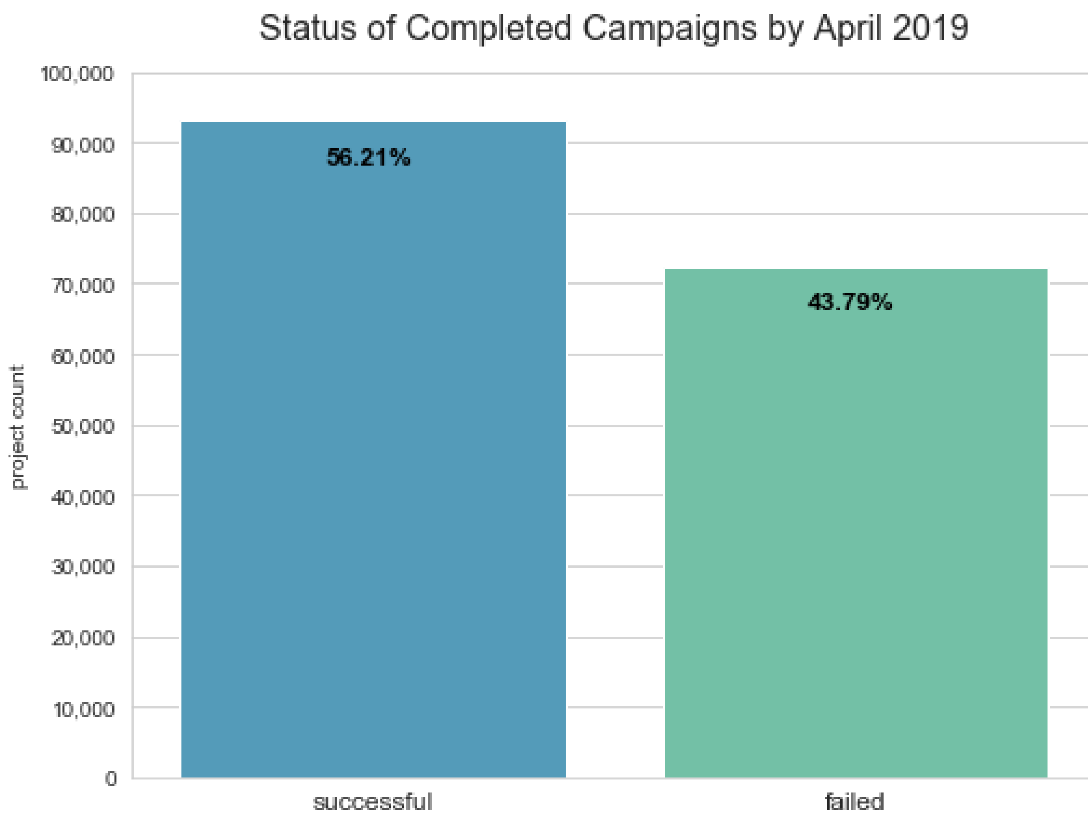


Here we see that since the launch of Kickstarter in 2009, most campaigns ended successfully (53.3%). 41.5% of all projects failed. A relatively small amount of projects never finished because they were either canceled or suspended.

What was the outcome of all completed projects?

Below we are going to plot the success and failure counts of projects that were completed ordinarily.

```
In [66]: # settings
         plt.figure(figsize=[8,6])

         # plot bar plor of completed projects only
         ax = sns.countplot(data=ks_compl, x='status',
                            color=sns.set_palette(status_colors),
                            order=ks_compl.status.value_counts().index);

         # annotate proportion
         for p in ax.patches:
             ax.text(p.get_x()+0.3, p.get_height()-6000,
                     str(round((p.get_height()/ len(ks_compl))*100,2)) + '%',
                     fontsize=12, color='black', weight='bold')

         # labels and ticks
         plt.title("Status of Completed Campaigns by April 2019", fontsize=16, pad=15)
         plt.xticks(fontsize=12)
         plt.xlabel(" ")
         format_yticks(ks_compl.status.value_counts().values.max(), 10000)
         plt.ylabel("project count")
         plt.show()
```



Out of all completed projects, there were {{format_num(n_compl_success)}} successfully funded projects in our data frame. More than half of all completed campaigns were successful. {{format_num(n_compl_fail)}} of all completed projects ended in failure. If we disregard projects that were either canceled or suspended, the proportion of successful campaigns was 56%.

7.0.2 Project Types

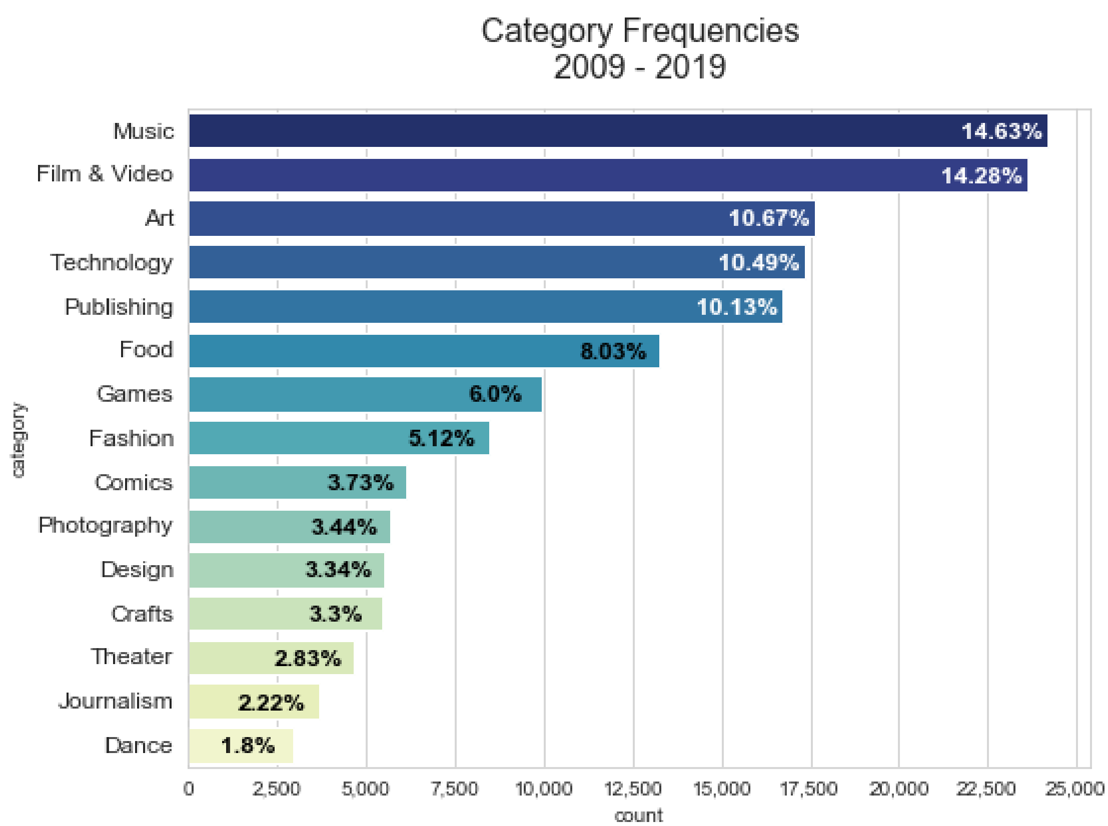
What kind of categories, subcategories and combined categories were popular?

To analyze project categories, I will start by visualizing the distribution of the parent categories.

Parent Categories

```
In [67]: # settings
         plt.figure(figsize=[8,6])

         # plot horizontal bars of main categories
         ax = sns.countplot(data=ks_compl, y='category', palette="YlGnBu_r",
                            order=ks_compl.category.value_counts().index);

         # annotate proportions
         cat_counts = ks_compl.category.value_counts()
         locs, labels = plt.yticks()
```

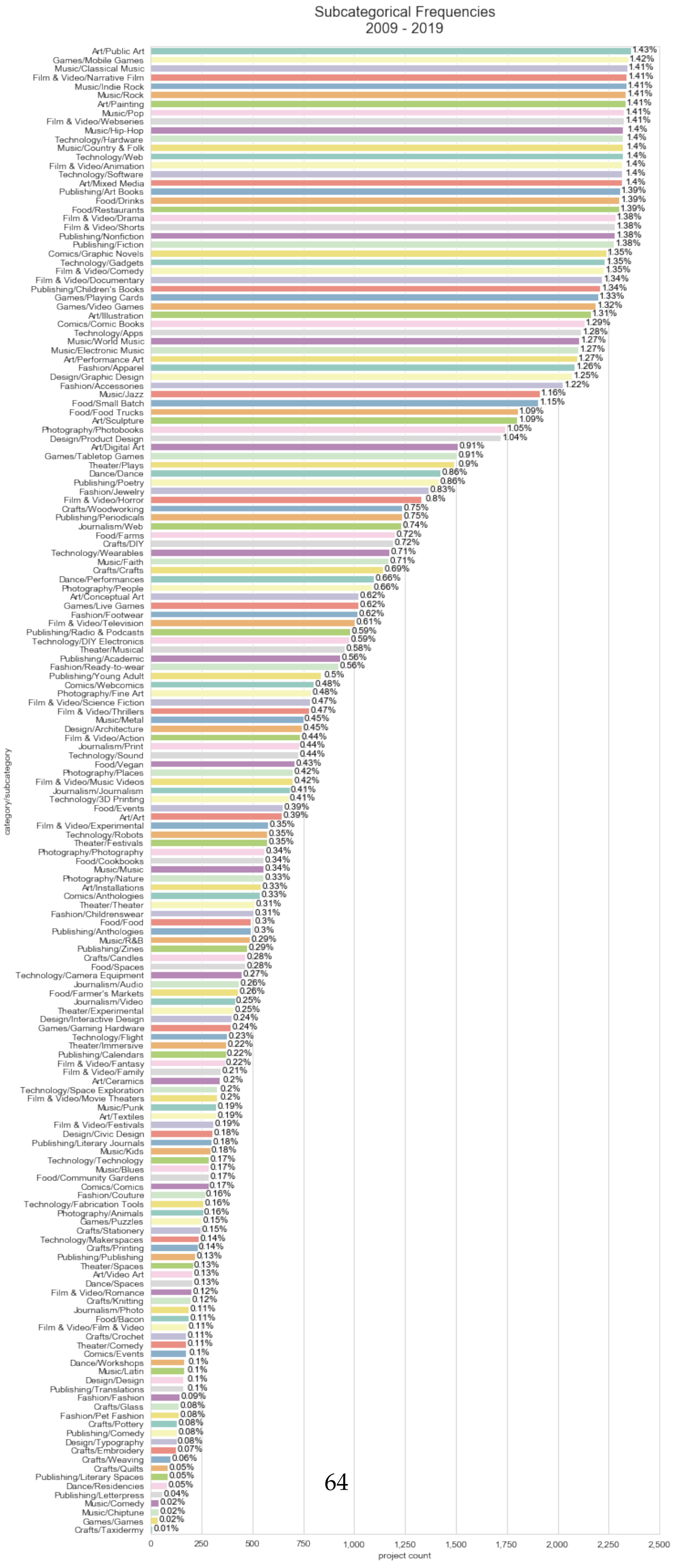
```
for loc, label in zip(locs, labels):
    count = int(cat_counts[label.get_text()])
    cat_rate = str(round(count*100 / n_compl_projects, 2)) + "%"
    # white annotation for top categories
    if count > 15000:
        plt.text(count-1300, loc+0.2, cat_rate, ha='center', color="white", fontsize=
     # black annotations for lower categories
    else:
        plt.text(count-1300, loc+0.2, cat_rate, ha='center', color="black", fontsize=

# labels and ticks
plt.title("Category Frequencies\n2009 - 2019", fontsize=16, pad=15);

plt.yticks(fontsize=12)
plt.ylabel("category")
format_xticks(ks_compl.category.value_counts().values.max(), 2500)
plt.show()
```



Subcategories

As subcategories can appear under several parent categories, I'm going to depict the project frequencies of combined categories, which considers the parent category and subcategory.

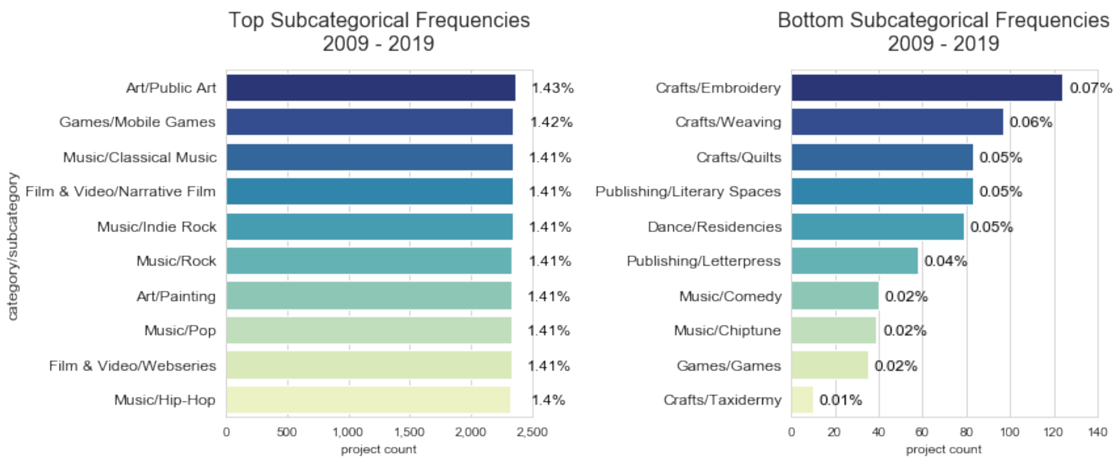
```
In [68]: # settings
         plt.figure(figsize=[10,30])

         # plot horizontal bars of main categories
         ax = sns.countplot(data=ks_compl, y='comb_cat', palette="Set3",
                            order=ks_compl.comb_cat.value_counts().index);

         # annotate proportions
         cat_counts = ks_compl.comb_cat.value_counts()
         locs, labels = plt.yticks()
         for loc, label in zip(locs, labels):
             count = int(cat_counts[label.get_text()])
             cat_rate = str(round(count*100 / n_compl_projects, 2)) + "%"
             plt.text(count+70, loc+0.15, cat_rate, ha='center', color="black")

         # labels and ticks
         plt.title("Subcategorical Frequencies\n2009 - 2019", fontsize=16, pad=15);
         plt.ylabel("category/subcategory")
         format_xticks(ks_compl.comb_cat.value_counts().values.max(), 250)
         plt.xlabel("project count")
         plt.show()
```


Subcategorical Frequencies
2009 - 2019
category/subcategory
project count
0
250
500
750
1,000
1,250
1,500
1,750
2,000
2,250
2,500
Art/Public Art 1.43%
Games/Mobile Games 1.42%
Music/Classical Music 1.41%
Film & Video/Narrative Film 1.41%
Music/Indie Rock 1.41%
Music/Rock 1.41%
Art/Painting 1.41%
Music/Pop 1.41%
Film & Video/Webseries 1.41%
Music/Hip-Hop 1.4%
Technology/Hardware 1.4%
Music/Country & Folk 1.4%
Technology/Web 1.4%
Film & Video/Animation 1.4%
Technology/Software 1.4%
Art/Mixed Media 1.4%
Publishing/Art Books 1.39%
Food/Drinks 1.39%
Food/Restaurants 1.39%
Film & Video/Drama 1.38%
Film & Video/Shorts 1.38%
Publishing/Nonfiction 1.38%
Publishing/Fiction 1.38%
Comics/Graphic Novels 1.35%
Technology/Gadgets 1.35%
Film & Video/Comedy 1.35%
Film & Video/Documentary 1.34%
Publishing/Children's Books 1.34%
Games/Playing Cards 1.33%
Games/Video Games 1.32%
Art/Illustration 1.31%
Comics/Comic Books 1.29%
Technology/Apps 1.28%
Music/World Music 1.27%
Music/Electronic Music 1.27%
Art/Performance Art 1.27%
Fashion/Apparel 1.26%
Design/Graphic Design 1.25%
Fashion/Accessories 1.22%
Music/Jazz 1.16%
Food/Small Batch 1.15%
Food/Food Trucks 1.09%
Art/Sculpture 1.09%
Photography/Photobooks 1.05%
Design/Product Design 1.04%
Art/Digital Art 0.91%
Games/Tabletop Games 0.91%
Theater/Plays 0.9%
Dance/Dance 0.86%
Publishing/Poetry 0.86%
Fashion/Jewelry 0.83%
Film & Video/Horror 0.8%
Crafts/Woodworking 0.75%
Publishing/Periodicals 0.75%
Journalism/Web 0.74%
Food/Farms 0.72%
Crafts/DIY 0.72%
Technology/Wearables 0.71%
Music/Faith 0.71%
Crafts/Crafts 0.69%
Dance/Performances 0.66%
Photography/People 0.66%
Art/Conceptual Art 0.62%
Games/Live Games 0.62%
Fashion/Footwear 0.62%
Film & Video/Television 0.61%
Publishing/Radio & Podcasts 0.59%
Technology/DIY Electronics 0.59%
Theater/Musical 0.58%
Publishing/Academic 0.56%
Fashion/Ready-to-wear 0.56%
Publishing/Young Adult 0.5%
Comics/Webcomics 0.48%
Photography/Fine Art 0.48%
Film & Video/Science Fiction 0.47%
Film & Video/Thrillers 0.47%
Music/Metal 0.45%
Design/Architecture 0.45%
Film & Video/Action 0.44%
Journalism/Print 0.44%
Technology/Sound 0.44%
Food/Vegan 0.43%
Photography/Places 0.42%
Film & Video/Music Videos 0.42%
Journalism/Journalism 0.41%
Technology/3D Printing 0.41%
Food/Events 0.39%
Art/Art 0.39%
Film & Video/Experimental 0.35%
Technology/Robots 0.35%
Theater/Festivals 0.35%
Photography/Photography 0.34%
Food/Cookbooks 0.34%
Music/Music 0.34%
Photography/Nature 0.33%
Art/Installations 0.33%
Comics/Anthologies 0.33%
Theater/Theater 0.31%
Fashion/Childrenswear 0.31%
Food/Food 0.3%
Publishing/Anthologies 0.3%
Music/R&B 0.29%
Publishing/Zines 0.29%
Crafts/Candles 0.28%
Food/Spaces 0.28%
Technology/Camera Equipment 0.27%
Journalism/Audio 0.26%
Food/Farmer's Markets 0.26%
Journalism/Video 0.25%
Theater/Experimental 0.25%
Design/Interactive Design 0.24%
Games/Gaming Hardware 0.24%
Technology/Flight 0.23%
Theater/Immersive 0.22%
Publishing/Calendars 0.22%
Film & Video/Fantasy 0.22%
Film & Video/Family 0.21%
Art/Ceramics 0.2%
Technology/Space Exploration 0.2%
Film & Video/Movie Theaters 0.2%
Music/Punk 0.19%
Art/Textiles 0.19%
Film & Video/Festivals 0.19%
Design/Civic Design 0.18%
Publishing/Literary Journals 0.18%
Music/Kids 0.18%
Technology/Technology 0.17%
Music/Blues 0.17%
Food/Community Gardens 0.17%
Comics/Comics 0.17%
Fashion/Couture 0.16%
Technology/Fabrication Tools 0.16%
Photography/Animals 0.16%
Games/Puzzles 0.15%
Crafts/Stationery 0.15%
Technology/Makerspaces 0.14%
Crafts/Printing 0.14%
Publishing/Publishing 0.13%
Theater/Spaces 0.13%
Art/Video Art 0.13%
Dance/Spaces 0.13%
Film & Video/Romance 0.12%
Crafts/Knitting 0.12%
Journalism/Photo 0.11%
Food/Bacon 0.11%
Film & Video/Film & Video 0.11%
Crafts/Crochet 0.11%
Theater/Comedy 0.11%
Comics/Events 0.1%
Dance/Workshops 0.1%
Music/Latin 0.1%
Design/Design 0.1%
Publishing/Translations 0.1%
Fashion/Fashion 0.09%
Crafts/Glass 0.08%
Fashion/Pet Fashion 0.08%
Crafts/Pottery 0.08%
Publishing/Comedy 0.08%
Design/Typography 0.08%
Crafts/Embroidery 0.07%
Crafts/Weaving 0.06%
Crafts/Quilts 0.05%
Publishing/Literary Spaces 0.05%
Dance/Residencies 0.05%
Publishing/Letterpress 0.04%
Music/Comedy 0.02%
Music/Chiptune 0.02%
Games/Games 0.02%
Crafts/Taxidermy 0.01%

Best Of Categories/Subcategories
Since there are so many subcategories, I'm going to plot the top and bottom proportion of combined categories.

In [69]:
```
# save 10 most popular combined categories
pop_subcats = ks_compl.comb_cat.value_counts().index[:10]

# save 10 most uncommon combined categories
unpop_subcats = ks_compl.comb_cat.value_counts().index[-10:]

# settings
plt.figure(figsize=[12,5])

# left plot: top subcategorical count as horizontal bars
plt.subplot(1,2,1)
ax = sns.countplot(data=ks_compl, y='comb_cat', palette="YlGnBu_r",
                   order=pop_subcats);

# annotate proportions
cat_counts = ks_compl.comb_cat.value_counts()
locs, labels = plt.yticks()
for loc, label in zip(locs, labels):
    count = int(cat_counts[label.get_text()])
    cat_rate = str(round(count*100 / n_compl_projects, 2)) + "%"
    plt.text(count+310, loc+0.15, cat_rate, ha='center', color="black", fontsize=12)

# labels and ticks
plt.yticks(fontsize=12)
plt.ylabel("category/subcategory", fontsize=12)
plt.title("Top Subcategorical Frequencies\n2009 - 2019", fontsize=16, pad=15);
format_xticks(ks_compl.comb_cat.value_counts().values.max(), 500)
plt.xlabel("project count")


# right plot: top subcategorical count as horizontal bars
plt.subplot(1,2,2)
ax = sns.countplot(data=ks_compl, y='comb_cat', palette="YlGnBu_r",
                   order=unpop_subcats);
plt.title("Bottom Subcategorical Frequencies\n2009 - 2019", fontsize=16, pad=15);

# annotate proportions
locs, labels = plt.yticks()
for loc, label in zip(locs, labels):
    count = int(cat_counts[label.get_text()])
    cat_rate = str(round(count*100 / n_compl_projects, 2)) + "%"
    plt.text(count+13, loc+0.15, cat_rate, ha='center', color="black", fontsize=12)
```

```
# labels and ticks
plt.yticks(fontsize=12)
plt.ylabel("category/subcategory")
format_xticks(130,20)
plt.xlabel("project count")
plt.ylabel("")
plt.tight_layout()
plt.show()
```

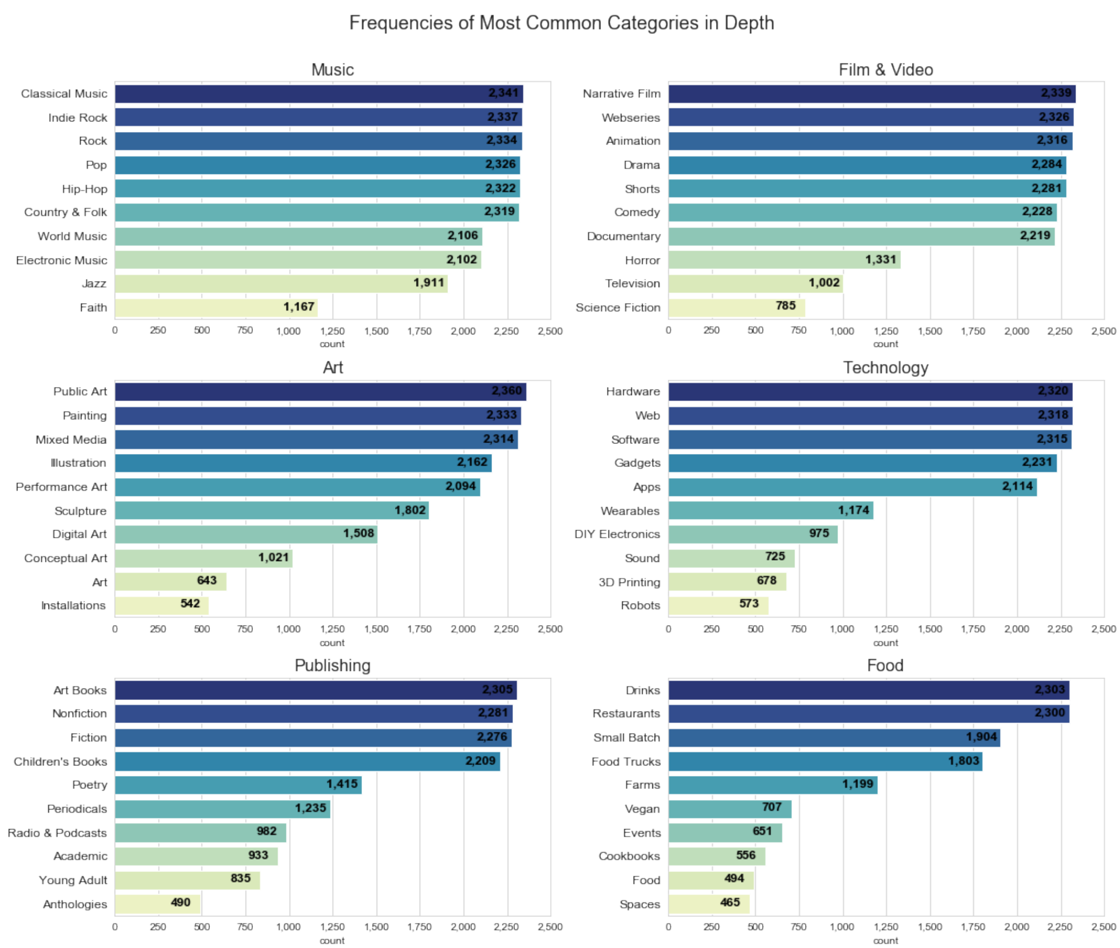


Popular Categories and their respective subcategories

Let's take a look at the 6 most common categories in depth. By separating the top 6 categories into subplots to evaluate respective top 10 subcategories, I hope to shed light what kind of projects are typically being funded on Kickstarter.

```
In [70]: # settings
         plt.figure(figsize=[15,12])


         # subplots
         for i, cat in enumerate(ks_compl.category.value_counts().index[:6]):
                 # filter dataframe by category
                 ks_compl_cat = ks_compl.query('category == @cat')

                 plt.subplot(3, 2, i+1)
                 # plot horizontal bars
                 ax = sns.countplot(data=ks_compl_cat, y='subcategory', palette='YlGnBu_r',
                                    order=ks_compl_cat.subcategory.value_counts()[:10].index);
                 # labels and ticks
                 plt.yticks(fontsize=12)
                 plt.ylabel("")
                 plt.subplots_adjust(bottom=-0.1)
```

```python
        format_xticks(ks_compl_cat.subcategory.value_counts().max(),250)

        # annotate
        cat_counts = ks_compl_cat.subcategory.value_counts()
        plt.title(f"{cat}", fontsize=16)
        locs, labels = plt.yticks()
        for loc, label in zip(locs, labels):
            count = cat_counts[label.get_text()]
            plt.text(count-110, loc+0.1, format_num(count), ha='center',
                     color="black", fontsize=12, fontweight='bold')

plt.tight_layout()
plt.suptitle("Frequencies of Most Common Categories in Depth", fontsize=18, y=1.04)
plt.show()
```



The above plots demonstrate the strong creative focus and B2B character of crowdfunding campaigns on Kickstarter. We can confirm that *Music*, *Film & Video* and *Art* were among the most frequent project categories.

By taking a more detailed look on subcategorical values, we found *Public Art*, *Classical Music* and *Mobile Games* as the most popular project types. The proportion of those subcategories was 1.4% each. Notice that the relative distribution of subcategories is relatively even. About one third of all subcategories range between relative shares of 1.4% to 1% of all projects. Thus, we do not find subcategories that stand out.

Generally, we clearly recognize a focus on creative disciplines. The top project types were ventures like Public Art, Classical Music, Art Books and Web Series. From a business perspective without knowing the details, such kind of projects are usually not known to speak to the public mainstream; nor do they typically generate high commercial incomes.

From a professional investor's perspective tech projects and food projects may have the greatest potential to break the low commercial potential. Although many of their subcategories (e.g. vegan, small batch, gadgets and wearables etc.) indicate a rater creative niche character.

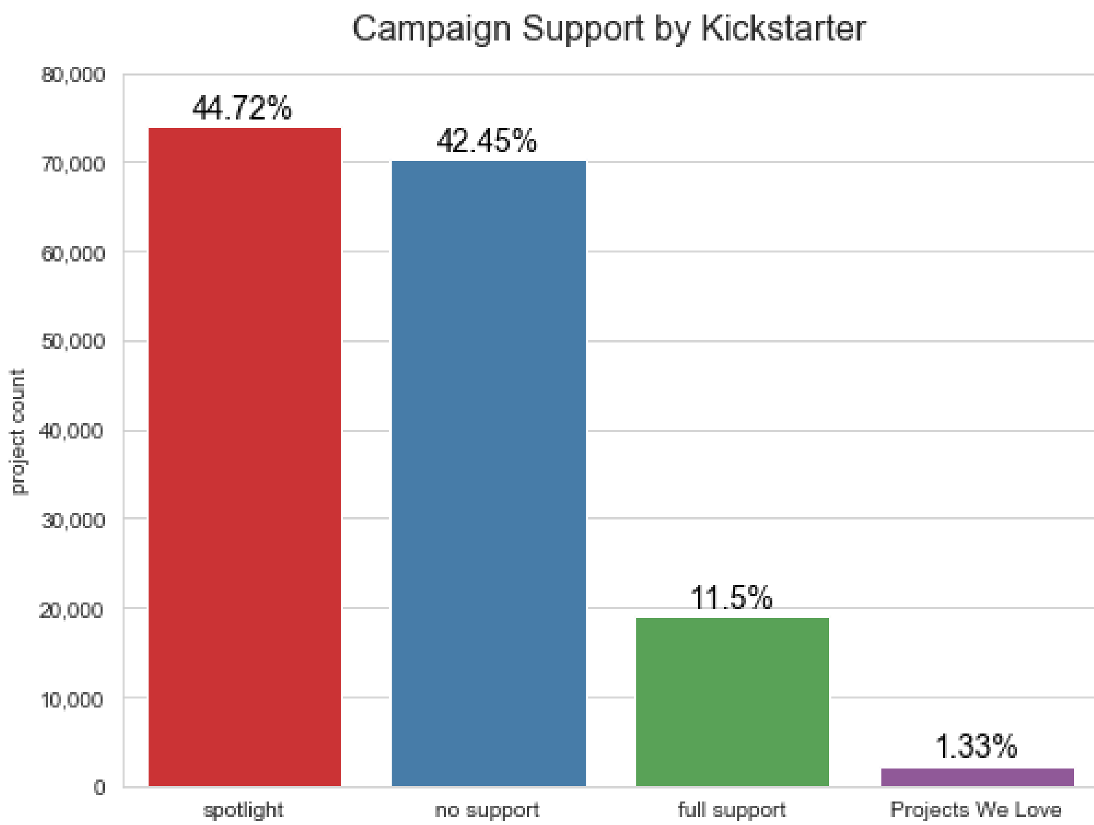
Due to mostly creative industries being represented here, we do not expect Kickstarter to be relevant for entrepreneurial ventures with a strong for-profit focus, nor high capital intensity, nor B2B projects. This doesn't surprise since crowdfunding as a financial tool usually attracts a private audience instead of professional investors.

7.0.3 Featured

How did Kickstarter promote campaigns?

As a next step, I'm going to investigate how Kickstarter supported projects. Let's start by plotting the value counts of the data point *"featured"*.

```
In [71]: # settings
         plt.figure(figsize=[8,6])

         # order
         feat_order = ks_compl.featured.value_counts().index

         # plot vertical bars
         ax = sns.countplot(data=ks_compl, x='featured', color=sns.set_palette(feat_color),
                            order=feat_order)

         # annotate percentages
         for i, feat in enumerate(feat_order):
             rate = (ks_compl.featured.value_counts().values[i] / n_compl_projects) * 100
             plt.text(i, ks_compl.featured.value_counts().values[i]+1000, str(round(rate, 2))
                      ha='center', fontsize=14, color="black")

         # ticks and labels
         plt.xlabel("")
         format_yticks(80000, 10000)
         plt.ylabel("project count")
         plt.title("Campaign Support by Kickstarter", fontsize=16, pad=15);
         plt.show();
```



44.8% of all projects were spotlighted by Kickstarter on their landing page. Nearly the same amount of projects was not at all promoted by Kickstarter. Every 11th project was fully featured by Kickstarter. To be precise, 11.5% of all completed projects were featured on the landing page and additionally picked by staff for the “Projects We Love” badge. Only a very small amount of project were awarded the badge, but were not promoted any further.

Overall, more than every second project was supported by Kickstarter.

7.0.4 Duration

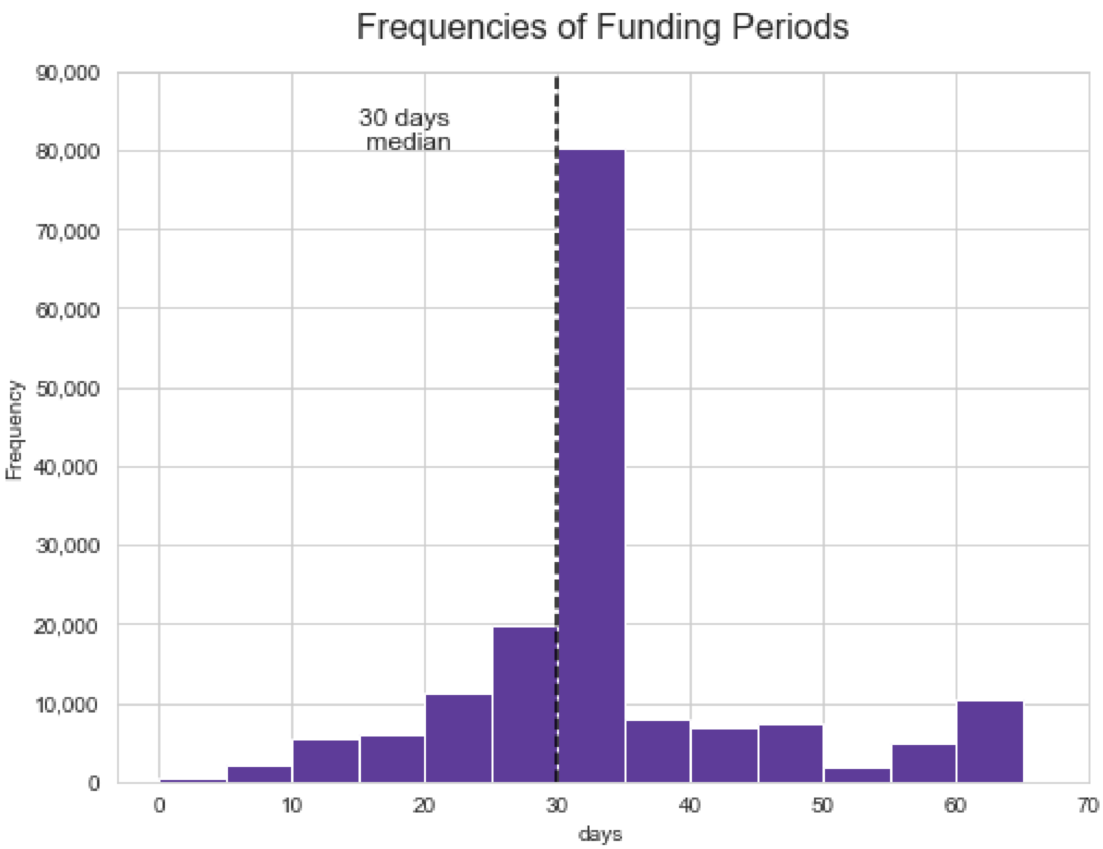
I suspect the funding duration to influence the probability of success and failure of a campaign. Thus, I will visually assess duration next.

How is the funding duration distributed across projects?

```
In [72]: ks_compl.duration.value_counts().head()
```

```
Out[72]: 30 days 00:00:00    58356
         60 days 00:00:00    8143
         29 days 23:00:00    6624
         30 days 01:00:00    5617
         45 days 00:00:00    4410
         Name: duration, dtype: int64
```

```
In [73]: # settings
         plt.figure(figsize=[8,6])

         # plot histogram of project duration
         ks_compl['duration_days'].plot.hist(color=duration_color, bins=np.arange(0, 70,5))

         # annotate median duration
         plt.axvline(ks_compl['duration_days'].median(), color='black', linestyle='--')

         # labels and titles
         plt.title("Frequencies of Funding Periods", fontsize=16, pad=15 );
         plt.text(15, 80000, str(ks_compl['duration_days'].median())[:-2] + " days\n median", f
         format_yticks(90000,10000)
         format_xticks(70,10)
         plt.xlabel("days")
         plt.show()
```



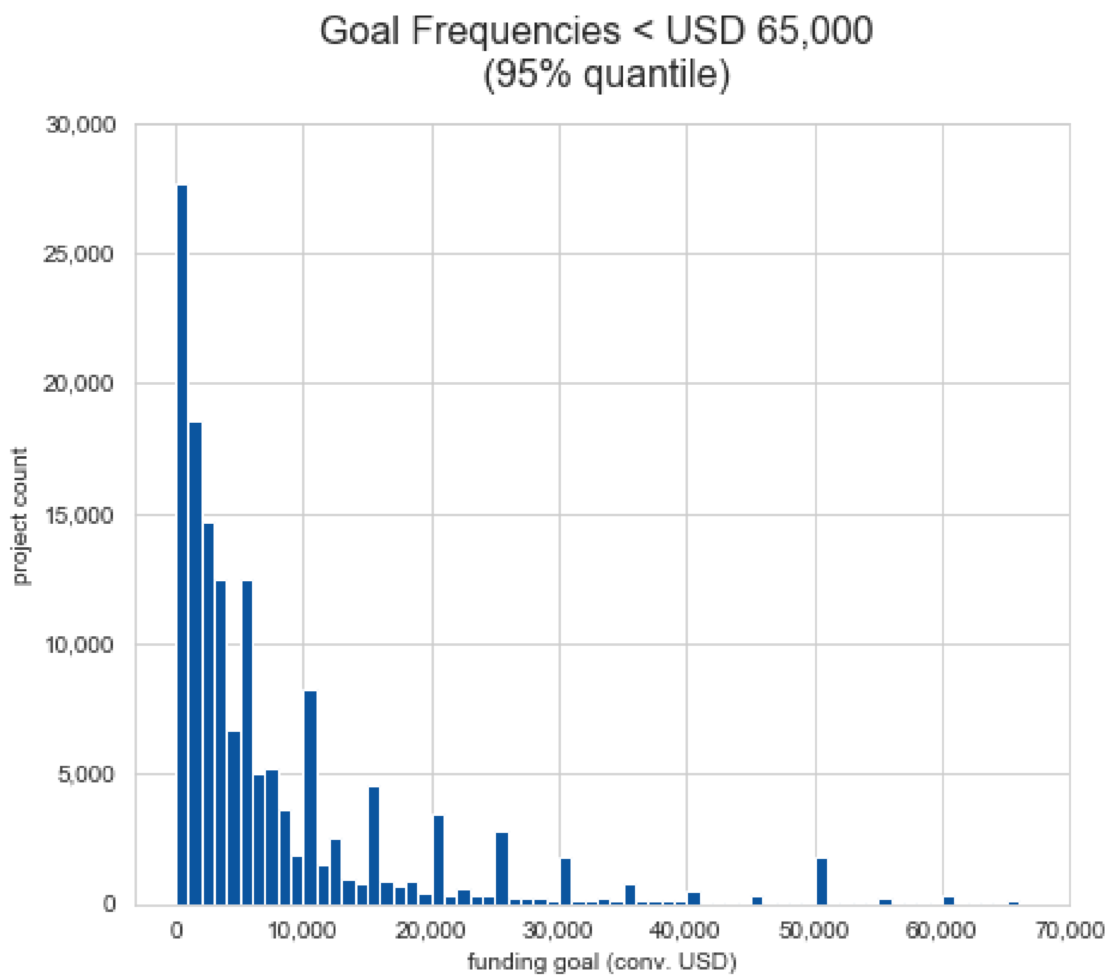
The above normally distributed plot shows that funding durations around 30 days dominated. There is second modal peak in durations at 60-65 days.

7.1 Goals

I assume that goals are one of the main predictors of whether a project succeeded or failed. From the above statistical assessment, I expect my visuals to be extremely skewed to the right. In order to make the plots readable, I will use different techniques. Aside from using the 95% quantile data frame, I will use log scales and I will group the data in multiple goal levels.

How are goals distributed across completed campaigns?

In [74]:
```
# style
plt.figure(figsize=[7,6])

# Create bins
bin_edges = np.arange(0, ks_compl_95.goal_hist_usd.max()+1000, 1000)

# plot bars of 95% quantile data
plt.hist(data = ks_compl_95, x = 'goal_hist_usd', bins = bin_edges, color=goal_color)

# labels and titles
plt.title("Goal Frequencies < USD 65,000 \n (95% quantile)", fontsize=16, pad=15)
format_xticks(goal_95, 10000)
plt.xlabel("funding goal (conv. USD)")
format_yticks(30000, 5000)
plt.ylabel("project count")

plt.show()
```

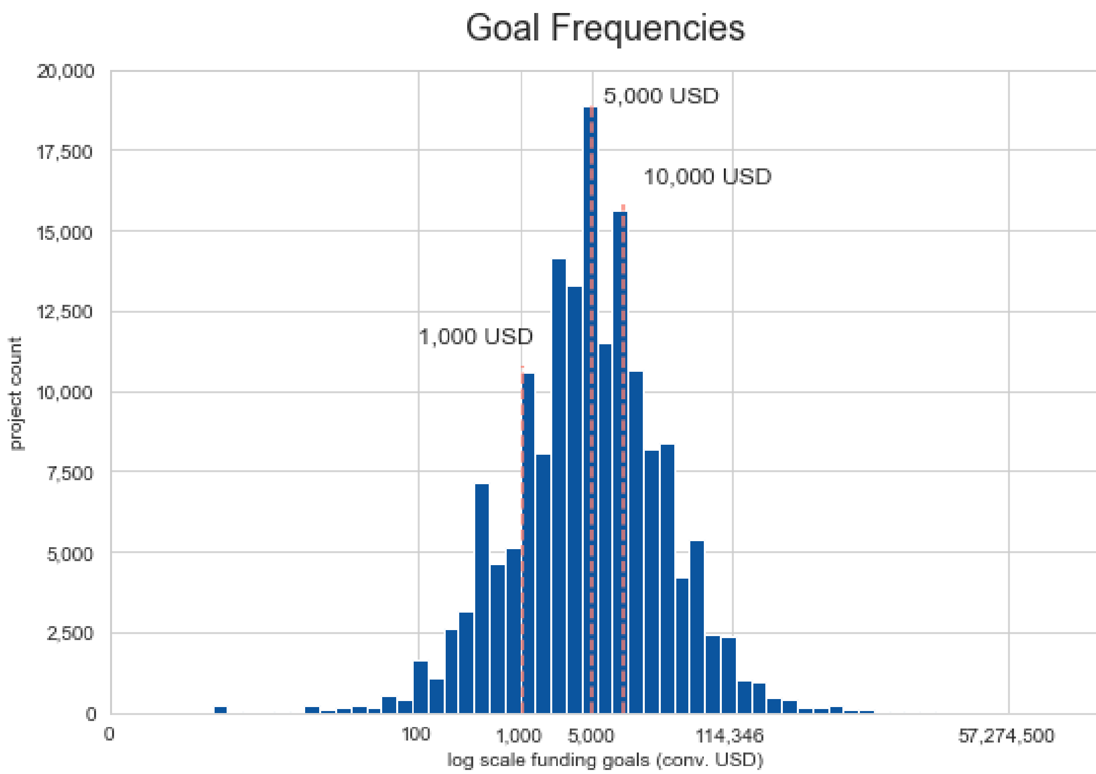


The visualization above depicts the distribution of funding goals of completed projects(95% quantile). Be aware that funding goals are cut off above USD 65k. Plotting the actually goals up to USD {{format_num(goal_max)}} would skew the curve further and result in an unreadable plot. Notice the accumulation of low funding goals and the long right tail of the plot. Characteristic for the above distribution are the multimodal peaks of funding goals that seem to occur on a regular frequency.

To better understand the distribution of funding goals, I will again plot the goal distribution of all completed project; this time using a logarithmic scale.

In [75]:
```
# settings
plt.figure(figsize=[9,6])
base_color = sns.color_palette("Blues_r")[0]

# create log scale and bin data
log_data = np.log10(ks_compl.goal_hist_usd)
log_bin_edges = np.arange(0, log_data.max()+0.15, 0.15)

# plot histogram using binned log data
```

```
plt.hist(log_data, bins = log_bin_edges, color=base_color);

# annotations

# calculate peaks
peaks = ks_compl.goal_hist_usd.value_counts().index[:3]
log_peaks = [np.log10(peak) for peak in peaks]
texts = [format_num(peak) + " USD" for peak in peaks]
ax = plt.gca()

# 5000 peak
ax.axvline(x=log_peaks[0], color='salmon', ymax=0.95, linestyle="dashed")
ax.annotate(texts[0], xy=(log_peaks[0]+0.11, 19000),fontsize=12)

# 10 000 peak
ax.axvline(x=log_peaks[1], color='salmon', ymax=0.79, linestyle="dashed")
ax.annotate(texts[1], xy=(log_peaks[0]+0.5, 16500),fontsize=12)

# 1000 peak
ax.axvline(x=log_peaks[2]+0.01999, color='salmon', ymax=0.539, linestyle="dashed")
ax.annotate(texts[2], xy=(log_peaks[2]-1, 11500),fontsize=12)

# labels and ticks
plt.title("Goal Frequencies", fontsize=18, pad=15)

format_yticks(20000, 2500)
plt.ylabel("project count")

x_ticks = [0.1, 100, 1000, goal_50,  round(goal_975,2), round(goal_outliers,2) ]
x_tick_labels = [format_num(x_tick) for x_tick in x_ticks]
plt.xticks(np.log10(x_ticks), x_tick_labels)
plt.xlabel('log scale funding goals (conv. USD)')

plt.show()
```



In contrast to the previous plot, this plot shows the full range of funding goals, including extremes and outliers. Using a log scale on the x-axis results in a rather symmetrical normal distribution of goals: the highest peak is at the median of USD 5k, the second highest peak occurs at USD 10k.

However, by using a log scale, the above visualization hides the extremely skewed nature of funding goals and may lead to misinterpretation. Moreover, the local maxima of funding goals are not as obvious. To bring the analysis of goals to the next level, I'm going to split goals into ordered categorical groups based on the aforementioned quantiles.

```
In [76]: # bin observations into ordinal goal categories
         bin_edges = [goal_min, goal_25, goal_50, goal_75, goal_95, goal_975, goal_outliers, go
         bin_names = ['low', 'medium', 'moderately high', 'high', 'very high', 'extreme', 'outl

         # Creates goal_level column
         pd.set_option('mode.chained_assignment', None)
         ks_compl['goal_level'] = pd.cut(ks_compl['goal_hist_usd'], bin_edges, labels=bin_names
         ks_success_95['goal_level'] = pd.cut(ks_success_95['goal_hist_usd'], bin_edges, labels
         ks_fail_95['goal_level'] = pd.cut(ks_success_95['goal_hist_usd'], bin_edges, labels=bi

         # create data frames filtered by each goal levels
         ks_compl_goal_low = ks_compl[ks_compl.goal_level == "low"]
         ks_compl_goal_medium = ks_compl[ks_compl.goal_level == "medium"]
         ks_compl_goal_moderate = ks_compl[ks_compl.goal_level == "moderately high"]
```

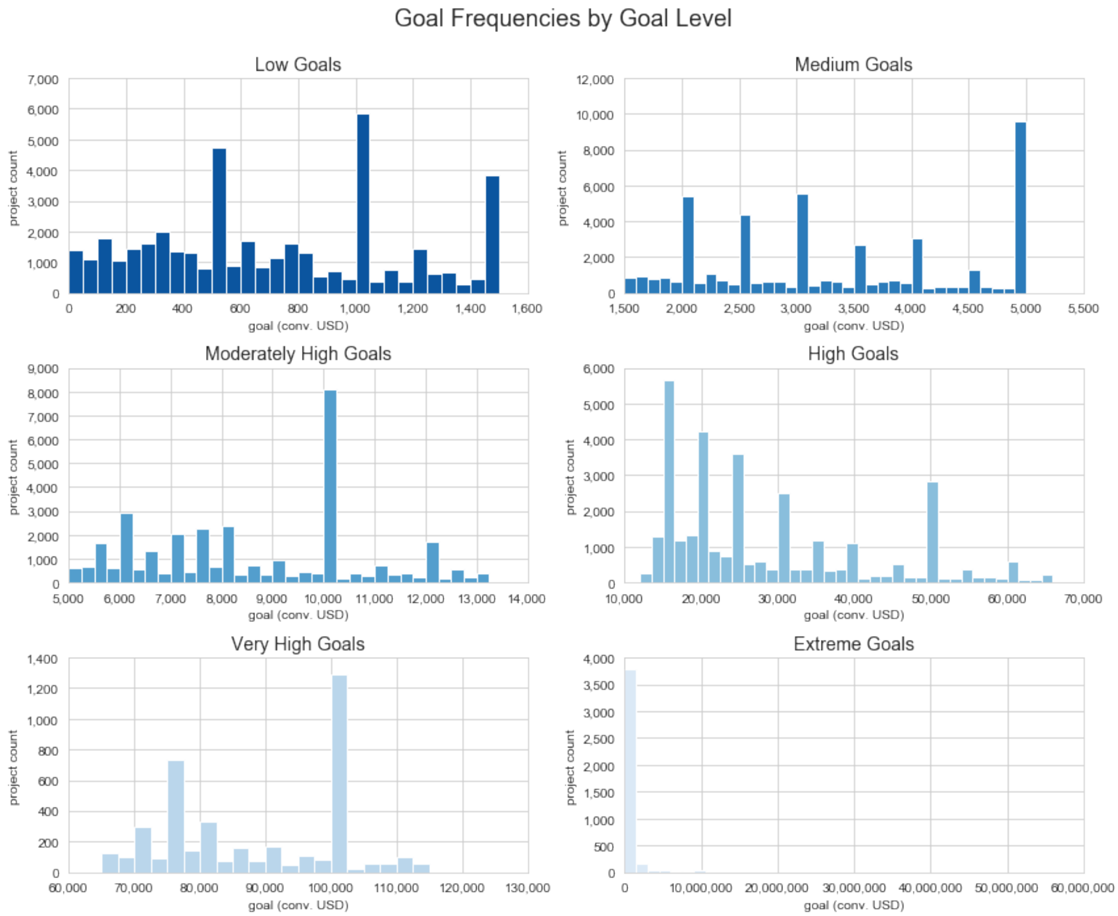
```
ks_compl_goal_high = ks_compl[ks_compl.goal_level == "high"]
ks_compl_goal_very_high = ks_compl[ks_compl.goal_level == "very high"]
ks_compl_goal_extreme = ks_compl[ks_compl.goal_level == "extreme"]

# cluster leveled data frames into a list
ks_goal_leveled = [ks_compl_goal_low, ks_compl_goal_medium,
                   ks_compl_goal_moderate, ks_compl_goal_high, ks_compl_goal_very_high
                   ks_compl_goal_extreme]

# show counts per goal level
ks_compl.goal_level.value_counts()
```

Out[76]:

```
medium               47697
low                  42477
moderately high      33915
high                 33090
very high            4136
extreme              4120
outliers             17
Name: goal_level, dtype: int64
```

In [77]:

```
# style
fig = plt.figure(figsize=[12,12])
base_color = sns.color_palette("Blues_r")

bin_sizes = [50, 100, 250, 1500, 2500, 1500000]
for i, level in enumerate(bin_names[:-1]):
    plt.subplot(4, 2, i+1)
    # create bins
    bin_edges_leveled = np.arange(0, ks_goal_leveled[i].goal_hist_usd.max()+bin_sizes
    # plot frequencies
    plt.hist(data = ks_goal_leveled[i], x = 'goal_hist_usd', bins = bin_edges_leveled

    # labels and ticks
    plt.title(level.title() +" Goals", fontsize=14)
    plt.xlabel("goal (conv. USD)")
    plt.ylabel("project count")
    plt.xlim(bin_edges[i],)
    xlocs, xlabels = plt.xticks()
    xlabels = [format_num(xloc) for xloc in xlocs]
    plt.xticks(xlocs, xlabels)
    ylocs, ylabels = plt.yticks()
    ylabels = [format_num(yloc) for yloc in ylocs]
    plt.yticks(ylocs, ylabels)
    plt.subplots_adjust(bottom=-0.3)

plt.suptitle("Goal Frequencies by Goal Level", fontsize=18, y=1.03)
plt.tight_layout()
plt.show()
```



To guide the attention towards the multi-modal peaks, I plotted the distribution of goals for each goal category. Due to the long right tail and to improve readability of the above graphs, I limited the graphs to goals under USD 57mi.

There are extreme outliers at the upper end of funding goals that are not easily to depict in a plot. In each goal category, there is a higher frequency of lower goals on the left side of the plot. However, there are remarkable peaks in every goal category that seem to march to a different drummer. Here the multi modal character of goals becomes apparent. Some of the most dominant goals are: USD 500, 1k 1,5k, 5k, 10k and 100l. Below, I will programmatically calculate the most important modes by goal level.

```
In [78]: # print summary
         for name, df in zip(bin_names, ks_goal_leveled):
             frequencies = df.goal_hist_usd.value_counts().index[:5]
             freq_counts = df.goal_hist_usd.value_counts().values[:5]
             print(f"\nFrequency peaks of {name} goal projects:")
             for i in range(5): print(f"USD {format_num(frequencies[i])}, count: {format_num(f
```

```
Frequency peaks of low goal projects:
USD 1,000, count: 5,579
```

```
USD 500, count: 4,196
USD 1,500, count: 3,502
USD 300, count: 1,242
USD 1,200, count: 1,109

Frequency peaks of medium goal projects:
USD 5,000, count: 9,308
USD 3,000, count: 5,158
USD 2,000, count: 4,997
USD 2,500, count: 3,949
USD 4,000, count: 2,789

Frequency peaks of moderately high goal projects:
USD 10,000, count: 7,889
USD 6,000, count: 2,447
USD 8,000, count: 2,048
USD 7,000, count: 1,593
USD 7,500, count: 1,578

Frequency peaks of high goal projects:
USD 15,000, count: 4,320
USD 20,000, count: 3,715
USD 25,000, count: 3,085
USD 50,000, count: 2,703
USD 30,000, count: 2,216

Frequency peaks of very high goal projects:
USD 100,000, count: 1,227
USD 75,000, count: 571
USD 80,000, count: 247
USD 70,000, count: 197
USD 85,000, count: 107

Frequency peaks of extreme goal projects:
USD 150,000, count: 399
USD 250,000, count: 315
USD 200,000, count: 264
USD 500,000, count: 202
USD 300,000, count: 147
```

Creator's funding goals can go up to several millions. However, 3 quarters of goals were below USD 13k. Our plots show a right-skewed goal distribution across all goal categories. Additionally, the distribution of goals has a multimodal character. Goals are usually defined at full numbers. The most frequent goals were:

1) USD 5k,

2) USD 10k,

3) USD 1k,

4) USD 3k

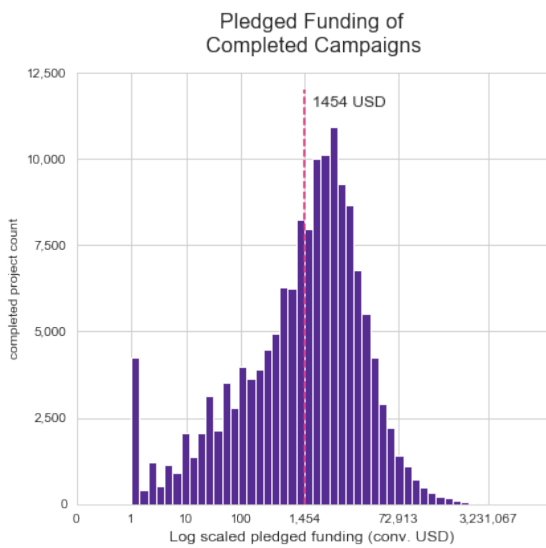
5) USD 4k.

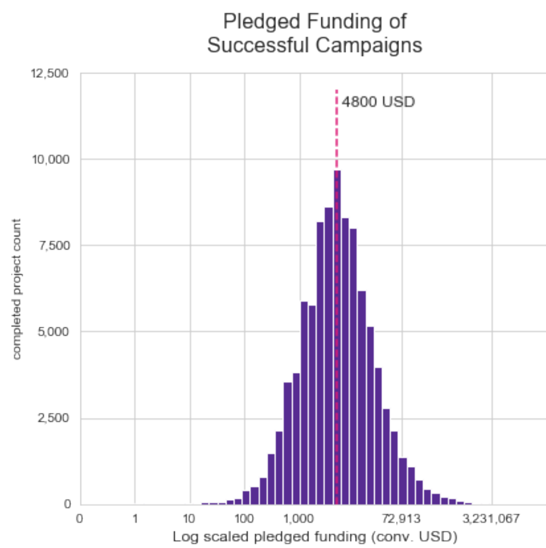
7.1.1 Pledged

How is the amount of funding distributed across completed projects?

In [79]:
```
# settings
plt.figure(figsize=[14,6])
base_color = sns.color_palette("Purples_r")[0]

# left plot: pledged amount all completed projects
plt.subplot(1,2,1)
# create log scale and bin data
df = ks_compl.pledged_hist_usd.replace(0, 0.01) # to avoid zero division error for lo
log_data = np.log10(df)
log_bin_edges = np.arange(0, log_data.max()+0.15, 0.15)

# plot histogram using binned log data
plt.hist(log_data, bins = log_bin_edges, color=base_color);

# annotate median
ax = plt.gca()
ax.axvline(x=np.log10(pledged_50), color='#dd1c77', ymax=0.96, linestyle="dashed")
ax.annotate(str(int(pledged_50)) + " USD", xy=(np.log10(pledged_50+500), 11500),fonts

# labels and ticks
plt.title("Pledged Funding of\n Completed Campaigns", fontsize=16, pad=15)

format_yticks(12500,2500)
plt.ylabel("completed project count")

x_ticks = [0.1, 1, 10, 100, pledged_50,  round(pledged_975,2), round(pledged_outliers
x_tick_labels = [format_num(x_tick) for x_tick in x_ticks]
plt.xticks(np.log10(x_ticks), x_tick_labels)
plt.xlabel('Log scaled pledged funding (conv. USD)', fontsize=12)

# right plot: pledged amount all completed projects
plt.subplot(1,2,2)

# create log scale and bin data
df = ks_compl_success.pledged_hist_usd.replace(0, 0.01) # to avoid zero division erro
log_data = np.log10(df)
```

```
log_bin_edges = np.arange(0, log_data.max()+0.15, 0.15)

# plot histogram using binned log data
plt.hist(log_data, bins = log_bin_edges, color=base_color);

# annotate median
ax = plt.gca()
ax.axvline(x=np.log10(df.median()), color='#dd1c77', ymax=0.96, linestyle="dashed")
ax.annotate(str(int(df.median())) + " USD", xy=(np.log10(pledged_50+4400), 11500),fon

# labels and ticks
plt.title("Pledged Funding of\nSuccessful Campaigns", fontsize=16, pad=15)

format_yticks(12500,2500)

plt.ylabel("completed project count")

x_ticks = [0.1, 1, 10, 100, 1000,  round(pledged_975,2), round(pledged_outliers,2) ]
x_tick_labels = [format_num(x_tick) for x_tick in x_ticks]
plt.xticks(np.log10(x_ticks), x_tick_labels)
plt.xlabel('Log scaled pledged funding (conv. USD)', fontsize=12)

plt.show()
```





Above I depicted the log scaled distribution of pledges. On the left side, I depicted all completed projects and the right plot shows the distribution of successful projects only.

In contrast to the distribution of goals, the bell curve of the pledged funding of all completed projects is non-symmetrical. The top of the curve is right off the median of USD 1,471. In spite of the right-skewed character of pledges, very low amounts of pledges are common when the funding period ended. A remarkable number of ventures actually ends a campaign with no funding at all. Please note that projects, that did not collect any investments are counted into the first bin of the histogram.

This result doesn't surprise if we take a look at the plot on the right. If we only consider successful projects, the distribution is a rather symmetrical, normally distributed curve. The axial shift towards very low pledges is hardly noticeable. On average successful projects generated a median funding of USD 4,800.

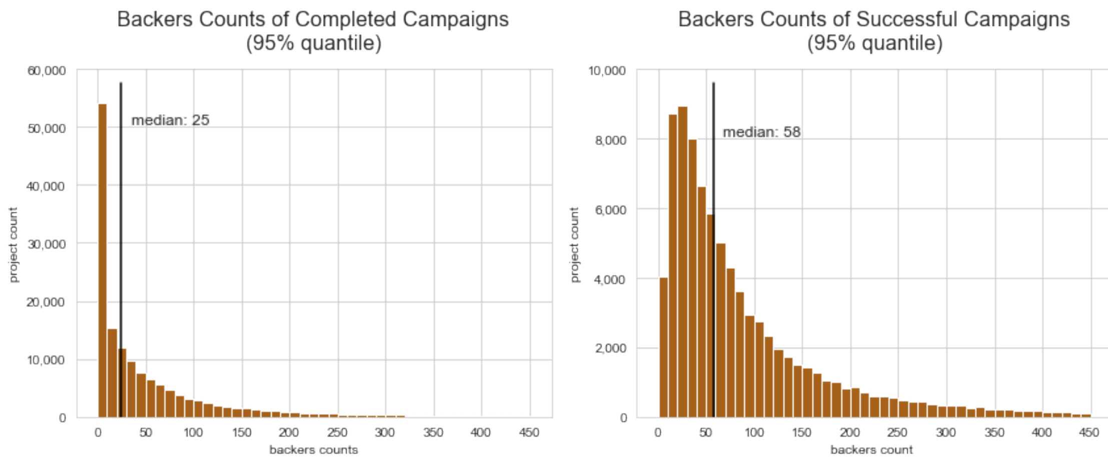
7.1.2 Backers

Let's move our attention to the number of supporters. By plotting the distribution of backers of completed projects, I hope to find answers to the question: How many backers does a projects usually achieve? And what number does it usually take to end a campaign in success?

How is the number of supporters distributed across projects?

In [80]:
```
# to depict distribution of backers, use 95 quantile dataframe
plt.figure(figsize=[12,5])
bin_edges = np.arange(0, ks_compl_95['backers_count'].max()+10, 10)

# left plot: total distribution of backers of all completed projects
plt.subplot(1,2,1)
plt.hist(data = ks_compl_95, x = 'backers_count', bins= bin_edges, color=backers_colo

# labels and titles
plt.title("Backers Counts of Completed Campaigns\n(95% quantile)", fontsize=16, pad=1
format_xticks(450, 50)
plt.xlabel("backers counts")
format_yticks(60000, 10000)
plt.ylabel("project count")

# annotate median
ax = plt.gca()
ax.axvline(x=backers_50, color='black', ymax=0.96)
ax.annotate("median: " + str(int(backers_50)), xy=(backers_50+10, 50500),fontsize=12)

# right plot: total distribution of backers of successful projects
plt.subplot(1,2,2)
plt.hist(data = ks_success_95, x = 'backers_count', bins=bin_edges, color=backers_col

# annotate median
ax = plt.gca()
backers_50_s = ks_success_95.backers_count.median()
ax.axvline(x=backers_50_s, color='black', ymax=0.96)
ax.annotate("median: " + str(int(backers_50_s)),
            xy=(backers_50_s+10, 8050),fontsize=12)

#labels and titles
plt.title("Backers Counts of Successful Campaigns\n(95% quantile)", fontsize=16, pad=
format_yticks(10000, 2000)
```

```
plt.ylabel("project count")
format_xticks(450, 50)
plt.xlabel("backers count ")

plt.tight_layout()
plt.show()
```



The above plots describe the distribution of the number of backers per project. On the left side, I took all completed projects into account, whereas the right plot considered successful projects only. In order to improve readability, I renounced very high and extreme backer counts by displaying 95% quantile data.

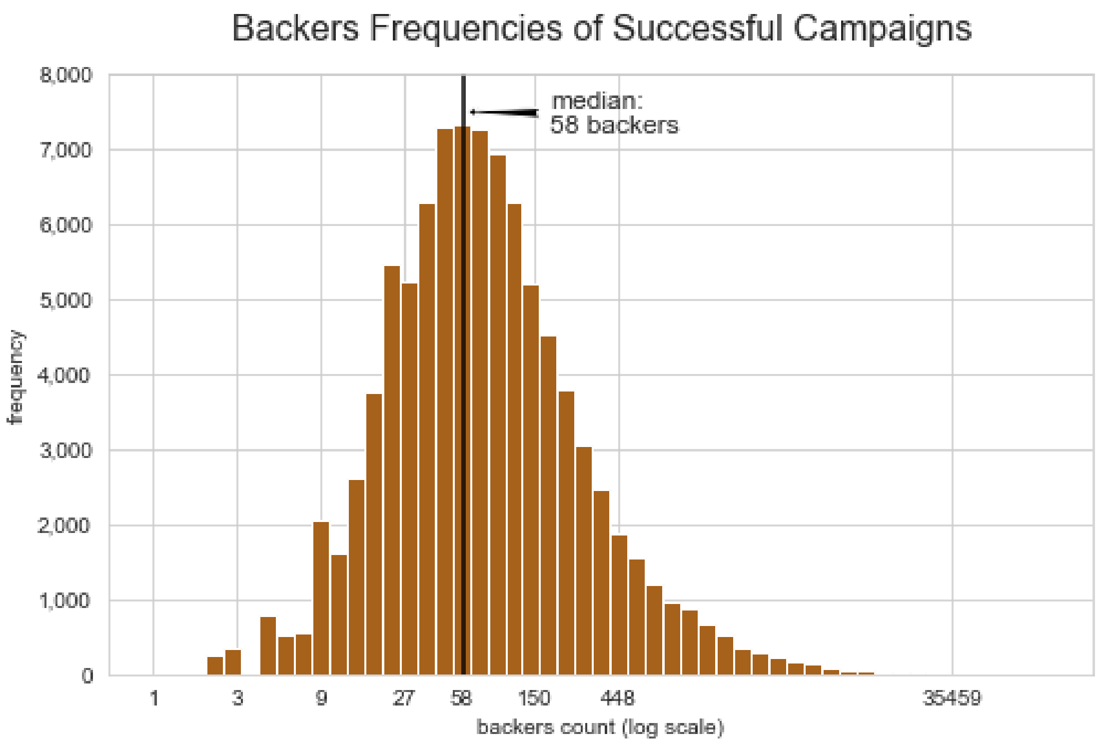
The distribution of the number of supporters across all completed projects demonstrates the dominance of a rather low number of backers. More than a quarter of all completed ventures convinced less than {{int(backers_25)}} supporters. The plot decreases sharply beyond 10 backers per project. The number of occurrences decreases smoothly thereafter. The occurrences of projects with higher supporter counts becomes less and less common.

The plot on the right visualizes successful campaigns. On average successful campaigns completed the funding with {{int(ks_compl_success.backers_count.median())}} supporters. However, most successful campaigns were supported by 20-50 backers. Higher number of backers become more and more unlikely. The 95% quantile data maxes at 450 backers per project.

To improve interpretation, I'm going to try a log scale approach below for successful projects.

```
In [81]: # plot using log scale
         plt.figure(figsize=[8,5])

         # log transform data
         log_data = np.log10(ks_compl_success['backers_count'])
         log_bin_edges = np.arange(0.001, log_data.max()+0.1, 0.1)

         # plot
         plt.hist(log_data, bins = log_bin_edges, color=backers_color)
```

```
# annotate median
ax = plt.gca()
ax.axvline(x=np.log10(backers_50_s), color='black')

# annotate binned peak
ax.annotate("median:\n" + str(round(int(backers_50_s))) + " backers", fontsize=12,
            xy=(log_trans(backers_50_s), 7490),
            xytext=(log_trans(backers_50_s)+0.5,7200),
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))

# ticks and labels
tick_locs = [1, 3, 9, 27, int(round(backers_50_s)), 150, int(round(backers_95)), int(
plt.xticks(np.log10(tick_locs),tick_locs)
plt.xlabel("backers count (log scale)")

format_yticks(8000,1000)
plt.ylabel("frequency")
plt.title("Backers Frequencies of Successful Campaigns", fontsize=16, pad=15)

plt.show()
```



The above visualization shows the distribution of backers counts of successful projects with a log scale applied on the data to offset the long right tail. The log-scale approach reveals a non-symmetrical bell shape of backers. In contrast to the relatively smoothly decreasing curve on the right side, the low side of backers counts describe a more irregularly shaped curve with pronounced occurrences of low backers counts per project.

50% of all successful campaigns acquired less than {{backers_50_s}} supporters. The highest successful backers count was {{format_num(ks_compl_success.backers_count.max())}} backers.

After analyzing each data point individually, I gained a general understanding about the relevant data points. In the following analyses, I'm going to focus on my 2 research questions. I will correlate relate variables against each other. The relationship of the variables will allow me to answer my research questions:

7.2 6.1 Is it still worthwhile financing your project on Kickstarter, now that crowdfunding has become mainstream?

In recent years, crowdfunding incited a lot of excitement. More and more project creators recognized crowdfunding as a form of investment and launched campaigns. Instead of asking professional investors or banks for funding, people sought funding from private supporters.

In the meantime, multiple platforms dedicated to specific purposes and applying different variations of crowdsourcing evolved globally. In the light of increased competition, creators of campaigns likely face bigger challenges when they court for attention and investment. Additionally, media often enough reported scams which may have deterred potential supporters from pledging their money.

I'm curious how its popularity and the saturated market affected campaigns. With thousands of campaigns competing against each other globally, we would expect lower chances of success today. Furthermore, it would make sense for project creators to realize lower fundraising goals.

In the following analysis, I'm going to investigate how crowdfunding as an investment opportunity on Kickstarter has evolved over time. My goal is to find an answer if running a campaign today still pays off compared to previous years. Did the overall conditions worsen due to the Kickstarter's popularity? How may have campaign characteristics changed on Kickstarter's 10th anniversary, compared to previous years?

This research topic clearly implies a time component. Thus, I'm going to depict the most relevant characteristics of the Kickstarter data set on a timeline. First of all, let's visualize Kickstarter's historical prosperity.

To plot the absolute counts of projects over a period of 10 years, I'm going to group completed projects by year and month using the campaign deadline. Due to zero counts in some of the 120 months, I will manually create a monthly index and add zero values to missing months. Finally, I will store the project counts into a dataframe.

```
In [82]: # create dataframe
         df_project_counts = pd.DataFrame(data={'total': [0.0]*120,
                                                'success':  [0.0]*120,
                                                'failed':  [0.0]*120,
                                                'date': dates})

         # fill data frame with absolute project counts per month
         for df, label in [(ks_compl, 'total'), (ks_compl_success, 'success'), (ks_compl_faile
             # calculate monthly abs. project counts
             counts = df.groupby([df.deadline.dt.year, df.deadline.dt.month])\
                                .count()['project_id']
             # the above grouping ignores months with zero counts, so we manually add zero val
```

```
    # re-create a new multi-index, this time including all 12 months per year
    levels = [counts.index.levels[0].values, range(1,13)]
    new_index = pd.MultiIndex.from_product(levels, names=['year', 'month'])
    # re-index counts and fill empty values with zero
    counts = counts.reindex(new_index, fill_value=0).values
    # remove months Jan-April 2014 and, May-Dec 2019
    counts = counts[4:-8]
    # add to dataframe
    df_project_counts[label] = counts

df_project_counts.tail(5)
```

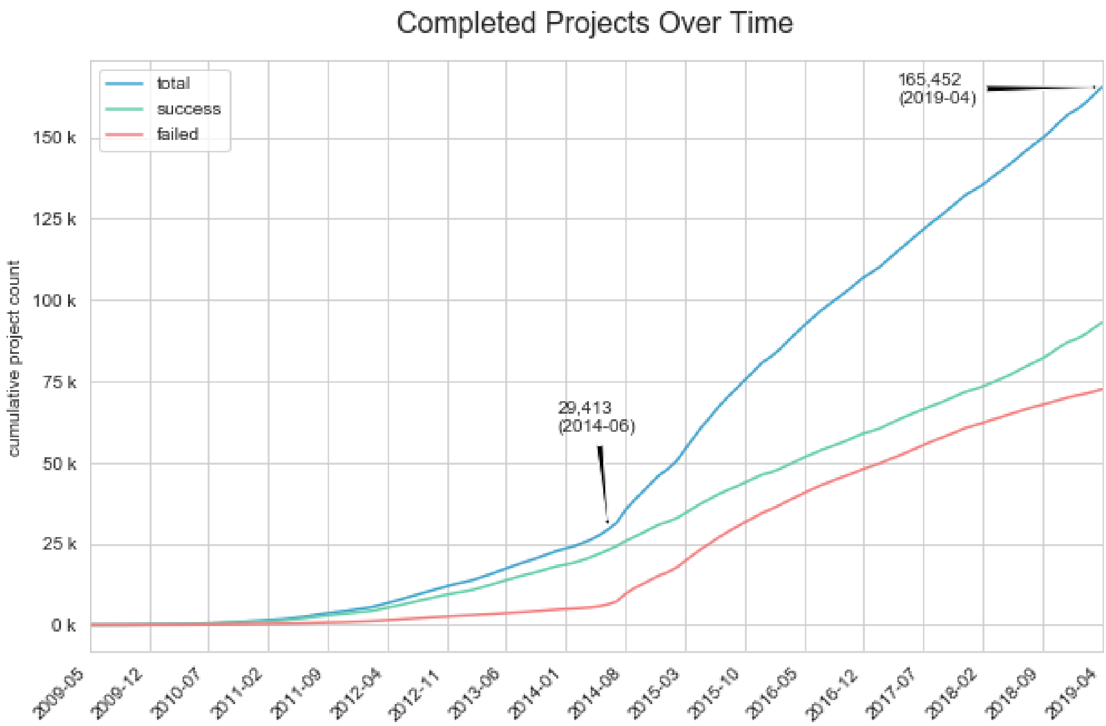
Out[82]:

	total	success	failed	date
115	2340	1578	762	2018-12-01
116	1543	958	585	2019-01-01
117	1862	1322	540	2019-02-01
118	2560	1913	647	2019-03-01
119	2481	1788	693	2019-04-01

In [83]:

```
# settings
plt.figure(figsize=[10,6])

# plot cumulative sum of project month after month of completed projects
for i, col in enumerate(df_project_counts.columns[:-1]):
    # calculate cumulative sum and plot
    ax = df_project_counts[col].cumsum().plot(color=status_colors[i])

# annotate June 2014
ax.annotate(format_num(df_project_counts.total.cumsum().values[61]) + "\n(2014-06)",
            xy=(61, df_project_counts.total.cumsum().values[61]),
            xytext=(55,df_project_counts.total.cumsum().values[61] + 30000),
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))

# annotate current number of projects
ax.annotate(format_num(df_project_counts.total.cumsum().values[-1])+ "\n(2019-04)",
            xy=(119, df_project_counts.total.cumsum().values[-1]),
            xytext=(95,df_project_counts.total.cumsum().values[-1]- 5000),
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))

# labels and titles
plt.title("Completed Projects Over Time", fontsize=16, pad=15)
plt.xlabel('campaign deadline (year, month)')

# improve readability of y ticks
ylabels = ['{:,.0f}'.format(ytick) + ' k' for ytick in ax.get_yticks() / 1000]
ax.set_yticklabels(ylabels)
plt.ylabel('cumulative project count')
```

```
# improve readability of y ticks
timeline_ticks(df_project_counts)

plt.legend()
plt.show()
```



After Kickstarter's launch in April 2009, it took about 3 years until the platform gained momentum. By 2012, the growth of projects started picking up speed slowly. Yet, it took another two years for Kickstarter to thrive. Suddenly, by mid 2014, the number of projects took a sharp upward turn. Ever since, the sum of campaigns has been linearly increasing.

In June 2014, our data set recorded a number of {{format_num(df_project_counts.total.cumsum().values[61])}} completed campaigns. In the following five years the absolute count had risen by a factor of six up to {{format_num(df_project_counts.total.cumsum().values[-1])}} projects.

Do creators have a higher risk of failure because of Kickstarter's popularity?

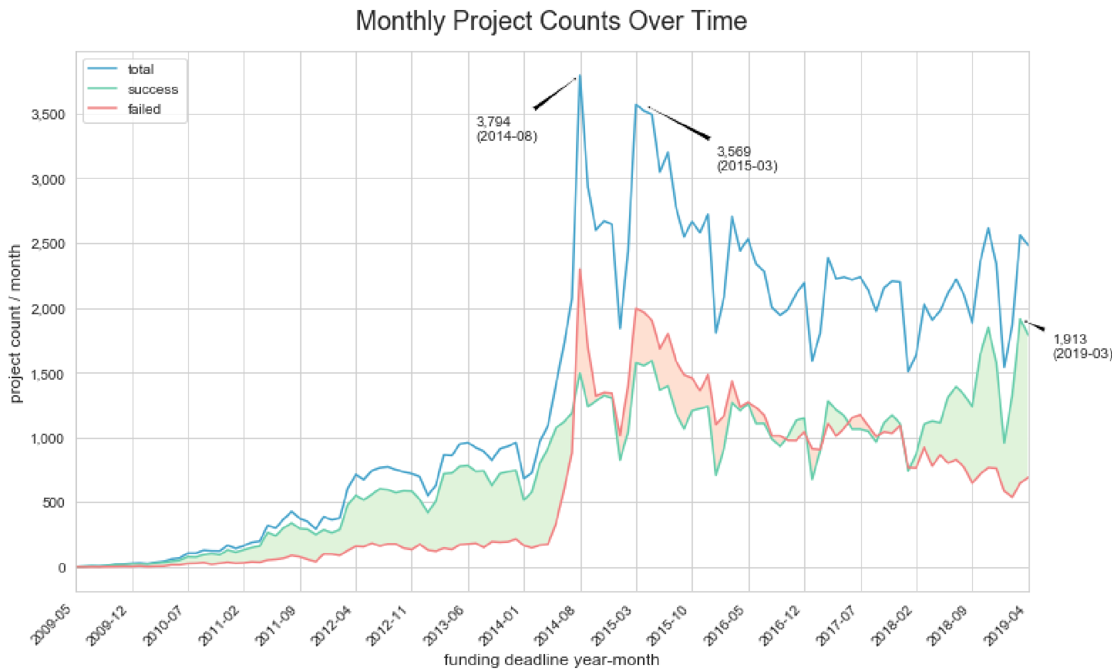
Interestingly, the absolute counts of failed and successful campaigns performed differently. Successful projects have been growing smoothly since mid 2012. In contrary, failed campaigns kept at a low rate up until Kickstarter's boom in mid 2014. Notice the sudden bend in the red line above. In the following years the sum of failed campaigns grew faster than successful campaigns. The cumulative sum of failed projects got closest to successful project counts in the years 2016 and 2017, though the absolute counts of failed campaigns never exceeded successful campaigns.

In the recent one and a half years, the counts of successful and failed projects has been diverging. The good news for potential creators: the number of failed campaigns has been decreasing recently.

Instead of visualizing cumulative project counts, I'm going to analyze the number of new campaigns month-by-month over the past 10 years.

In [84]:
```
# settings
plt.figure(figsize=[12,7])

# plot monthly counts of projects of completed projects by month over time
for i, col in enumerate(df_project_counts.columns[:-1]):
    ax = df_project_counts[col].plot(color=status_colors[i])

# annotate peaks
ymax_1  = max(df_project_counts.total)
xmax_1 = str(df_project_counts[df_project_counts.total == ymax_1].date.values[0])[:7]
ax.annotate(format_num(ymax_1) + "\n(" + str(xmax_1) + ")", xy=(63, ymax_1),
            xytext=(50, ymax_1-500),
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))

ymax_2  = df_project_counts.total.sort_values().values[-2]
xmax_2 = str(df_project_counts[df_project_counts.total == ymax_2].date.values[0])[:7]
ax.annotate(format_num(ymax_2) + "\n(" + str(xmax_2) +")", xy=(71, ymax_2),
            xytext=(80, ymax_2-500),
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))

ymax_3  = max(df_project_counts.success)
xmax_3 = str(df_project_counts[df_project_counts.success == ymax_3].date.values[0])[:
ax.annotate(format_num(ymax_3) + "\n(" + str(xmax_3)+")", xy=(118, ymax_3),
            xytext=(122, ymax_3-300),
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))


# highlight differences
ax.fill_between(np.arange(0,120), df_project_counts.success, df_project_counts.failed
                where=df_project_counts.failed >= df_project_counts.success,
                facecolor=fill_red, interpolate=True)
ax.fill_between(np.arange(0,120), df_project_counts.success, df_project_counts.failed
                where=df_project_counts.success >= df_project_counts.failed,
                facecolor=fill_green, interpolate=True)

# # labels and titles
plt.title("Monthly Project Counts Over Time", fontsize=18, pad=15)

ylabels = ['{:,.0f}'.format(ytick) for ytick in ax.get_yticks()]
ax.set_yticklabels(ylabels)
plt.ylabel('project count / month', fontsize=12)

timeline_ticks(df_project_counts)
plt.xlabel('funding deadline year-month', fontsize=12)
```

```
plt.legend(loc=2)
plt.show()
```



The blue line of the plot depicts the sum of new fundings that finished every months projects.

During the first 4 years, funding activities on the Kickstarter increased at a slow but steady rate. By the beginning of 2014, Kickstarter's performance exploded. Within a few months the number of campaigns skyrocketed and reached an all time high. {{format_num(ymax_1)}} projects terminated in August 2014. In the following months project counts decreased, before Kickstarter experienced a second boom in March/April. In the following months and years project counts settled. Nevertheless, with roughly 2k new projects each month, activities remained on a high level up until today. Since 2018, the number of campaigns ending each month has been increasing notably.

Over the entire time, there have been remarkable cyclic activity setbacks. I suppose the season or time of year may be one explanation. I'm going to explore this topic later as it may be one factor contributing to the success of a campaign.

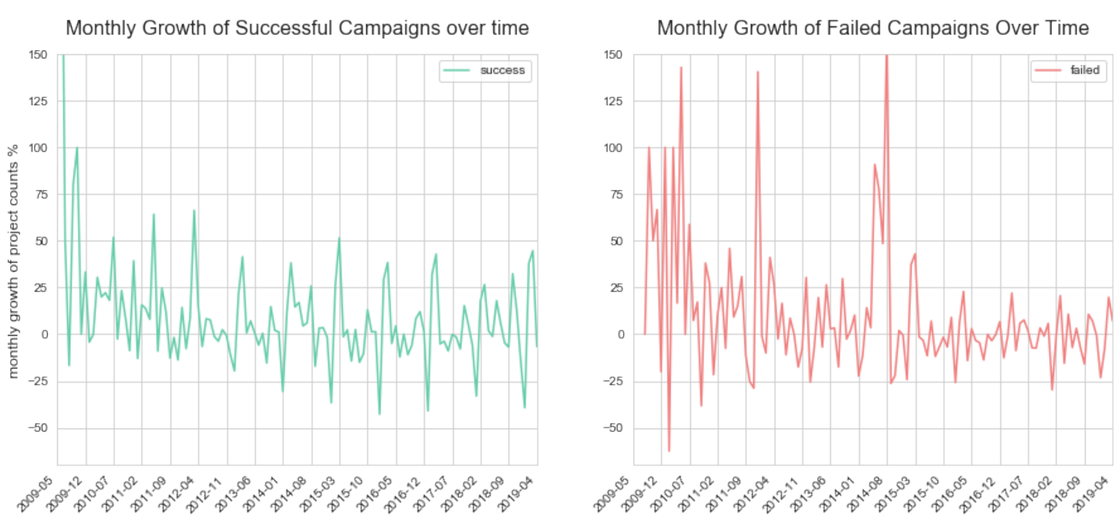
If we turn our attention to the green and red lines of failed and successful projects, we notice an interesting pattern. Until the hype in August 2014, there have always been more successful than failed projects, growing at a stronger rate.

When Kickstarter became popular, the number of failed ventures suddenly peaked and exceeded successful projects. Only by the end of 2016 the number of successful and failed projects started to be more balanced.

Finally, by the beginning of 2018, Kickstarter turned monthly successful and failed project counts upside down. Ever since, campaigns ending in success have become more likely while flops have been declining notably. 2018 was a highly successful year for creators: {{round(len(ks_compl_success[ks_compl_success.deadline.dt.year == 2018]) / len(ks_compl[ks_compl.deadline.dt.year == 2018])* 100, 2)}}% of campaigns celebrated successful funding. Actually, the highest number of successful campaigns ever was recorded only recently, in March 2019.

To fully understand, Kickstarter's lifecycle, let's plot monthly growth rates.

```
In [85]: # settings
         plt.figure(figsize=[15,6])

         # calculate monthly growth rates of successful and black projects
         success_r = df_project_counts['success'].pct_change()*100
         failure_r = df_project_counts['failed'].pct_change()*100

         # # left plot: monthly growth successful campaigns
         plt.subplot(1,2,1)
         ax = success_r.plot(color=cust_green)
         plt.ylim(-70, 150) # limit yaxis to remove initial fluctuation
         plt.legend()

         # labels and titles
         plt.title("Monthly Growth of Successful Campaigns over time", fontsize=16, pad=15)
         plt.ylabel('monthly growth of project counts %', fontsize=12)
         timeline_ticks(df_project_counts)

         plt.subplot(1,2,2)
         ax = failure_r.plot(color=cust_red)
         plt.ylim(-70, 150) # limit yaxis to remove initial fluctuation

         plt.title("Monthly Growth of Failed Campaigns Over Time", fontsize=16, pad=15)
         plt.ylabel('')
         timeline_ticks(df_project_counts)

         plt.legend()
         plt.show()
```



The above plots depict monthly growth rates of successful and failed campaigns. Before Kickstarter's hype started, growth rates show strong, but irregular amplitudes, especially in failed campaigns. The relative growth declined slightly until the hype year 2014. The growth of failed campaigns skyrocketed in August, whereas the increased popularity hardly impacted successful campaigns.

The growth of successful campaigns has been following a relatively regular 'heartbeat' since 2010. Successful campaigns were clearly subject to seasonal fluctuations.

Finally, by the beginning of 2018, we notice slightly increasing growth rates in successful campaigns. In contrast, failed campaigns were less affected by seasons. The growth rates of failed campaigns were relatively constant since mid 2015.

While increased competition certainly impacted the hype year 2014, we cannot confirm that due to more competition today, there is less of a chance to win a campaign. On the contrary, chances to succeed have never been better.

Generally, the effects of competition impact failed campaigns stronger than successful campaigns. In fact, despite increasing project counts since 2018, the number of successful campaigns have also been increasing.

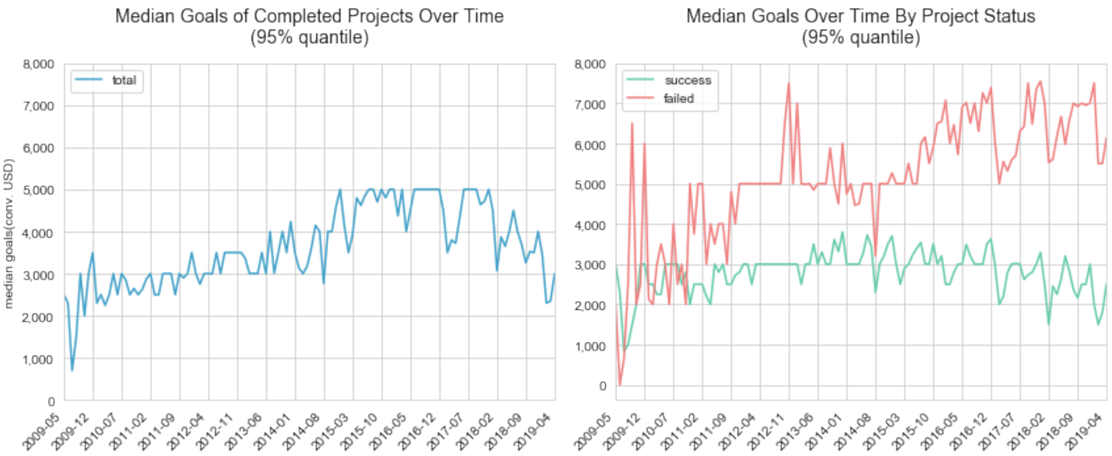
Did funding goals decrease, now that crowdfunding has become mainstream?

As we found that creators have higher chances nowadays, detractors may argue that there was a trade-off between the amount of funding raised and success rates. After all, to spread the total financial capacity on additional campaigns, may result in less funding for an individual creator.

Thus, I'm going to plot the monthly median goals of completed projects on a timeline. In order to avoid extreme values distorting the plot, I'm going to use the 95% quantile data frame. Adding a second plot with separate curves of successful and failed campaigns will help to answer the question, if creators may have sought for lower goals in exchange for increased chances of success.

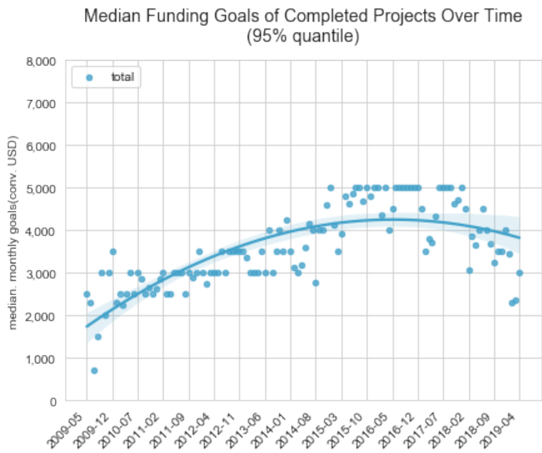
In [86]:
```
# settings
plt.figure(figsize=[12,5])

# calculate monthly median goals of completed projects of 95 quantile data frame
# total
goals_grouped = ks_compl_95.groupby([ks_compl_95.deadline.dt.year,
                                    ks_compl_95.deadline.dt.month]).median()['goal_hi
# success
goals_grouped_s = ks_success_95.groupby([ks_success_95.deadline.dt.year,
                                    ks_success_95.deadline.dt.month]).median()['goal_
# failed
ks_compl_95_f = ks_compl_95[ks_compl_95.status == 'failed']
goals_grouped_f= ks_compl_95_f.groupby([ks_compl_95_f.deadline.dt.year,
                                    ks_compl_95_f.deadline.dt.month]).median()['goal_
# insert 0 occurence for 2009-6
goals_grouped_f = np.insert(goals_grouped_f,1,0)

# create dataframe
df_goals = pd.DataFrame(data={'total':goals_grouped,
                              'success':goals_grouped_s,
```

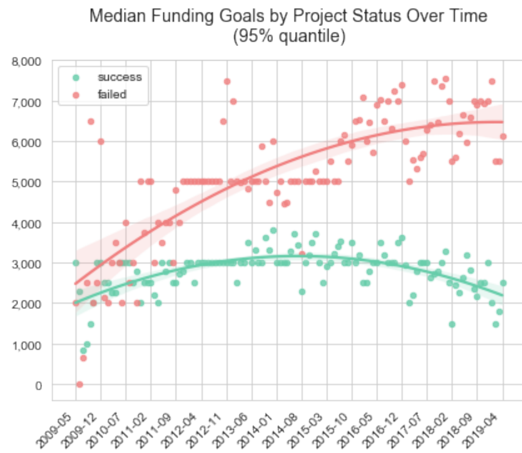
```
                                    'failed': goals_grouped_f,
                                    'date': dates})

# left plot: line plot of monthly median goals of all completed projects
plt.subplot(1,2,1)
ax = df_goals.total.plot(color=cust_blue);

# ticks and labels
plt.xlabel("")
timeline_ticks(goals_grouped)
plt.tight_layout()
format_yticks(8000,1000)
plt.ylabel("median goals(conv. USD)")
plt.title("Median Goals of Completed Projects Over Time\n(95% quantile)", fontsize=14
plt.legend(loc=2)

# right plot: line plot of monthly median goals of successful anf failed projects
plt.subplot(1,2,2)
ax = df_goals.success.plot(color=cust_green);
ax = df_goals.failed.plot(color=cust_red);

# ticks and labels
plt.xlabel("")
timeline_ticks(goals_grouped)
format_yticks(8000, 1000)
plt.ylabel("")
plt.title("Median Goals Over Time By Project Status\n(95% quantile)", fontsize=14, pad

plt.tight_layout()
plt.legend()

plt.show()
```



The course of the line plots reminds me of a second degree polynomial curve. I find the seasonal fluctuations make the plot difficult to read. To draw a clearer picture, I will try a scatterplot approach and fit a polynomial regression trend line.

In [87]:
```
# scatterplots of monthly means and fit a polynomial regression of 2nd degree

# settings
plt.figure(figsize=[15,5])

# we got 120 months, so we chuck our x axis into 120 ticks
df_goals['date'] = np.arange(0, len(goals_grouped), 1)

# left plot: median goals of all completed projects
plt.subplot(1,2,1)
ax = sns.regplot(x=df_goals['date'].values, y=df_goals['total'],
                 color=cust_blue,
                 scatter_kws={"s": 20},
                 order=2, ci=95, truncate=True, label="total");

timeline_ticks(df_goals)
format_yticks(8000, 1000)
plt.ylabel("median. monthly goals(conv. USD)")
plt.title("Median Funding Goals of Completed Projects Over Time\n(95% quantile)", fon
plt.legend(loc=2)

# # right plot: median goals of successful and failed projects
plt.subplot(1,2,2)
ax = sns.regplot(x=df_goals['date'], y=df_goals['success'],
                 color=cust_green,
                 scatter_kws={"s": 20},
                 order=2, ci=95, truncate=True, label="success");
ax = sns.regplot(x=df_goals['date'], y=df_goals['failed'],
                 color=cust_red,
                 scatter_kws={"s": 20},
                 order=2, ci=95, truncate=True, label="failed");

# ticks and labels
timeline_ticks(df_goals)
format_yticks(8000, 1000)
plt.ylabel("")
plt.title("Median Funding Goals by Project Status Over Time\n(95% quantile)", fontsize
plt.legend()
plt.show()
```






```
In [88]: df_goals.tail()
```

Out[88]:

	total	success	failed	date
115	4,000.0	3,000.0	7,000.0	115
116	3,453.149999914437	2,000.0	7,500.0	116
117	2,302.416481366293	1,500.0	5,500.0	117
118	2,350.0	1,800.0	5,500.0	118
119	3,000.0	2,500.0	6,135.230000012376	119

```
In [89]: # mean goals hype years
         print("mean goals 2014-2016: " + str(df_goals[(df_goals.date > 56) & (df_goals.date <=
         # mean goals 2018
         print("mean goals since 2018: " + str(df_goals[df_goals.date > 101]['success'].mean()
```

```
mean goals 2014-2016: 3109.715939409531
mean goals since 2018: 2443.4323554595567
```

To find out how funding goals performed over time, I depicted their monthly median values. First, I used a line plot, but found the plot difficult to read because of the strong seasonal fluctuations. Instead, I tried a scatterplot approach and fitted a second degree polynomial regression line to depict the relationship.

In the early years funding goals were usually chosen around USD 2k - 3k. They gradually increased and peaked in the years 2015-2017. Then, creators usually asked for USD 4k - 5k.

In the recent two years, goals have been setting back to the levels of earlier years. Project creators indeed tend to seek less optimistic goals.

If we separate projects by their status into successful and failed campaigns, we notice an interesting behavior: successful campaigns generally aim for lower funding goals compared to failed campaigns. Over the course of the years, the gap between successful and failed goals has been developing further apart. Only after 2018, failed project goals stagnated.

Successful goals have risen modestly during the hype years 2014 to early 2016, generally staying under median goals of USD 3,100. Ever since, successful goals have been declining. Today, the median goal is almost at the level of the early years, close to USD 2.5k. In comparison, failed goals were between USD 6k-7k by April 2019.

In general, the widening of the gap suggests that not only the behavior of project creators who defined funding goals changed over time. I suspect changes in Kickstarter's overall financial capacity. Additionally, the willingness of supporters to pledge may has decreased concurrently.

To conclude, the hype in 2014 positively impacted the goals. However, with more crowdfunding campaigns running on Kickstarter, we can confirm that successful funding goals have been decreasing.

A perception of a funding's success is not only determined by the success or failure of a campaign. Creators surely value the amount of raised money to start their businesses. Since a campaign does not end when the goal was reached, creators can collect the surplus of pledges until the end of a campaign. So, let's turn our attention to the actual pledged funding amount now.

How did the funding capacity develop compared to goals over time?

To start with, I'm going to plot the monthly sum of pledges on a 10 year timeline. Again, I'm going to work on the 95% quantile data frame to avoid distortion of pledges and goals.

```
In [90]: # assess monthly sum of fundings
         ks_compl_95.groupby([ks_compl_95.deadline.dt.year,
                              ks_compl_95.deadline.dt.month])['pledged_hist_usd'].sum().sort_va
```

```
Out[90]: deadline  deadline
         2009      5           3,354.0
                   6           11,566.48
                   8           14,829.470000000001
                   7           22,156.79
                   9           26,072.8
                   10          56,225.549999999996
                   11          85,538.90999999999
         2010      1           99,412.70999999999
                   3           109,432.06000000001
                   2           112,723.91
         2009      12          123,912.96999999999
         2010      4           190,511.56
                   5           208,593.24
                   6           256,623.92
                   11          365,861.37
                   7           382,823.57
                   8           387,223.06999999995
                   9           395,157.98000000004
         2011      1           438,867.57999999996
         2010      10          478,213.6699999999
         2011      2           549,230.9099999999
                   3           615,994.8100000002
         2010      12          635,255.5700000001
         2011      4           713,326.39
                   6           1,166,661.27
                   11          1,274,112.5900000003
                   5           1,348,393.9999999998
```

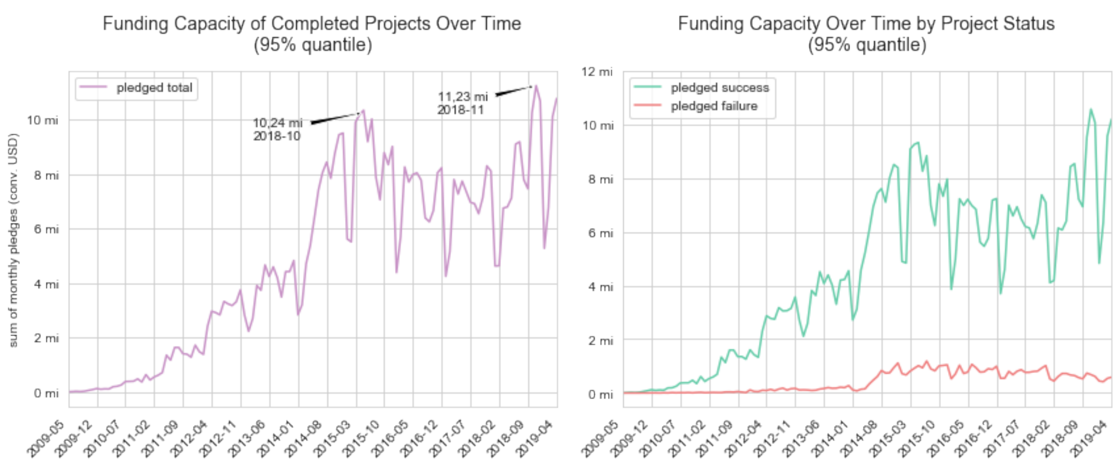
2012	2	1,376,812.4400000002
2011	10	1,384,674.7899999998
	9	1,403,617.7999999998
2012	1	1,476,562.74
2011	8	1,629,495.7200000007
	7	1,632,609.4400000002
	12	1,717,003.6600000001
2013	1	2,224,133.2173422812
2012	3	2,410,648.149999999
2013	2	2,693,864.027891957
2012	12	2,820,046.9425547034
	6	2,828,632.68
2014	1	2,829,171.141070151
2012	5	2,908,522.8300000005
	4	2,961,956.49
	9	3,169,145.1499999994
2014	2	3,193,839.932445659
2012	8	3,230,245.5200000005
	10	3,309,015.1800000006
	7	3,319,774.25
2013	9	3,480,287.828695204
	4	3,729,746.0975198476
2012	11	3,741,195.422924926
2013	3	3,906,947.2411773303
	8	4,182,925.3763741143
	6	4,235,123.686219366
2017	1	4,240,462.300010932
2016	1	4,379,754.928213647
2013	10	4,411,824.137376824
	11	4,418,173.127825063
	7	4,587,998.7888244195
2018	1	4,619,952.868906908
	2	4,630,072.940170688
2013	5	4,657,134.318719608
2014	3	4,704,210.282138481
2013	12	4,819,964.678516853
2017	2	5,144,841.938621923
2019	1	5,267,860.015027448
2014	4	5,368,476.142287493
2015	2	5,503,965.302044706
	1	5,612,577.419904875
2016	2	5,684,082.525331068
	9	6,241,415.850700967
2014	5	6,373,288.878033667
2016	8	6,385,498.700380617
2017	9	6,539,482.498246869
2016	10	6,657,521.260804398
2018	3	6,742,809.06505597

```
2019       2          6,754,485.086600815
2018       4          6,786,822.798454159
2017       8          6,905,661.592334376
           7          6,956,129.676780776
2015       9          7,050,980.299936099
2018       5          7,113,831.716542935
2017       10         7,125,698.4659685055
           4          7,261,170.150567917
           6          7,345,458.218532994
2014       6          7,407,581.924189638
2018       9          7,451,939.681779435
2016       4          7,698,908.252589801
2017       5          7,731,913.046843275
2016       7          7,766,998.952809195
2018       8          7,784,079.329859508
2017       3          7,791,974.53038087
2014       9          7,837,104.354866528
2015       8          7,880,329.743968704
2016       5          7,980,051.6251730705
           6          8,034,562.497577917
           11         8,041,055.654321086
2014       7          8,051,105.925799172
2017       12         8,101,482.1264104815
2016       12         8,222,085.787706705
           3          8,253,065.51184933
2017       11         8,292,091.223308355
2015       11         8,336,295.261765867
2014       8          8,431,994.545028124
           10         8,756,338.291285425
2015       10         8,780,126.388291199
           12         9,004,487.472798584
2018       6          9,087,905.75693264
           7          9,175,891.554121457
2015       6          9,180,194.397754641
2014       11         9,436,422.550105827
           12         9,494,911.639444323
2015       3          9,887,275.345657712
           7          10,012,000.090708505
2019       3          10,097,819.656059505
2015       4          10,163,247.323237322
2018       10         10,248,494.201852078
2015       5          10,331,936.367928388
2018       12         10,668,202.76208135
2019       4          10,764,330.836713124
2018       11         11,237,098.310608251
Name: pledged_hist_usd, dtype: float64
```

```
In [91]: # settings
```

```
plt.figure(figsize=[12,5])

# calculate monthly median pledges of completed projects of 95 quantile data frame
# total
pledged_grouped_sum = ks_compl_95.groupby([ks_compl_95.deadline.dt.year,
                                   ks_compl_95.deadline.dt.month])['pledged_hist_usd
# success
pledged_grouped_sum_s = ks_success_95.groupby([ks_success_95.deadline.dt.year,
                                   ks_success_95.deadline.dt.month])['pledged_hist_u
# failed
pledged_grouped_sum_f= ks_fail_95.groupby([ks_fail_95.deadline.dt.year,
                                   ks_fail_95.deadline.dt.month])['pledged_hist_usd']
# insert 0 occurence for 2009-6
pledged_grouped_sum_f = np.insert(pledged_grouped_sum_f,1,0)

# create dataframe
df_pledged_sum = pd.DataFrame(data={'total':pledged_grouped_sum,
                                'success':pledged_grouped_sum_s,
                                'failed': pledged_grouped_sum_f,
                                'date': dates})

# left plot: line plot of monthly median pledges of all completed projects
plt.subplot(1,2,1)
ax = df_pledged_sum.total.plot(color=pledged_color, label='pledged total');

# annotate peaks
ymax_1  = max(pledged_grouped_sum)
xmax_1 = str( df_pledged_sum[df_pledged_sum.total == ymax_1].date.values[0])[:7]
ax.annotate(format_num(ymax_1)[:5] + " mi" + "\n" + str(xmax_1), xy=(114, ymax_1),
            xytext=(90, ymax_1- 1000000),
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))

ymax_2  = ks_compl_95.groupby([ks_compl_95.deadline.dt.year,
                              ks_compl_95.deadline.dt.month])['pledged_hist_usd']\
                              .sum().sort_values().values[-5]
xmax_2 = str(df_pledged_sum[df_pledged_sum.total == ymax_2].date.values[0])[:7]
ax.annotate(format_num(ymax_2)[:5] + " mi" + "\n" + str(xmax_2), xy=(72, ymax_2),
            xytext=(45, ymax_2- 1000000),
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))

# ticks and labels
plt.xlabel("")
timeline_ticks(df_pledged_sum)

# improve readability of y ticks
ylabels = ['{:,.0f}'.format(ytick) + ' mi' for ytick in ax.get_yticks() / 1000000]
ax.set_yticklabels(ylabels)
plt.ylabel("sum of monthly pledges (conv. USD)")
```

```
plt.title("Funding Capacity of Completed Projects Over Time\n(95% quantile)", fontsize
plt.legend(loc=2)

# right plot: line plot of monthly median pledges of successful anf failed projects
plt.subplot(1,2,2)
ax = df_pledged_sum.success.plot(color=cust_green, label="pledged success");
ax = df_pledged_sum.failed.plot(color=cust_red, label="pledged failure");

# ticks and labels
plt.xlabel("")
timeline_ticks(df_pledged_sum)
plt.yticks(np.arange(0, 12000000+1, 2000000))
ylabels = ['{:,.0f}'.format(ytick) + ' mi' for ytick in ax.get_yticks() / 1000000]
ax.set_yticklabels(ylabels)
plt.ylabel("")
plt.title("Funding Capacity Over Time by Project Status\n(95% quantile)", fontsize=14
plt.tight_layout()
plt.legend()
plt.show()
```



In the beginning years, the monthly collected financial backing increased at a steady rate from zero to plus USD 4mi. By the beginning of 2014 the funding capacity peaked sharply. We recorded the 5th highest funding capacity of USD {{format_num(ymax_2)}} in {{xmax_2}}. From 2015 - 2017 the total investment capacity fell into a recession. However, by late 2017 pledges started to recover. Ultimately, 2018 was the year with the highest recorded funding capacity. In November, there was a record of USD {{format_num(ymax_1)}} financial backing available for all projects.

On the right side, I divided the pledged funding into two plots: one for successful and one for failed projects. The curve of successful campaigns is remarkably similar to the plot of the total funding capacity on the left. Considering this, it doesn't surprise that the red curve of failed pledges remained on a low level across the entire 10 years of recording. By the beginning of 2015 "lost" pledges started to rise a little bit to roughly 1 mi. They have been decreasing slowly since 2016. Apparently, the amount of "lost" investments has never been a significant problem. The overwhelming majority of funding flowed into successful campaigns.

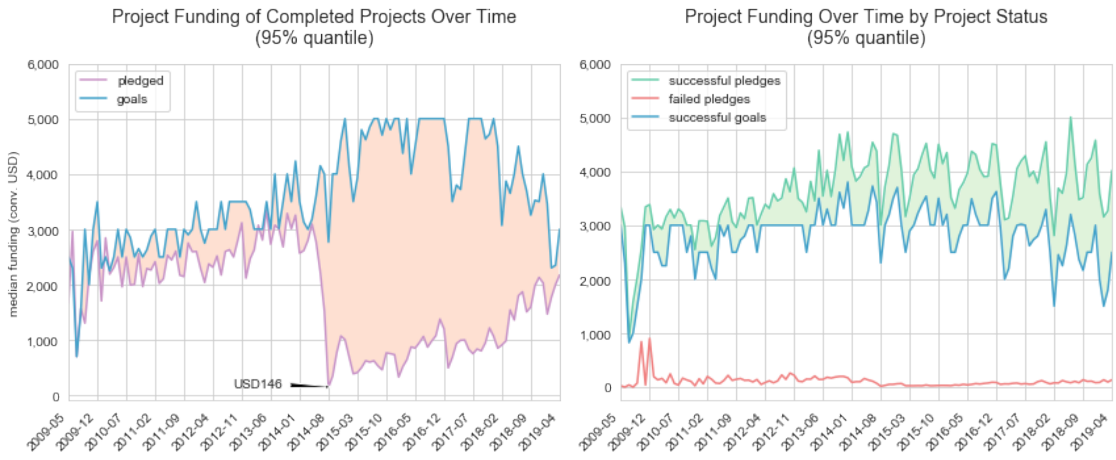
It suggests that there is usually no close race towards reaching a funding goal. There doesn't seem to be much ambiguity to whether a campaign appeals to the supporter audience, nor whether it will end in success or failure.

The above plots should tune creators more optimistic to run a campaign nowadays. In Kickstarter's history, there has never been more funding available. At the same time, success rates in 2018 were on an all time high. If we compare this plot of the funding capacity to the development of goals, the behavior is contradicting.

When goals peaked during the years 2015 - 2017, the pledged funding and the success rates were in a recession. 2018 was a record year of the total available funding, yet goals have been decreasing. It seems like goals were overrated during 2015 to 2017. As for today's declining goals despite the growing funding capacity, higher competition could explain it. So, let's include project counts into our analysis and plot pledges and goals relative to project counts. In the case of a continuous ratio between funding and projects, we'd expect a horizontal line. In the case of increased competition negatively affecting projects, we'd expect a declining line.

In [92]:
```
# settings
plt.figure(figsize=[12,5])

# calculate monthly median pledges of completed projects of 95 quantile data frame
# total
pledged_median = ks_compl_95.groupby([ks_compl_95.deadline.dt.year,
                                    ks_compl_95.deadline.dt.month]).median()['pledged_
# success
pledged_median_s = ks_success_95.groupby([ks_success_95.deadline.dt.year,
                                    ks_success_95.deadline.dt.month]).median()['pledge
# failed
pledged_median_f= ks_fail_95.groupby([ks_fail_95.deadline.dt.year,
                                    ks_fail_95.deadline.dt.month]).median()['pledged_
# insert 0 occurence for 2009-6
pledged_median_f = np.insert(pledged_median_f,1,0)

# create dataframe
df_pledged_median = pd.DataFrame(data={'total':pledged_median,
                                'success':pledged_median_s,
                                'failed': pledged_median_f,
                                'date': dates})

# # left plot: line plot of monthly median pledges of all completed projects
plt.subplot(1,2,1)
ax = df_pledged_median.total.plot(color=pledged_color, label='pledged');
ax = df_goals.total.plot(color=cust_blue, label='goals');

# highlight negative differences
ax.fill_between(np.arange(0,120), pledged_median, df_goals.total ,
                where=df_goals.total >= pledged_median,
                facecolor=fill_red, interpolate=True)

# annotate minima
```

```
ymin  = min(pledged_median)
xmin = str(df_pledged_median[df_pledged_median.total == ymin].date.values[0])[:7]
ax.annotate("USD" + format_num(ymin), xy=(64, ymin),
            xytext=(40, ymin),
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))

# ticks and labels
plt.xlabel("")
timeline_ticks(pledged_median)
plt.tight_layout()
format_yticks(6000,1000)
plt.ylabel("median funding (conv. USD)")
plt.title("Project Funding of Completed Projects Over Time\n(95% quantile)", fontsize=
plt.legend(loc=2)

# right plot: line plots of monthly median pledged of successful anf failed projects
plt.subplot(1,2,2)
ax = df_pledged_median.success.plot(color=cust_green, label="successful pledges");
ax = df_pledged_median.failed.plot(color=cust_red, label="failed pledges");
# add goals successfull achieved to compare
ax = df_goals.success.plot(color=cust_blue, label='successful goals');

# highlight overhead
ax.fill_between(np.arange(0,120), df_pledged_median.success,
                df_goals.success , where=df_pledged_median.success >= df_goals.succes
                facecolor=fill_green, interpolate=True)

# ticks and labels
plt.xlabel("")
timeline_ticks(pledged_median)
format_yticks(6000,1000)
# plt.yticks(np.arange(0, 6000+1, 1000))
plt.ylabel("")
plt.title("Project Funding Over Time by Project Status\n(95% quantile)", fontsize=14,
plt.tight_layout()
plt.legend()
plt.show()
```



Let's turn our attention first to the left plot. This time, I depicted the relative median pledges per project and added the development of median goals to compare how pledges pledges compared to median goals. Over a period of 10 years, there has always been a little negative gap between the median goals and the median funding pledged.

Most obviously, the relative funding per project dropped dramatically by mid 2014. From more than USD 3k by the end of 2013, the median pledges decreased to only USD 146 in August 2014. This event fell into the same time when the number of projects on Kickstarter exploded and the platform experienced a significant boost in funding capacity. This proof for a disproportionate growth of campaigns activities and investments. The number of creators and campaigns grew faster than the count of backers actively supporting projects. In the light of this, competition likely was a main driver for increased failure rates and lower average funding in 2014.

Since Kickstarter's hype year 2014, the funding overhead remained. The good news is: since 2018 it has been recovering. On Kickstarter anniversary, the overhead between the available funding capacity and goals converged to the level of before 2014.

Comparing the purple line on the left to the green line on the right changes our perspective. The course of successful pledges draws a comparably horizontal line. Ignoring the seasonal fluctuations, since mid 2013, the successfully collected funding has been relatively stable at a median of USD 4k per project.

In the hype year, successful projects actually raised higher average investments. In contrast, the relative funding capacity of all projects went through the floor. In spite of this, creators of successful campaigns did not have to fear losses in funding opportunities due to higher competition. I suspect the backers audience to have a univocal taste for specific campaign characteristics when they take the decision to invest. The additional campaigns may have not been appealing to the audience, were not fitting crowdfunding as an investment strategy or were generally of low quality.

The green area under the right plot depicts the surplus of pledges exceeding successful goals. On average, creators have been able to raise more than they had asked for once the campaign was successful. Since 2017 the positive gap of pledges has been widening, in spite of declining goals.

In the year 2014 USD {{format_num(ks_compl_success[ks_compl_success.deadline.dt.year == 2014]['pledged_hist_usd'].sum())}} was collected successfully. The amount doubled in 2018, when Kickstarter was able to distribute USD {{format_num(ks_compl_success[ks_compl_success.deadline.dt.year ==

2018]['pledged_hist_usd'].sum())}} to successful campaigns. In the light of this, since 2018 campaign creators benefited from Kickstarter's popularity because of the increasing funding capacity.

Can we attribute the increased funding capacity to an increased backers audience or do supporters just pledge higher amounts of money? In the first case, creators would likely need to put up higher efforts into their campaign's success to convince a higher number of backers.

Do creators have to convince more backers to successfully finish a campaign today?

To start with, let's plot the absolute numbers of backers participating in a campaign on a timeline.

```
In [93]: # assess backers counts monthly over 10 years
         ks_compl_95.groupby([ks_compl_95.deadline.dt.year,
                              ks_compl_95.deadline.dt.month])['backers_count']\
                              .sum().sort_values()
```

```
Out[93]: deadline  deadline
         2009      5             111
                   7             181
                   6             268
                   9             442
                   8             597
                   10           1008
         2010      2            1417
                   1            1425
         2009      11           1441
         2010      3            1543
         2009      12           2102
         2010      4            2752
                   5            2899
                   6            3831
                   11           5613
                   7            5703
                   9            5935
                   8            6030
         2011      1            6469
         2010      10           6565
                   12           8752
         2011      2            8927
                   3            8927
                   4           10222
                   6           15381
                   11          17346
                   9           17417
                   10          17895
                   5           18621
         2012      1           19974
         2011      7           20027
         2012      2           20223
```

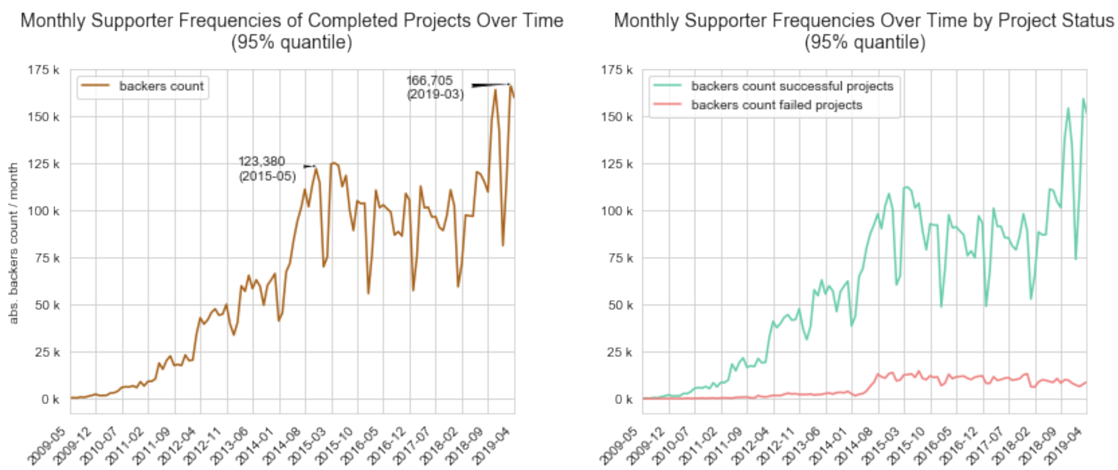
2011	8	22422
	12	22911
2013	1	33529
2012	3	33927
	5	39305
	12	39325
2013	2	40382
2014	1	41064
2012	6	41558
	4	42666
	9	44059
	10	44574
2014	2	45287
2012	7	45429
	8	47369
2013	9	49366
2012	11	49832
2016	1	55542
2013	4	56720
2017	1	57114
2013	6	58158
2018	1	59117
2013	8	59393
	3	59629
	10	59948
	7	62768
	11	62810
	5	65202
	12	66162
2014	3	67053
2015	1	69738
2018	2	71305
2014	4	71559
2015	2	74930
2017	2	75582
2016	2	77022
2019	1	81012
2014	5	83877
2016	10	86076
	8	86605
	9	88406
2015	9	89002
2017	9	89012
	8	90641
2014	6	94004
2017	6	96186
	7	96324
2018	5	96564

```
        4        96797
2017    10       97023
2018    3        97164
2016    7        98808
2015    8        99689
2016    6        100532
2014    7        100912
2017    4        101025
2016    4        101107
2017    5        101380
2014    9        101568
2017    12       102056
2016    5        102591
2015    11       103260
        12       103466
        10       104741
2016    12       105113
        11       108673
2018    9        109477
2016    3        110388
2017    11       110552
2014    8        110897
2015    6        112312
2017    3        112533
2014    10       113138
        12       114063
2018    8        114985
2019    2        116697
2015    7        118205
2018    7        118925
        6        120141
2014    11       121904
2015    5        123380
        3        124331
        4        124812
2018    12       141995
        10       147486
2019    4        159556
2018    11       163703
2019    3        166705
Name: backers_count, dtype: int64
```

In [94]:
```
# settings
plt.figure(figsize=[12,5])

# calculate monthly sum of backers counts of 95 quantile data frame
# total
backers_grouped_sum = ks_compl_95.groupby([ks_compl_95.deadline.dt.year,
```

```
                                    ks_compl_95.deadline.dt.month])['backers_count'].s
# success
backers_grouped_sum_s = ks_success_95.groupby([ks_success_95.deadline.dt.year,
                                    ks_success_95.deadline.dt.month])['backers_count']
# failed
backers_grouped_sum_f= ks_fail_95.groupby([ks_fail_95.deadline.dt.year,
                                    ks_fail_95.deadline.dt.month])['backers_count'].su
# insert 0 occurence for 2009-6
backers_grouped_sum_f = np.insert(backers_grouped_sum_f,1,0)

# create dataframe
df_backers_sum = pd.DataFrame(data={'total':backers_grouped_sum,
                                'success':backers_grouped_sum_s,
                                'failed': backers_grouped_sum_f,
                                'date': dates})

# left plot: line plot of backers counts of all completed projects
plt.subplot(1,2,1)
ax = df_backers_sum.total.plot(color=backers_color, label='backers count');

# annotate peaks
# all time max
ymax_1  = max(backers_grouped_sum)
xmax_1 = str( df_backers_sum[df_backers_sum.total == ymax_1].date.values[0])[:7]
ax.annotate(format_num(ymax_1)+ "\n(" + str(xmax_1)+")", xy=(119, ymax_1),
            xytext=(90, ymax_1-7000),
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))

# first peak ever in 11/2014
ymax_2  = ks_compl_95.groupby([ks_compl_95.deadline.dt.year,
                              ks_compl_95.deadline.dt.month])['backers_count']\
                              .sum().sort_values().values[-8]
xmax_2 = str(df_backers_sum[df_backers_sum.total == ymax_2].date.values[0])[:7]
ax.annotate(format_num(ymax_2)  + "\n(" + str(xmax_2) +")", xy=(67, ymax_2),
            xytext=(45, ymax_2-7000),
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))

# ticks and labels
plt.xlabel("")
timeline_ticks(df_backers_sum)

# improve readability of y ticks
ylabels = ['{:,.0f}'.format(ytick) + ' k' for ytick in ax.get_yticks() / 1000]
ax.set_yticklabels(ylabels)
plt.ylabel("abs. backers count / month")
plt.title("Monthly Supporter Frequencies of Completed Projects Over Time\n(95% quanti
plt.legend(loc=2)
```

```
# right plot: line plots of backers counts of successful anf failed projects
plt.subplot(1,2,2)
ax = df_backers_sum.success.plot(color=cust_green, label="backers count successful pro
ax = df_backers_sum.failed.plot(color=cust_red, label="backers count failed projects")

# ticks and labels
plt.xlabel("")
timeline_ticks(df_backers_sum)
plt.yticks(np.arange(0, 175000+1, 25000))
ylabels = ['{:,.0f}'.format(ytick) + ' k' for ytick in ax.get_yticks() / 1000]
ax.set_yticklabels(ylabels)
plt.ylabel("")
plt.title("Monthly Supporter Frequencies Over Time by Project Status\n(95% quantile)"
plt.tight_layout()
plt.legend()
plt.show()
```



The course of monthly absolute backers counts over time reminds of the monthly aggregated sum of pledges. The number of supporters grew at a steady rate. Then, in 2014, exploded, peaking at {{format_num(ymax_2)}} supporters in {{xmax_2}}. One year earlier there were only 68,125 backers offering financial funding, meaning the number of backers doubled within a year.

Late 2015 to 2017, backers counts relapsed, yet remained above 100k monthly backers in peak times. Since 2018 the growth of backers counts has been recovering, counting record after record. Ultimately, in March 2019, the month before Kickstarter's anniversary, the highest number of financial supporters ever was recorded: {{format_num(ymax_1)}}.

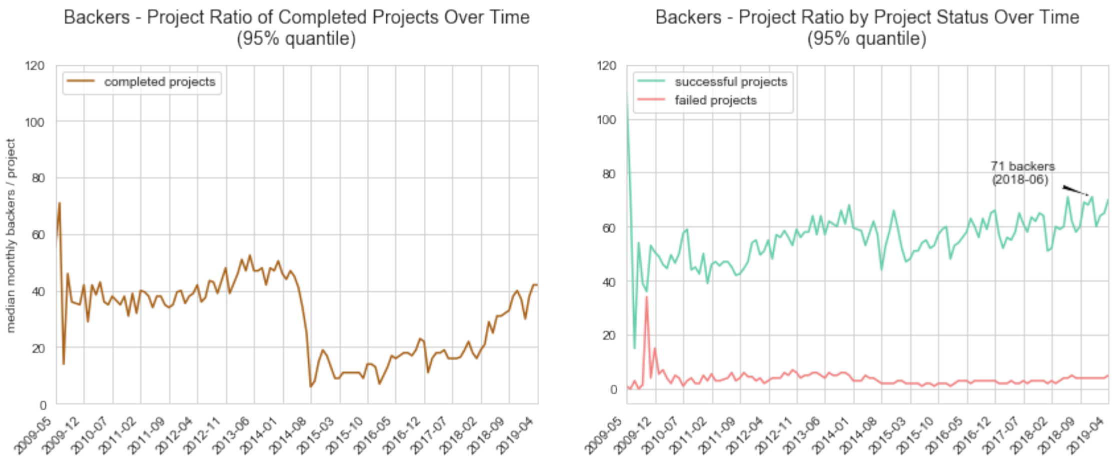
Like project counts, goals and pledges, the number of active supporters is subject to heavy cyclic recessions.

Visualizing backers counts of successful projects only (green line, right plot), primarily mirrors the total amount of active supporters from the plot on the left. And again, considering the low red line, supporters betting on the wrong horse seem to be a minority. According to these plots Kickstarter continuously attracted more project supporters or encouraged investors to pledge for multiple projects. This counts towards Kickstarter becoming more valuable for creators over the years.

The increasing number of backers is likely the explanation for stable funding capacity over time. To prove this, I am going to depict the ratio of backers to creators.

In [95]:
```
# settings
plt.figure(figsize=[12,5])

# calculate monthly median of backers counts of 95 quantile data frame
# total
backers_grouped_r = ks_compl_95.groupby([ks_compl_95.deadline.dt.year,
                                    ks_compl_95.deadline.dt.month])['backers_count'].m
# success
backers_grouped_s_r = ks_success_95.groupby([ks_success_95.deadline.dt.year,
                                    ks_success_95.deadline.dt.month])['backers_count']
# failed
backers_grouped_f_r= ks_fail_95.groupby([ks_fail_95.deadline.dt.year,
                                    ks_fail_95.deadline.dt.month])['backers_count'].me
# insert 0 occurence for 2009-6
backers_grouped_f_r = np.insert(backers_grouped_f_r,1,0)

# create dataframe
df_backers_r = pd.DataFrame(data={'total':backers_grouped_r,
                                'success':backers_grouped_s_r,
                                'failed': backers_grouped_f_r,
                                'date': dates})

# left plot: line plot of median backers by completed projects
plt.subplot(1,2,1)
ax = df_backers_r.total.plot(color=backers_color, label='completed projects');

# ticks and labels
plt.xlabel("")
timeline_ticks(df_backers_r)
plt.yticks(np.arange(0, 121, 20))

plt.ylabel("median monthly backers / project")
plt.title("Backers - Project Ratio of Completed Projects Over Time\n(95% quantile)", f
plt.legend(loc=2)

# right plot: line plots of avg backers by successful or failed project
plt.subplot(1,2,2)
ax = df_backers_r.success.plot(color=cust_green, label="successful projects");
ax = df_backers_r.failed.plot(color=cust_red, label="failed projects");

# annotate recent maximum
ymax_1  = df_backers_r.success.sort_values().values[-3]
xmax_1 = str(df_backers_r[df_backers_r.success == ymax_1].date.values[1])[:7]
```

```
ax.annotate(format_num(ymax_1)+ " backers\n(" + str(xmax_1)+")", xy=(115, ymax_1),
            xytext=(90, ymax_1+5),
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))

# ticks and labels
plt.xlabel("")
timeline_ticks(df_backers_r)
plt.yticks(np.arange(0, 121, 20))
plt.ylabel("")
plt.title("Backers - Project Ratio by Project Status Over Time\n(95% quantile)", font
plt.tight_layout()
plt.legend(loc=2)
plt.show()
```



The average number of backers per project over time explains the phenomenon of the overall stable rates of success and funding as well as the recent increase in pledged funding. Note that the average number of backers per successful project has been increasing over time (right plot, green line). In October 2018, there was a record of a median of 72 backers supporting each project. Therefore, we can conclude that the increasing number of active supporters compensated for increased competition among creators.

In the plot on the left, the sharp drop of backers of completed projects in August 2014 doesn't come with a surprise. Apparently, the number of campaigns grew faster than the audience of backers. Ever since, the average number of supporters almost doubled and is now almost on the same level as before the hype. At the same time, it is puzzling that the dent and the remarkable growth of is hardly notable in successful campaigns. It seems like supporters have been investing mostly in successful campaigns.

Compared to the crash of relative investments, the anomaly of a decreased backers/project ratio in August 2014 seems to be more discreet. Thus, we got to ask, how did the financial funding overhead in August 2014 came to be? One assumption is that users were hesitant to invest and contributed with rather small pledges. To prove my hypothesis, I'm going to depict the relative amount each supporter pledged.

In [96]:
```
# add the average amount pledged per supporter to each campaign
for df in [ks_compl_95, ks_success_95, ks_fail_95]:
    df['pledged_rate'] = (df['pledged_hist_usd'] / df['backers_count']).fillna(0)

# assess the average amount pledged per user / project each month.
ks_compl_95.groupby([ks_compl_95.deadline.dt.year,
                     ks_compl_95.deadline.dt.month])['pledged_rate']\
                     .mean().sort_values()
```

Out[96]:
```
deadline  deadline
2009      8           25.592927606219806
          5           27.631818181818183
2014      8           47.887541856760926
2009      9           49.534867846568616
          6           54.81850706311233
2010      8           55.41239695789137
2015      3           55.627832306769946
          2           56.00643667444149
2014      9           56.78907692437308
2016      1           58.042252844780045
          3           58.779006098627995
2019      2           58.84227589734179
2010      11          59.07579121996007
2018      2           59.49935832517218
2016      5           59.51383840128036
          2           59.65464841171469
2014      10          59.65730860658391
2019      3           59.72928685348439
2016      4           59.94800099379007
2019      1           60.056002313474444
2015      8           60.257674374904056
          9           61.10286949307058
2009      12          61.46945291190793
2015      4           61.86616882419452
2017      9           61.96772984289825
2018      8           61.993520283612156
2017      3           61.99500128728499
2018      3           62.13239305358084
2017      7           62.310266754615824
2009      11          62.34342486489976
2017      2           62.42221710030338
2016      8           62.556400771363194
2010      9           62.556852133883574
2017      4           62.570550252508156
2016      9           62.589262703199296
2015      6           62.895159619458695
2013      2           62.92562203849084
2012      2           63.08833459497963
```

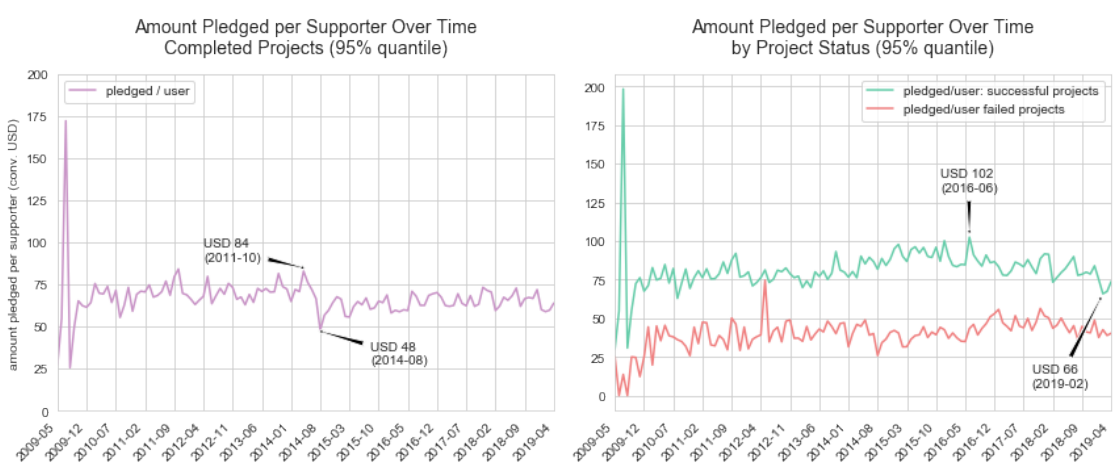
2017	10	63.25800955038446
2012	6	63.5576688072674
2017	6	63.72762632138182
2019	4	63.90788479548574
2014	11	64.17086348999948
2015	11	64.18275720936461
2010	1	64.24987859327238
	6	64.27015410516296
2013	4	64.34245612690535
2015	5	64.82822272107367
2014	1	64.90767987064675
2015	10	65.0609334795228
2009	10	65.22840045991926
2018	5	65.5963910019374
2012	3	65.66241796849077
	12	66.1705135137792
	1	66.17324640411863
2015	1	66.21966266675376
2014	7	66.45722111493603
2018	9	66.48202860939139
	11	66.68312228177608
2015	7	66.9492852416158
2018	10	67.23928176367323
	4	67.3625092713024
2017	1	67.39793399365284
2011	4	67.45158514624336
2013	1	67.5055200491074
2014	12	67.66291316758387
2016	7	67.94389448552985
2012	4	67.94860563153509
2018	6	68.2316652633085
2012	7	68.24424755850829
2017	8	68.30874528662736
2011	5	68.43969077622317
2016	10	68.44339548418775
2011	8	68.61127653377962
2015	12	68.72874376330483
2011	12	68.77811967912947
2013	3	69.02940280137643
2012	9	69.13457688807375
2010	12	69.14278825865419
	4	69.33493869008359
2017	5	69.43915940546493
2016	11	69.45264050272796
2011	11	69.6793628102941
2010	3	69.77994328214783
2016	12	70.15313059894544
2013	8	70.40927249543404

```
2018      1         70.49333896086468
2011      2         70.52782028602647
2013      9         70.6067865685547
2011      6         70.67455463960619
2014      3         70.74958754450566
2013      6         70.83393456478862
2016      6         70.88874499131485
2011      1         70.98143795776745
2017      12        71.40803715356998
2010      7         71.45876705374577
2014      6         71.80494924097195
2018      12        71.88659563549156
2014      2         71.97565525152062
2013      12        72.25235780563624
          7         72.53851032149385
          5         72.63151470051493
2012      8         72.64421569429811
2018      7         72.81529006498431
2012      11        73.19340712367321
2010      10        73.24753062078682
2017      11        73.27774291318057
2013      11        73.68282074923859
2010      5         73.81430651280368
2011      3         74.68331480822602
2010      2         75.50838863919874
2012      10        75.60306206118334
2014      5         76.16447696555542
2011      7         76.96075914542565
          9         79.54651334266929
2012      5         79.73592140641263
2013      10        81.46978035481902
2014      4         82.86121932553053
2011      10        84.13647124779307
2009      7         172.0173663751215
Name: pledged_rate, dtype: float64
```

In [97]:
```
# settings
plt.figure(figsize=[12,5])

# calculate monthly median pledged rte of completed projects of 95 quantile data fram
# total
pledged_rate_grouped = ks_compl_95.groupby([ks_compl_95.deadline.dt.year,
                                  ks_compl_95.deadline.dt.month])['pledged_rate'].me
# success
pledged_rate_grouped_s = ks_success_95.groupby([ks_success_95.deadline.dt.year,
                                  ks_success_95.deadline.dt.month])['pledged_rate']
# failed
pledged_rate_grouped_f= ks_fail_95.groupby([ks_fail_95.deadline.dt.year,
```

```
                                    ks_fail_95.deadline.dt.month])['pledged_rate'].mea
# insert 0 occurence for 2009-6
pledged_rate_grouped_f = np.insert(pledged_rate_grouped_f,1,0)

# create dataframe
df_pledged_rate = pd.DataFrame(data={'total': pledged_rate_grouped,
                                'success': pledged_rate_grouped_s,
                                'failed': pledged_rate_grouped_f,
                                'date': dates})

# # left plot: line plot of monthly relative pledges for all completed projects
plt.subplot(1,2,1)
ax = df_pledged_rate.total.plot(color=pledged_color, label='pledged / user');

# annotate peaks
# peak in 4/2014
ymax_1  = ks_compl_95.groupby([ks_compl_95.deadline.dt.year,
                              ks_compl_95.deadline.dt.month])['pledged_rate']\
                              .mean().sort_values().values[-2]
xmax_1 = str(df_pledged_rate[df_pledged_rate.total == ymax_1].date.values[0])[:7]
ax.annotate("USD " + format_num(ymax_1)  + "\n(" + str(xmax_1) +")", xy=(60, ymax_1),
            xytext=(35, ymax_1+5),
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))

# low in 08/2014
ymin = ks_compl_95.groupby([ks_compl_95.deadline.dt.year,
                            ks_compl_95.deadline.dt.month])['pledged_rate']\
                            .mean().sort_values().values[2]
xmin = str(df_pledged_rate[df_pledged_rate.total == ymin].date.values[0])[:7]
ax.annotate("USD " + format_num(ymin)  + "\n(" + str(xmin) +")", xy=(62, ymin),
            xytext=(75, ymin-20),
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))

# ticks and labels
plt.xlabel("")
timeline_ticks(df_pledged_rate)

# improve readability of y ticks
plt.yticks(np.arange(0, 201, 25))
plt.ylabel("amount pledged per supporter (conv. USD)")
plt.title("Amount Pledged per Supporter Over Time\nCompleted Projects (95% quantile)"
plt.legend(loc=2)

# right plot: line plot of onthly relative pledges, divided into successful anf faile
plt.subplot(1,2,2)
ax = df_pledged_rate.success.plot(color=cust_green, label="pledged/user: successful p
ax = df_pledged_rate.failed.plot(color=cust_red, label="pledged/user failed projects"
```

```
# annotate peaks
# peak in 6/2016
ymax_3  = ks_success_95.groupby([ks_success_95.deadline.dt.year,
                                 ks_success_95.deadline.dt.month])['pledged_rate']\
                                 .mean().sort_values().values[-2]
xmax_3 = str(df_pledged_rate[df_pledged_rate.success == ymax_3].date.values[0])[:7]
ax.annotate("USD " + format_num(ymax_3)  + "\n(" + str(xmax_3) +")", xy=(85, ymax_3),
            xytext=(78, ymax_3+30),
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))

# low in 08/2014
ymin_2 = ks_success_95.groupby([ks_success_95.deadline.dt.year,
                                 ks_success_95.deadline.dt.month])['pledged_rate']\
                                 .mean().sort_values().values[5]
xmin_2 = str(df_pledged_rate[df_pledged_rate.success == ymin_2].date.values[0])[:7]
ax.annotate("USD " + format_num(ymin_2)  + "\n(" + str(xmin_2) +")", xy=(117, ymin_2)
            xytext=(100, ymin_2-60),
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))

# ticks and labels
plt.xlabel("")
timeline_ticks(df_pledged_rate)
plt.ylabel("")
plt.yticks(np.arange(0, 201, 25))
plt.title("Amount Pledged per Supporter Over Time\nby Project Status (95% quantile)",
plt.tight_layout()
plt.legend()
plt.show()
```



The mean pledges by supporter were comparatively constant over the past 10 years. It roughly varied around a mean of USD {{format_num(df_pledged_rate.total.mean())}} per backer.

The relative investment spent on projects dropped from an all time high in April 2014 to an all time low in August 2014. The rate recovered in the following years but was a little lower compared to the initial years.

For campaigns ending in success, creators were able to expect on average USD {{format_num(df_pledged_rate.success.mean())}} per supporter.

Turning our attention to the plot on the right reveals that the drop in relative pledges per project did not affect successful projects. On the contrary: users were willing to spent a little more in between 2015 - 2017 and a little less on failed projects. This may have contributed to balance the investment stability of successful projects during the recession years.

Since late 2018, we observe that the amount pledged per individual has been declining. In order to make up for the loss, creators have to compete for more investors to raise the same amount of funding as in previous years. In 2018, successful projects had to expect on average USD {{format_num(ks_success_95[ks_success_95.deadline.dt.year == 2016]['pledged_rate'].mean() - ks_success_95[ks_success_95.deadline.dt.year == 2018]['pledged_rate'].mean())}} less per backer than in the record year 2016.

The question is whether we can attribute the recent negative development to more competition. On the one hand, we can argue that due to an increased number of projects, supporters tend to diversify their investment across multiple projects or became more risk averse. On the other hand, creators themselves may have chosen lower amounts of fixed incentives to attract a greater number of supporters. Unfortunately, we lack the data to gain a deeper understanding about this question.

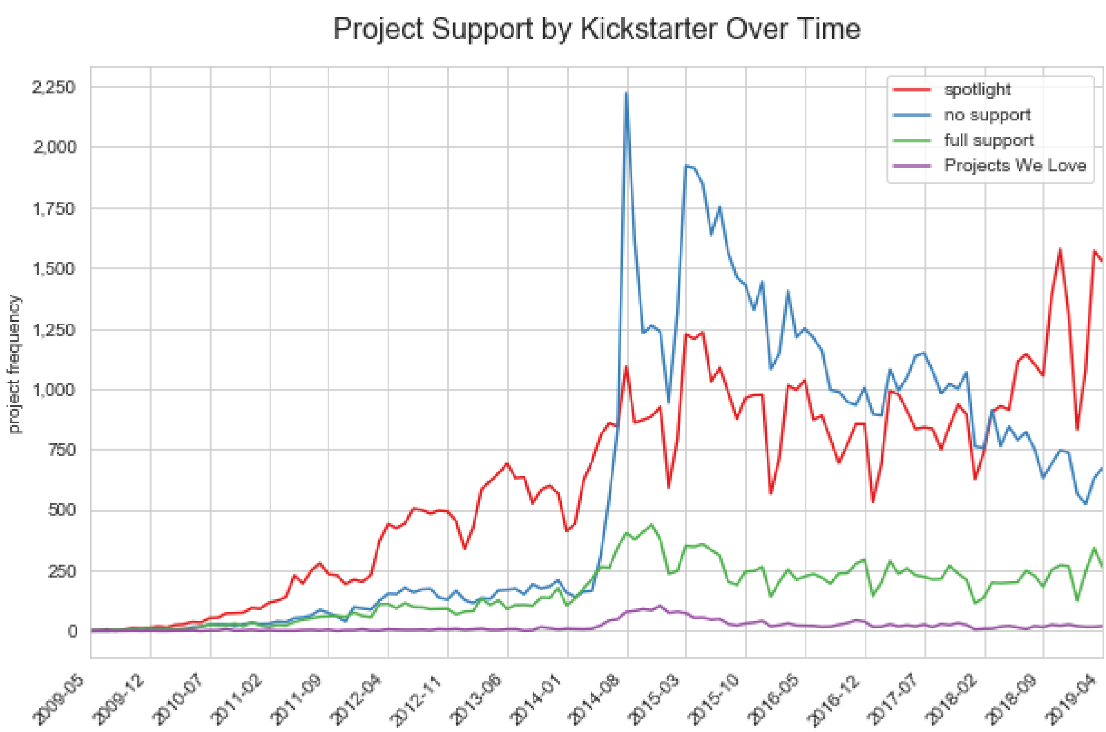
In general, supporters seem to be hesitant to invest in projects that will eventually fail. On average they invested a mean of only USD {{format_num(df_pledged_rate.failed.mean())}}. This may be an indication for supporters being able to determine the value, quality and chances of success of campaigns, in spite of a greater choice of projects on the platform.

As we will see in my second research topic, Kickstarter as a platform has quite some power over success and failure rates of projects. As a main actor of making crowdfunding mainstream, Kickstarter should have the potential power and tools to drive competition and engagement. Presumably, one of Kickstarter's main objective is to successfully fund as many projects as possible. One of their main tools to support campaigns is by promoting projects on their landing page and on multiple social media channels and by awarding the "Projects We Love" badge. With increasing competition, do creators nowadays have less of a chance to get Kickstarter's support?

Do creators nowadays have a lower chance to be promoted by Kickstarter?

In [98]:
```
# Visualize how Kickstarter supported projects over time absolute values
fig, ax = plt.subplots(figsize=(10,6))

# create empty dataframe
df_featured = pd.DataFrame(data={'no support': [0.0]*120,
                                 'Projects We Love': [0.0]*120,
                                 'spotlight': [0.0]*120,
                                 'full support': [0.0]*120,
                                 'date': dates})

# fill data frame with absolute project counts
for label, df in ks_compl.groupby([ks_compl.featured]):
    # calculate monthly abs. project counts
    counts = ks_compl[ks_compl.featured == label].groupby([ks_compl.deadline.dt.year,
                                                           ks_compl.deadline.dt.month]
```

```
    # the above grouping ignores months with zero counts, so we manually add zero val
    # re-create a new multi-index, this time including all 12 months per year
    levels = [counts.index.levels[0].values, range(1,13)]
    new_index = pd.MultiIndex.from_product(levels, names=['year', 'month'])
    # re-index counts and fill empty values with zero
    counts = counts.reindex(new_index, fill_value=0).values
    # remove months Jan-April 2014 and, May-Dec 2019
    counts = counts[4:-8]
    # add to dataframe
    df_featured[label] = counts

# plot each featured value on a line
for label in ks_compl.featured.value_counts().index:
    ax = df_featured[label].plot(color=sns.set_palette(feat_color), label=label);

# ticks and labels
timeline_ticks(df_featured)
plt.xlabel("")

format_yticks(2250, 250)
plt.ylabel("project frequency")

plt.title("Project Support by Kickstarter Over Time", fontsize=16, pad=15);
plt.legend()
plt.show();
```



Investigating the absolute numbers of the support offered by Kickstarter reveals that campaigns only receiving the badge "Projects We Love" has been constantly low, almost irrelevant.

The same is true for projects being fully featured. Except for a modest rise in the hype year 2014, the absolute count of fully supported projects was relatively constantly ranging around 250 each month. Therefore, creators can assume a limited budget of projects being fully supported.

More interesting is the course of projects being spotlighted or not backed by Kickstarter. Non-featured projects, depicted by the blue line, were minor in comparison to spotlighted projects until mid 2014. While the number of spotlighted projects was smoothly increasing in May 2009 to early 2015, counts of non-supported projects exploded in August 2018 and reached a second peak in March/April 2015. Ever since, projects that have been denied support have been declining smoothly and reached a surprisingly low number of only {{df_featured['no support'].values[-2]}} in March 2019.

In contrast, spotlighted projects have been growing at a steady rate. There was a dent of stagnation during the recession years late 2015 to 2017. Additionally, especially spotlighted projects have been subject to seasonal fluctuations.

Before concluding about Kickstarter's project support strategy, let's look at the relative numbers of project support. I am certain, the peak in the hype year, the latest increase in supported projects and the seasonal fluctuations can be partly explained by the number of projects on the platform.

In [99]:
```
# calculate relative project support by dividing featured project counts by monthly p
for label in ks_compl.featured.value_counts().index:
    df_featured[label] = (df_featured[label] / df_project_counts['total'])*100
```

In [100]:
```
# assess featured proportions
df_featured
```

Out[100]:

	no support	Projects We Love	spotlight \
0	50.0	0.0	0.0
1	0.0	0.0	50.0
2	14.285714285714285	0.0	85.71428571428571
3	16.666666666666664	0.0	0.0
4	18.181818181818183	0.0	54.54545454545454
5	9.523809523809524	4.761904761904762	57.14285714285714
6	21.73913043478261	0.0	43.47826086956522
7	10.714285714285714	3.571428571428571	46.42857142857143
8	25.806451612903224	0.0	58.06451612903226
9	11.538461538461538	0.0	53.84615384615385
10	13.88888888888889	2.7777777777777777	66.66666666666666
11	13.953488372093023	2.3255813953488373	62.7906976744186
12	24.59016393442623	3.278688524590164	60.65573770491803
13	24.637681159420293	0.0	49.275362318840585
14	23.58490566037736	1.8867924528301887	50.0
15	25.471698113207548	1.8867924528301887	51.886792452830186
16	20.155038759689923	6.2015503875969	55.81395348837209
17	16.129032258064516	0.8064516129032258	58.87096774193549
18	21.951219512195124	1.6260162601626018	60.97560975609756

19	19.642857142857142	2.380952380952381	56.547619047619044
20	19.58041958041958	0.6993006993006993	64.33566433566433
21	17.682926829268293	1.8292682926829267	70.73170731707317
22	20.526315789473685	0.5263157894736842	65.78947368421053
23	18.090452261306535	0.5025125628140703	70.35175879396985
24	16.5625	0.3125	71.5625
25	18.6046511627907	0.9966777408637874	65.11627906976744
26	17.2972972972973	1.0810810810810811	67.56756756756756
27	20.327102803738317	0.46728971962616817	65.42056074766354
28	19.733333333333334	1.3333333333333335	62.66666666666667
29	16.857142857142858	0.0	65.42857142857143
30	13.310580204778159	1.023890784982935	65.8703071672355
31	25.257731958762886	0.7731958762886598	54.63917525773196
32	25.47945205479452	1.9178082191780823	55.61643835616439
33	23.28042328042328	0.5291005291005291	61.111111111111114
34	20.627062706270628	0.33003300330033003	61.05610561056105
35	21.568627450980394	0.9803921568627451	61.904761904761905
36	22.551928783382788	0.741839762611276	62.908011869436194
37	24.09152086137281	0.5383580080753702	59.89232839838493
38	20.757180156657963	0.5221932114882507	65.92689295039165
39	22.2509702457956	0.646830530401035	64.55368693402329
40	23.169107856191744	0.3994673768308922	64.4474034620506
41	18.80108991825613	1.08991825613079	67.71117166212534
42	17.916666666666668	0.8333333333333334	68.47222222222223
43	23.959827833572454	1.291248206599713	65.13629842180775
44	23.09090909090909	0.7272727272727273	61.63636363636363
45	18.225039619651348	1.109350237717908	67.67036450079239
46	15.704387990762125	1.1547344110854503	67.6674364896074
47	15.33101045296167	0.4645760743321719	71.77700348432056
48	17.702845100105375	0.42149631190727077	68.59852476290833
49	17.708333333333336	0.7291666666666666	72.08333333333333
50	19.001085776330076	0.8686210640608035	68.62106406080348
51	16.7973124300112	0.11198208286674133	71.10862262038073
52	23.42233009708738	0.3640776699029126	63.713592233009706
53	19.188596491228072	1.7543859649122806	63.925438596491226
54	19.763694951664874	1.1815252416756177	64.4468313641246
55	21.770833333333332	0.625	59.166666666666664
56	23.099415204678362	1.3157894736842104	60.23391812865497
57	19.28374655647383	1.1019283746556474	61.15702479338842
58	16.735537190082646	0.7231404958677686	64.35950413223141
59	15.215398716773601	0.8249312557286892	64.25297891842347
60	22.190611664295876	1.5647226173541962	57.46799431009957
61	32.147024504084015	2.5087514585764294	50.11668611435239
62	40.2415458937198	2.3671497584541066	40.77294685990338
63	58.539799683711124	2.055877701634159	28.755930416447022
64	54.94205862304021	2.828902522154056	29.31152010906612
65	47.30769230769231	3.4615384615384617	33.53846153846154
66	47.21078247847249	3.182328715836765	33.171096967427935

67	46.74735249621785	3.9334341906202726	35.02269288956127
68	51.11352525801195	4.019554589896796	32.10211841390549
69	54.0484997944924	3.2470201397451706	32.511302918207974
70	53.824600728495376	2.045390865788736	34.29532081815634
71	54.31818181818182	1.5340909090909092	34.26136363636363
72	52.87718293730318	1.5745777268823362	35.299169768107646
73	53.70734908136483	1.541994750656168	33.79265091863517
74	54.74703310430981	1.5615240474703311	33.9787632729544
75	56.20726880172724	1.0075566750629723	35.48038862900324
76	57.299843014128726	0.8634222919937204	34.37990580847723
77	53.62101313320825	1.125703564727955	36.06003752345216
78	51.35553834237025	1.3168086754453912	37.72269558481797
79	52.97575312270389	1.5062454077883909	35.819250551065394
80	59.81205085682698	0.9950248756218906	31.343283582089555
81	54.91606714628298	1.1031175059952039	34.24460431654676
82	51.940850277264325	1.146025878003697	37.486136783733826
83	49.6517820565342	0.9012699713232282	40.80294961081524
84	49.368088467614534	0.8293838862559242	40.91627172195892
85	51.75363558597091	0.8554319931565441	37.33960650128314
86	50.7227332457293	0.700832238282961	38.93999123959702
87	49.77511244377811	0.8495752123938031	39.63018490754623
88	50.82304526748971	1.286008230452675	35.699588477366255
89	47.585513078470825	1.6096579476861168	38.78269617706238
90	44.23897581792319	2.0862968231389285	40.54054054054054
91	45.8485401459854	1.7335766423357664	39.00547445255474
92	56.35220125786164	1.0062893081761006	33.52201257861635
93	49.38956714761376	0.9433962264150944	38.51276359600444
94	45.26404023470243	1.1316010058675607	41.53394803017603
95	44.64928057553957	0.8093525179856115	43.92985611510791
96	46.7828418230563	1.0277033065236818	40.66130473637176
97	51.17328519855595	0.8122743682310468	37.63537906137184
98	51.31755247878517	1.1612326931665922	37.561411344350155
99	50.28063610851263	0.7015902712815716	39.05519176800748
100	49.67088607594937	1.4177215189873418	38.0253164556962
101	47.24153917477978	1.1126564673157162	39.17477978674084
102	45.3968253968254	1.4512471655328798	42.40362811791383
103	48.61300591177808	1.0914051841746248	40.700318326512054
104	50.53050397877984	0.3978779840848806	41.51193633952255
105	46.18204031765424	0.5497861942577886	44.89920586438607
106	45.0419338924519	0.493339911198816	44.647261963492845
107	40.031479538300104	0.8919202518363064	48.7408184679958
108	42.69094587759231	1.0116337885685383	46.23166413758219
109	37.28733459357278	0.6616257088846881	52.55198487712666
110	36.965330932012606	0.36019810895992793	51.4633048176497
111	35.7653791130186	0.9060562708631379	52.5035765379113
112	33.54564755838641	0.7961783439490446	55.9447983014862
113	29.35429056924384	1.0620220900594732	58.87850467289719
114	28.52772466539197	0.8030592734225621	60.30592734225622

115	31.45299145299145	1.1111111111111112	56.02564102564103
116	36.681788723266365	1.2313674659753726	53.98574206092028
117	28.141783029001072	0.8592910848549946	57.84103114930183
118	24.6484375	0.625	61.328125
119	27.166465135026197	0.7658202337767029	61.467150342603794

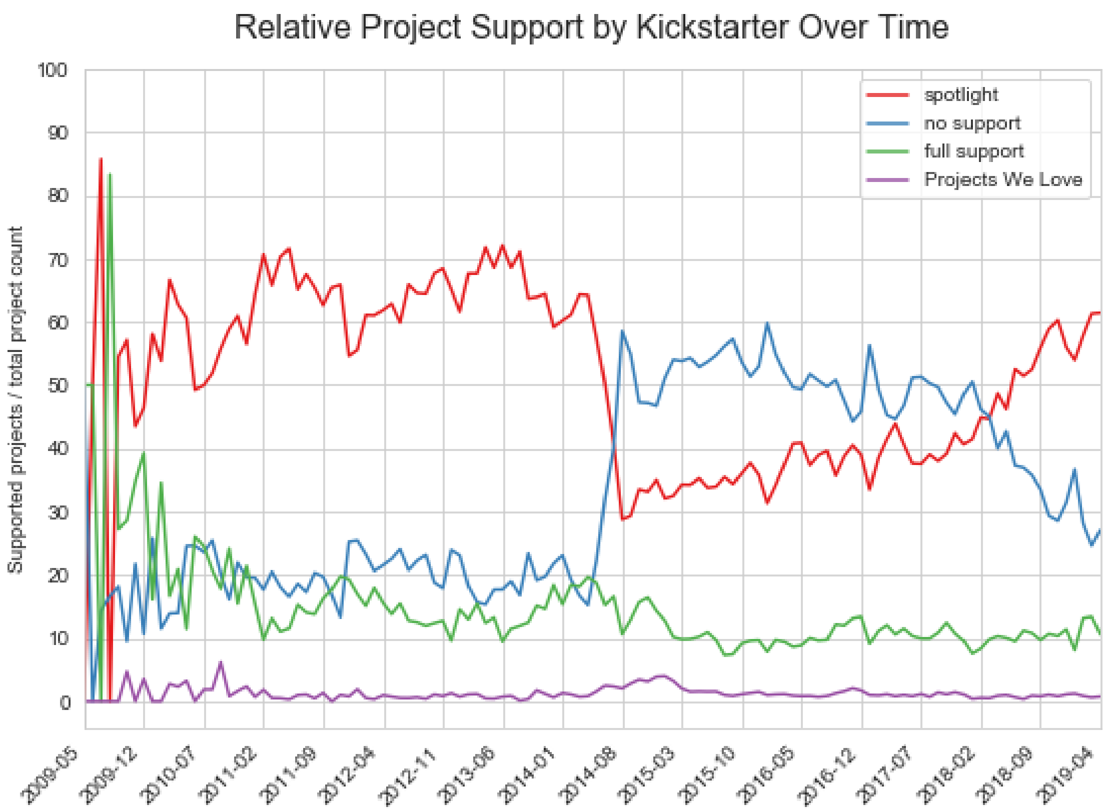
	full support	date
0	50.0	2009-05-01
1	50.0	2009-06-01
2	0.0	2009-07-01
3	83.33333333333334	2009-08-01
4	27.27272727272727	2009-09-01
5	28.57142857142857	2009-10-01
6	34.78260869565217	2009-11-01
7	39.285714285714285	2009-12-01
8	16.129032258064516	2010-01-01
9	34.61538461538461	2010-02-01
10	16.666666666666664	2010-03-01
11	20.930232558139537	2010-04-01
12	11.475409836065573	2010-05-01
13	26.08695652173913	2010-06-01
14	24.528301886792452	2010-07-01
15	20.754716981132077	2010-08-01
16	17.829457364341085	2010-09-01
17	24.193548387096776	2010-10-01
18	15.447154471544716	2010-11-01
19	21.428571428571427	2010-12-01
20	15.384615384615385	2011-01-01
21	9.75609756097561	2011-02-01
22	13.157894736842104	2011-03-01
23	11.055276381909549	2011-04-01
24	11.5625	2011-05-01
25	15.282392026578073	2011-06-01
26	14.054054054054054	2011-07-01
27	13.785046728971961	2011-08-01
28	16.266666666666666	2011-09-01
29	17.71428571428571	2011-10-01
30	19.795221843003414	2011-11-01
31	19.329896907216497	2011-12-01
32	16.986301369863014	2012-01-01
33	15.079365079365079	2012-02-01
34	17.986798679867988	2012-03-01
35	15.546218487394958	2012-04-01
36	13.798219584569733	2012-05-01
37	15.477792732166892	2012-06-01
38	12.793733681462141	2012-07-01
39	12.548512289780078	2012-08-01
40	11.984021304926765	2012-09-01

41	12.397820163487738	2012-10-01
42	12.777777777777777	2012-11-01
43	9.612625538020087	2012-12-01
44	14.545454545454545	2013-01-01
45	12.995245641838352	2013-02-01
46	15.473441108545035	2013-03-01
47	12.427409988385598	2013-04-01
48	13.27713382507903	2013-05-01
49	9.479166666666666	2013-06-01
50	11.509229098805646	2013-07-01
51	11.98208286674132	2013-08-01
52	12.5	2013-09-01
53	15.131578947368421	2013-10-01
54	14.60794844253491	2013-11-01
55	18.4375	2013-12-01
56	15.350877192982457	2014-01-01
57	18.457300275482094	2014-02-01
58	18.181818181818183	2014-03-01
59	19.706691109074242	2014-04-01
60	18.776671408250355	2014-05-01
61	15.227537922987164	2014-06-01
62	16.618357487922705	2014-07-01
63	10.648392198207695	2014-08-01
64	12.917518745739603	2014-09-01
65	15.692307692307692	2014-10-01
66	16.435791838262823	2014-11-01
67	14.296520423600606	2014-12-01
68	12.764801738185769	2015-01-01
69	10.19317714755446	2015-02-01
70	9.83468758755954	2015-03-01
71	9.886363636363637	2015-04-01
72	10.249069567706842	2015-05-01
73	10.958005249343831	2015-06-01
74	9.71267957526546	2015-07-01
75	7.304785894206549	2015-08-01
76	7.456828885400315	2015-09-01
77	9.193245778611631	2015-10-01
78	9.604957397366382	2015-11-01
79	9.698750918442322	2015-12-01
80	7.849640685461582	2016-01-01
81	9.73621103117506	2016-02-01
82	9.426987060998151	2016-03-01
83	8.643998361327325	2016-04-01
84	8.886255924170616	2016-05-01
85	10.051325919589392	2016-06-01
86	9.636443276390715	2016-07-01
87	9.745127436281859	2016-08-01
88	12.191358024691358	2016-09-01

```
89  12.022132796780683 2016-10-01
90  13.134186818397344 2016-11-01
91  13.412408759124087 2016-12-01
92  9.119496855345911  2017-01-01
93  11.154273029966703 2017-02-01
94  12.070410729253982 2017-03-01
95  10.611510791366907 2017-04-01
96  11.528150134048257 2017-05-01
97  10.379061371841155 2017-06-01
98  9.95980348369808   2017-07-01
99  9.962581852198316  2017-08-01
100 10.886075949367088 2017-09-01
101 12.471024571163653 2017-10-01
102 10.748299319727892 2017-11-01
103 9.595270577535244  2017-12-01
104 7.5596816976127315 2018-01-01
105 8.368967623701893  2018-02-01
106 9.817464232856437  2018-03-01
107 10.335781741867786 2018-04-01
108 10.065756196256954 2018-05-01
109 9.49905482041588   2018-06-01
110 11.211166141377758 2018-07-01
111 10.824988078206962 2018-08-01
112 9.713375796178344  2018-09-01
113 10.70518266779949  2018-10-01
114 10.363288718929255 2018-11-01
115 11.41025641025641  2018-12-01
116 8.101101749837978  2019-01-01
117 13.157894736842104 2019-02-01
118 13.398437499999998 2019-03-01
119 10.60056428859331  2019-04-01
```

In [101]:
```
# Visualize how Kickstarter supported projects over time relative values
# settings
plt.figure(figsize=[9,6])

# plot each featured value on a line
for label in ks_compl.featured.value_counts().index:
    ax = df_featured[label].plot(color=sns.set_palette(feat_color),label=label);

# ticks and labels
timeline_ticks(df_featured)
plt.xlabel("")

plt.yticks(np.arange(0, 101, 10))
plt.ylabel("Supported projects / total project count");

plt.title("Relative Project Support by Kickstarter Over Time", fontsize=16, pad=15);
```

```
plt.legend()
plt.show();
```



While campaigns being awarded the "Projects We Love" badge has been remaining constant at low level, fully backed projects have been fluctuating roughly around 10% of all projects since mid 2015.

The proportions of spotlighted and non-supported campaigns have changed significantly. The proportion turned upside down in the hype year 2014. With the rise of competing projects, the number of non-supported project rose from 20% to roughly 55%. At the same time, the proportion of projects being featured on the landing page fell dramatically. In August 2014, the rate dropped prom plus 60% to below 30%. This certainly wasn't the easiest time to succeed with a crowdfunding campaign due to the high number of competing projects and a low backers-projects ratio.

However, the chances of support became more promising. The proportion of spotlighted campaigns have been gradually growing, while projects receiving no backing by Kickstarter have been decreasing. In early 2018, the ratio rolled back. Today, more than 60% of all crowdfundings were spotlighted and only around 27% of campaigns did not gain any support by Kickstarter. As we will see further down, the success chances are much higher once Kickstarter promotes a campaign.

The increasing development of support is surprising. We know that recently a greater number of creators have been asking for funding. The competition increased, yet the chances of support have not been more promising. Obviously, Kickstarter must have adapted their strategy or website tools to actively spotlight a higher amount of projects. This may be one of the main drivers of increased numbers of successful campaigns.

7.2.1 6.2 Summary: Is it still worthwhile financing your project on Kickstarter, now that crowdfunding has become mainstream?

The short answer: yes, chances today are better than ever. In spite of increasing project numbers and therefore higher competition, there have never been more campaigns ending successfully than today. Also, the collected pledges for each successful project have been staying on a relatively stable level.

However, in 2014, crowdfunding campaigns suffered from Kickstarter fast growth. In August 2014, the number of campaigns exploded. With the increase in project counts, we found an abnormal high percentage of projects failing. {{format_num(max(df_project_counts.failed)100 / df_project_counts[df_project_counts.failed == max(df_project_counts.failed)][‘total’].values[0])}}% of campaigns flopped. During 2015 - 2017 project counts were in recession, but remained at a high level. In those times the likelihood to fail minimally exceeded success rates {{format_num(ks_compl_failed[ks_compl_failed.deadline.dt.year.isin([2014, 2015, 2016, 2017])][‘project_id’].count() 100 / ks_compl[ks_compl.deadline.dt.year.isin([2014, 2015, 2016, 2017])][‘project_id’].count()) }}:{{format_num(ks_compl_success[ks_compl_success.deadline.dt.year.isin([2014, 2015, 2016, 2017])][‘project_id’].count() *100 / ks_compl[ks_compl.deadline.dt.year.isin([2014, 2015, 2016, 2017])][‘project_id’].count())}}%.

Nevertheless, the overall percentage of successful campaigns have been relatively stable, in 2014 and today. Higher competition on Kickstarter primarily affected those campaigns that eventually failed.

By the beginning of 2018, Kickstarter turned success and failure rates upside down. Ever since, campaigns ending in success have become more likely, while flops have been declining notably. In 2018, 63% of completed campaigns ended in success. Actually, the highest monthly count of successful campaigns ever recorded was only recently, in March 2019. Chances to win were {{format_num(max(df_project_counts.success)*100 / df_project_counts[df_project_counts.success == max(df_project_counts.success)][‘total’].values[0])}}%.

The current trend to collect a higher funding seems as promising. We would expect the recent increase in competing projects, lower funding goals and the tendency to pledge greedier investments to negatively impact campaigns. Yet, the overall financial backing per project has been relatively constant since 2014. On average creators were able to raise a median of USD {{format_num(ks_compl_success[‘pledged_hist_usd’].median())}} if the campaign ended in success. Fortunately, in 2018, creators were able to expect a median of USD {{format_num(ks_compl_success[ks_compl_success.deadline.dt.year == 2018][‘pledged_hist_usd’].median())}}.

We found the backer-project ratio to be the most obvious explanation to balance increased competition. Clearly, in 2014, there was a huge overhead between investment supply and demand caused by a lack of potential supporters. This gap has been progressively closing. Yes, Kickstarter has become mainstream, but the platform also became mature. Today, founders mostly benefit from an increased number of supporters.

The tendency of individuals to pledge higher during the recession years 2015-2017 for successful campaigns may have contributed to keep the financial potential of crowdfunding stable. However, since late 2018, the amount pledged per individual has been declining. In order to make up for the loss, creators have to compete for more investors to raise the same amount of funding. In 2018, successful projects had to expect on average USD {{format_num(ks_success_95[ks_success_95.deadline.dt.year == 2016][‘pledged_rate’].mean() - ks_success_95[ks_success_95.deadline.dt.year == 2018][‘pledged_rate’].mean())}} less per backer than in the record year 2016.

The question is whether we can attribute the recent negative development to competition and popularity. On the one hand, due to an increased number of projects, supporters are able to diversify their investment across multiple projects or they became more risk averse. On the other hand, creators themselves may have chosen rewards of lower value to attract a greater number of supporters. Unfortunately, we lack the data to gain deeper understanding about this question.

In general, supporters seem to be more and more hesitant to invest in projects that eventually fail. In spite of a greater choice of projects available, supporters seem to take univocal decisions. Their ability to filter to determine the value, quality and chances of success of campaigns may have improved. One possibility to support this is Kickstarter's increasing role in the promotion of campaigns.

The proportion of spotlighted and non-supported campaigns has been changing over time significantly. With increased competing projects in the hype year 2014, the rate of projects without any promotional support increased dramatically from 20% to roughly 55%. Only 30% were featured in August 2014. This certainly wasn't the easiest time to succeed with a crowdfunding campaign due to the high competition.

Since the hype year, the proportion of spotlighted campaigns has been gradually growing while the number of projects receiving no promotion have been decreasing. Ultimately, since early 2018 projects being featured overturned the project counts receiving no support. Today, more than 60% of all crowdfundings are spotlighted on Kickstarter's channels and only around 27% of campaigns do not gain any support. As we will see further down, the chances for success are much higher once Kickstarter selected a campaign to be featured.

Although creators today tend to set their goals lower than in previous years, it doesn't seem to affect the total funding raised. The pledged funding was surprisingly stable for successful projects over time. On average, creators have been able to raise more than they had asked for once the campaign was successful. In spite of declining goals, the surplus of pledges has been widening since 2017. In the year 2014 the sum of USD {{format_num(ks_compl_success[ks_compl_success.deadline.dt.year == 2014]['pledged_hist_usd'].sum())}} was collected by successful campaigns. The amount doubled in 2018, when Kickstarter was able to distribute USD {{format_num(ks_compl_success[ks_compl_success.deadline.dt.year == 2018]['pledged_hist_usd'].sum())}} to successful campaigns. I suspect the advantage of lower funding goals to be connected with Kickstarter's all-or-nothing approach. Creator's setting lower goals can reach their funding earlier and eventually benefit from success affirmation effects. They may also be perceived as less greedy.

The overall positive mainstream effects did not contribute to a closer race between successful and failed campaigns. The collected pledges and number of backers of failed campaigns underperformed significantly.

In conclusion, I cannot attribute Kickstarter to become mainstream with severe disadvantages for business starters. Clearly, creators have to compete with an increased number of additional campaigns. At the same time, there are more backers and therefore more potential investment available. The proportion of projects being funded successfully has been increasing lately, so has the median pledged funding per project. One main driver is likely the chance to be promoted on Kickstarter's landing page. On the downside, creators may expect a little lower investments per capita.

It seems like the characteristics of what makes a campaign likely to succeed have become clearer. I suppose due to crowdfunding becoming mainstream, project creators, the backers audience and the Kickstarter platform itself mostly benefited from growth and learning effects. Today, stakeholders may have a better mutual understanding about what type of projects are particularly suited for crowdfunding. Additionally, they may have better insights about a campaign's features to eventually make a trusted decision. We are going to look at possible characteristics connected to success in our second research question.

7.3 What determines the success of a crowdfunding campaign on Kickstarter?

Based on our data set, we are going to investigate what specific project features are correlated with a higher chance for success. To start with, I'm going to look into the type of a project by analyzing project categories.

7.3.1 Categories

Were there any changes in the popularity of the type of projects?

As we know, over the past 10 years of Kickstarter's existence, crowdfunding has only been developing as a mainstream funding opportunity. Insofar, we found that user behavior and project characteristics changed over time. Since our goal is to identify possible success predictors that are valid today, I will first aim at gaining a general understanding about possible trends in the popularity of project categories.

There are two types of categories, I'm going to investigate the main project *category* and the subcategory values of a project found it the column *comb cat*.

To start with, I'm going to plot the relative project counts of each parent category by year. As there are 15 categories, showing all of them in one timeline would make interpretation difficult. Hence, I will facet categories into 3 categories per plot.

```
In [102]: # utility function to generate dataframe suitable for a timeline
          def create_timeline_df(df, feature):
              # initialize list of lists of categories with each 120 values
              columns = df[feature].value_counts().index
              data = [[0]*len(df[feature].value_counts())]*120

              # create empty DataFrame
              df_counts = pd.DataFrame(data, columns = columns)

              for cat in df[feature].value_counts().index:
                      # extract observations by category and group by year
                      df_cat = df[df[feature] == cat]
                      # calculate monthly abs. project counts
                      counts = df_cat.groupby([df_cat.deadline.dt.year,
                                               df_cat.deadline.dt.month])\
                                               .count()['project_id']
                      # manually create multi levels
                      levels = [range(2009,2020), range(1,13)]
                      new_index = pd.MultiIndex.from_product(levels, names=['year', 'month'])
                      # re-index counts and fill empty values with zero
                      counts = counts.reindex(new_index, fill_value=0).values
                      # remove months Jan-April 2014 and, May-Dec 2019
                      counts = counts[4:-8]
                      counts = counts*100 / ks_monthly_counts['count_monthly']
```

```
            # add to dataframe d
            df_counts[cat] = counts

    return df_counts

# assess latest development
df_cat_counts = create_timeline_df(ks_compl,  "category")
df_cat_counts.tail()
```

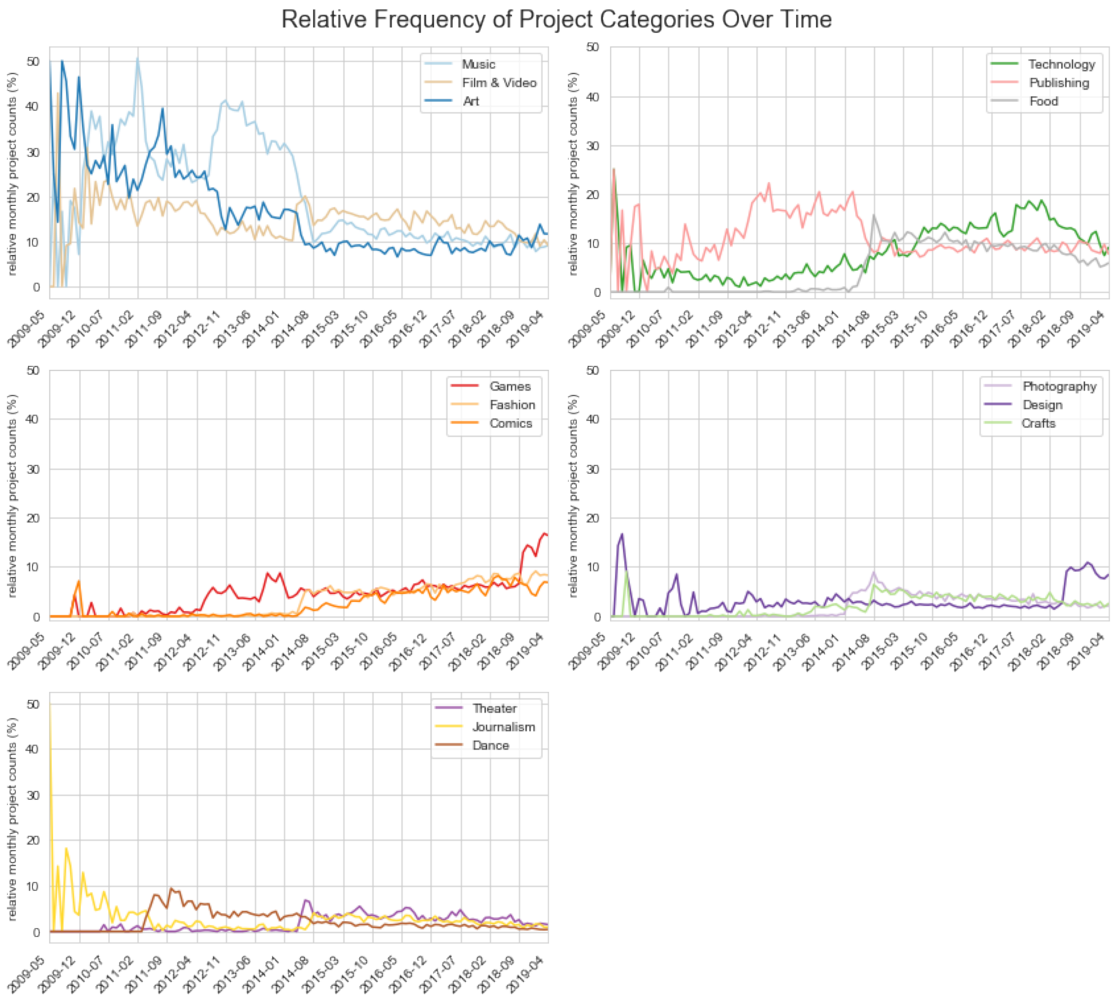
Out[102]:

```
                  Music        Film & Video                Art  \
115 10.213675213675213 9.871794871794872  8.632478632478632
116 7.777057679844459  11.730395333765392 10.823071937783538
117 8.646616541353383  8.968850698174007  13.80236305048335
118 8.7890625          10.3515625         11.71875
119 9.109230149133413  9.028617492946392  11.688835147118098

            Technology          Publishing               Food  \
115 11.752136752136753 8.504273504273504 6.282051282051282
116 12.313674659753726 8.165910563836682 6.869734283862606
117 9.559613319011815  7.894736842105263 5.1020408163265305
118 7.421875           9.6875            5.390625
119 9.068923821039903  7.738814993954051 5.88472390165256

                 Games           Fashion             Comics  \
115 13.88888888888889  8.290598290598291 4.615384615384615
116 12.119248217757615 9.138042773817238 4.1477640959170445
117 15.467239527389903 8.270676691729323 5.961331901181525
118 16.7578125         8.4375            6.953125
119 16.324062877871825 8.3031035872632   6.852075775896815

           Photography             Design             Crafts  \
115 1.9658119658119657 10.341880341880342 2.2222222222222223
116 2.527543745949449  8.684381075826312  2.268308489954634
117 1.7185821697099892 7.841031149301826  2.953813104189044
118 2.03125            7.6171875          1.875
119 2.136235388956066  8.424022571543732  2.5796049979846836

               Theater         Journalism              Dance
115 1.5811965811965811 1.1111111111111112 0.7264957264957265
116 1.2313674659753726 1.6202203499675956 0.5832793259883344
117 1.7722878625134264 1.6111707841031149 0.4296455424274973
118 1.640625           0.9375             0.390625
119 1.4913341394598951 0.9270455461507456 0.4433696090286175
```

In [103]:

```
# settings
fig = plt.figure(figsize=[12,10])
j = 0
g_count = 0
```

```python
# create 5 suplots, plotting 3 categroies each
for i in range(1,6):
    plt.subplot(3, 2, i)

    # take 3 categories per loop, in descending order
    for cat in ks_compl.category.value_counts()[j:j+3].index:
        # plot
        df_cat_counts[cat].plot(color=category_colors[g_count], label=cat);

        # labels and ticks
        g_count+=1
        plt.tight_layout()
        timeline_ticks(df_cat_counts)
        plt.yticks(np.arange(0, 50+1, 10))
        plt.xlabel("")
        plt.ylabel("relative monthly project counts (%)")
        plt.legend()
    j+=3

plt.suptitle("Relative Frequency of Project Categories Over Time", fontsize=18, y=1.0
plt.show()
```



The relative popularity of project categories changed over time. Music, Film and Art dominated the early years. As of today, those are still popular categories, but have lost momentum. Publishing was also quite popular in the beginning years, but has lost popularity since August 2014.

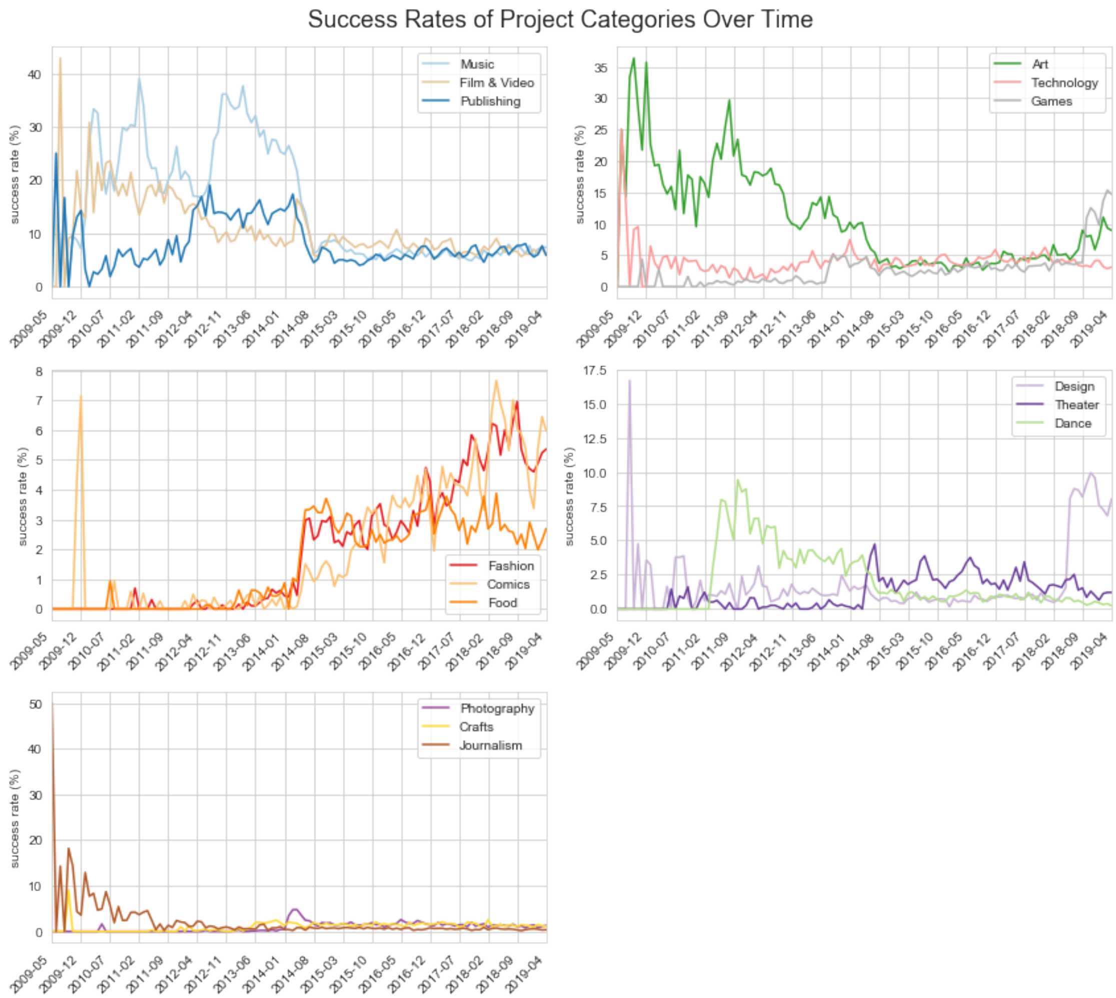
Technology ventures got the biggest boost in popularity, but the proportion of tech project has been declining since 2017.

Since 2018, the most remarkable changes occurred. Games, Fashion and Design suddenly gained popularity. Nowadays, Games count for 16% of projects. Most other categories seem to have settled below 10%.

Does a project category impact chances of success?

```
In [104]: # calculate success rates
          df_cat_s = create_timeline_df(ks_compl_success,  "category")

          # settings
          fig = plt.figure(figsize=[12,10])
          j = 0
```

```
g_count = 0

# create 5 suplots, plotting 3 categroies each
for i in range(1,6):
    plt.subplot(3, 2, i)

    # take 3 categories per loop, in descending order
    for cat in ks_compl_success.category.value_counts()[j:j+3].index:
        # plot
        df_cat_s[cat].plot(color=category_colors[g_count], label=cat);

        # labels and ticks
        g_count+=1
        plt.tight_layout()
        timeline_ticks(df_cat_s)
        plt.xlabel("")
        plt.ylabel("success rate (%)")
        plt.legend()
    j+=3

plt.suptitle("Success Rates of Project Categories Over Time", fontsize=18, y=1.02)
plt.show()
```

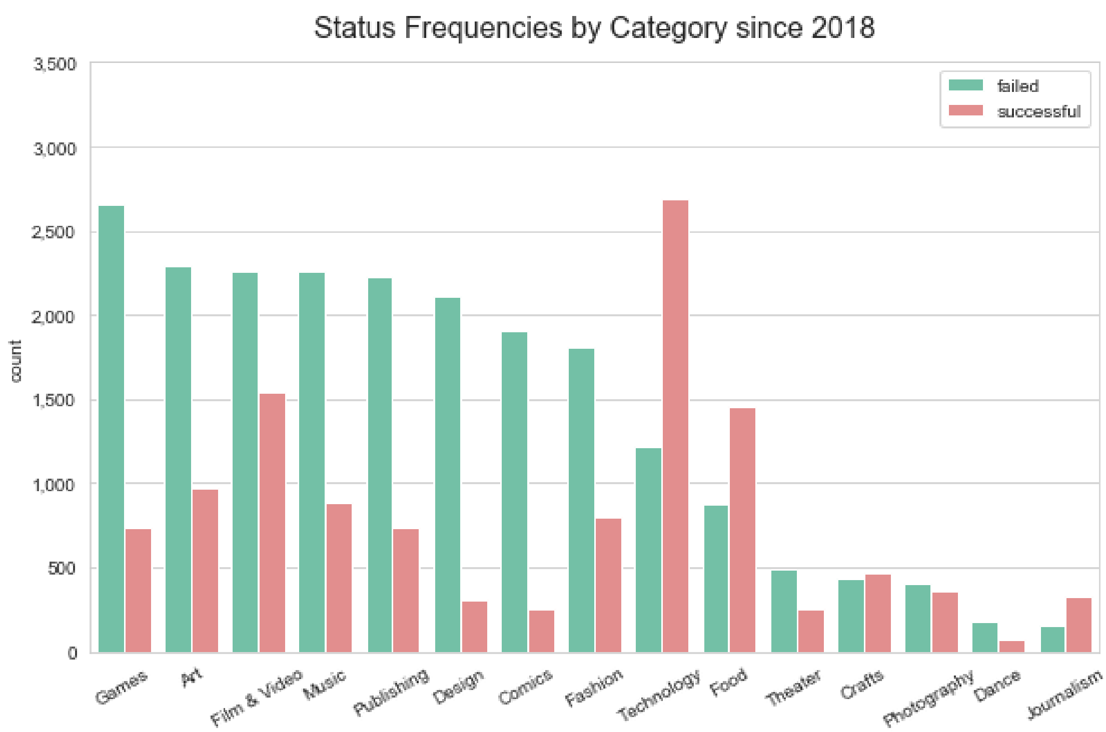


The popularity of projects changed over time. So have the chances for success. Music, Film & Video, Publishing, Art and Dance became less likely to succeed. On the other hand, success rates of Games, Fashion, Comics, Food and Design have been increasing since 2018. Interestingly, the most obvious changes occurred by the beginning of 2018.

As we don't want to distort our success predictors with old-fashioned data, we are going to focus on the most recent years from 2018 and 2019.

```
In [105]: #settings
          plt.figure(figsize=[10,6])

          # filter projects younger than 2017
          ks_compl_18 = ks_compl[ks_compl.deadline.dt.year > 2017]

          # order by success
          order = ks_compl_18[ks_compl_18.status == 'successful'].category.value_counts().inde

          # plot clustered bar chart - qualitative variables counts
```

```
ax = sns.countplot(data = ks_compl_18, x = 'category', hue = 'status',
                   color =  sns.set_palette([cust_green, cust_red]),
                   order=order)

# reset legend to avoid overlap
ax.legend(loc = 'upper right', ncol = 3, framealpha = 1, title = 'status')

# ticks and labels
plt.title("Status Frequencies by Category since 2018", fontsize=16, pad=14);
plt.legend(("failed", "successful"))
format_yticks(3500, 500)
plt.xticks(rotation=30)
plt.xlabel("")
plt.show()
```

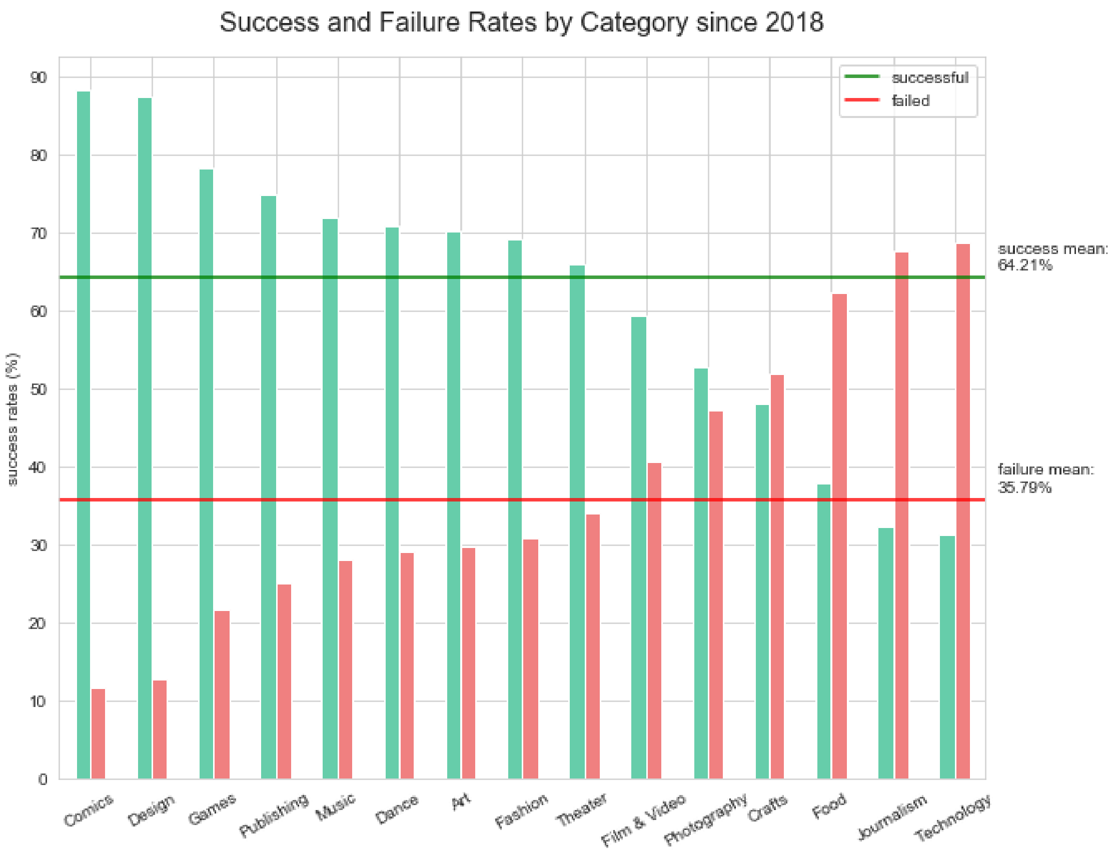


In absolute counts Games, Design and Art stand out to be extraordinary successful categories. Compared to other categories, technology projects have the highest occurrences in unsuccessful project counts. Photography, Dance and Journalism generally performed poorly.

As we visualized absolute values above, we may misinterpret the actual success rates. In the plot below, we calculate relative frequencies of each category.

```
In [106]: # ordering
          pop_cats = ks_compl_18.category.value_counts().index
          cat_counts = ks_compl_18.category.value_counts()
```

```
# calculate success and failure rates
def calc_rate(category, status):
    cat_df = ks_compl_18[ks_compl_18.category == category]
    return (len(cat_df[cat_df.status == status]) / len(cat_df)) * 100

cat_success = [calc_rate(cat,"successful") for cat in pop_cats]
cat_failed = [calc_rate(cat,"failed") for cat in pop_cats]

# create a new dataframe based success and failure rates
df = pd.DataFrame({'success': cat_success, 'failed': cat_failed}, index=pop_cats)

# order by success rates
df.sort_values(by=['success'], ascending=False, inplace=True)

# plot
df.plot.bar(rot=30, figsize=(10,8), color = sns.set_palette([cust_green, cust_red]))

# plot means
p_18_success = len(ks_compl_18[ks_compl_18.status == 'successful']) / len(ks_compl_18
p_18_failed = 100 - p_18_success
plt.axhline(p_18_success, color='g')
plt.axhline(p_18_failed, color='r')

# annotate
plt.title("Success and Failure Rates by Category since 2018", fontsize=16, pad=15);
plt.text(14.7, p_18_success+1, "success mean:\n" + str(round(p_18_success, 2)) + "%"
plt.text(14.7, p_18_failed+1, "failure mean:\n" + str(round(p_18_failed, 2)) + "%")
plt.yticks(np.arange(0, 100, 10))
plt.ylabel("success rates (%)")
plt.xlabel("")
plt.legend(("successful", "failed"))
plt.show()
```



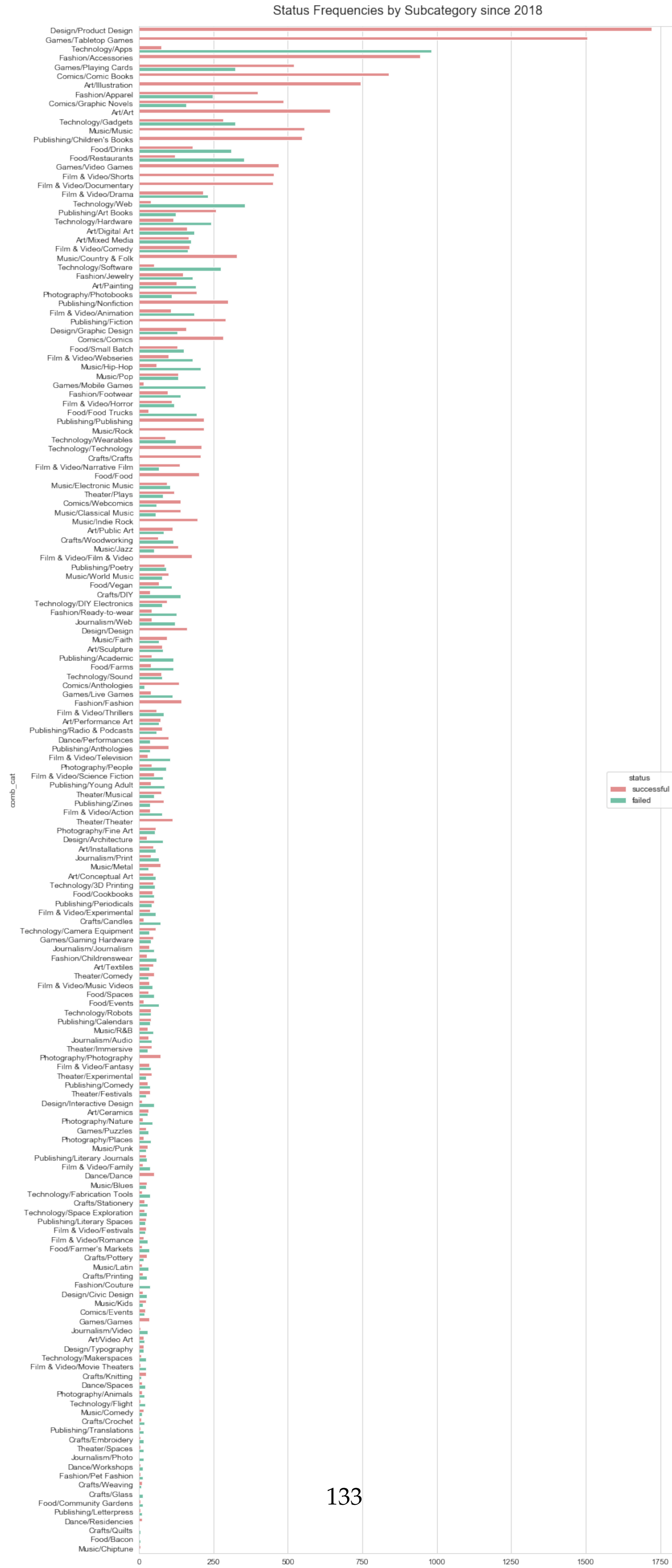
The above success and failure rates suggest a strong relationship between the project type and the likelihood to succeed. Since 2018 Design, Comics and Games have been performing extraordinarily, realizing success rates of plus 80%.

However, Crafts, Food, Journalism and Technology were rather likely to fail. A creator's chance of success was under 50%. Due to the popularity, this result is especially tragic for tech-related campaigns. 69% of all tech projects failed since 2018.

Combined categories

Plot absolute frequencies of combined category to understand the relevance of subcategories in the recent months.

```
In [107]: # settings
          plt.figure(figsize=[12,35])

          # plot clustered bar chart - qualitative variables counts
          ax = sns.countplot(data = ks_compl_18, y = 'comb_cat',  hue='status',
                             color = sns.set_palette([cust_red, cust_green]),
                             order=ks_compl_18.comb_cat.value_counts().index)

          # ticks and labels
          plt.title("Status Frequencies by Subcategory since 2018", fontsize=16, pad=14);
          ax.legend(loc=5, title = 'status')
          plt.show()
```


Status Frequencies by Subcategory since 2018
comb_cat
count
status
successful
failed
0
250
500
750
1000
1250
1500
1750

Plot success rates of subcategories. Start by creating a dataframe with relative success rates by subcategory.

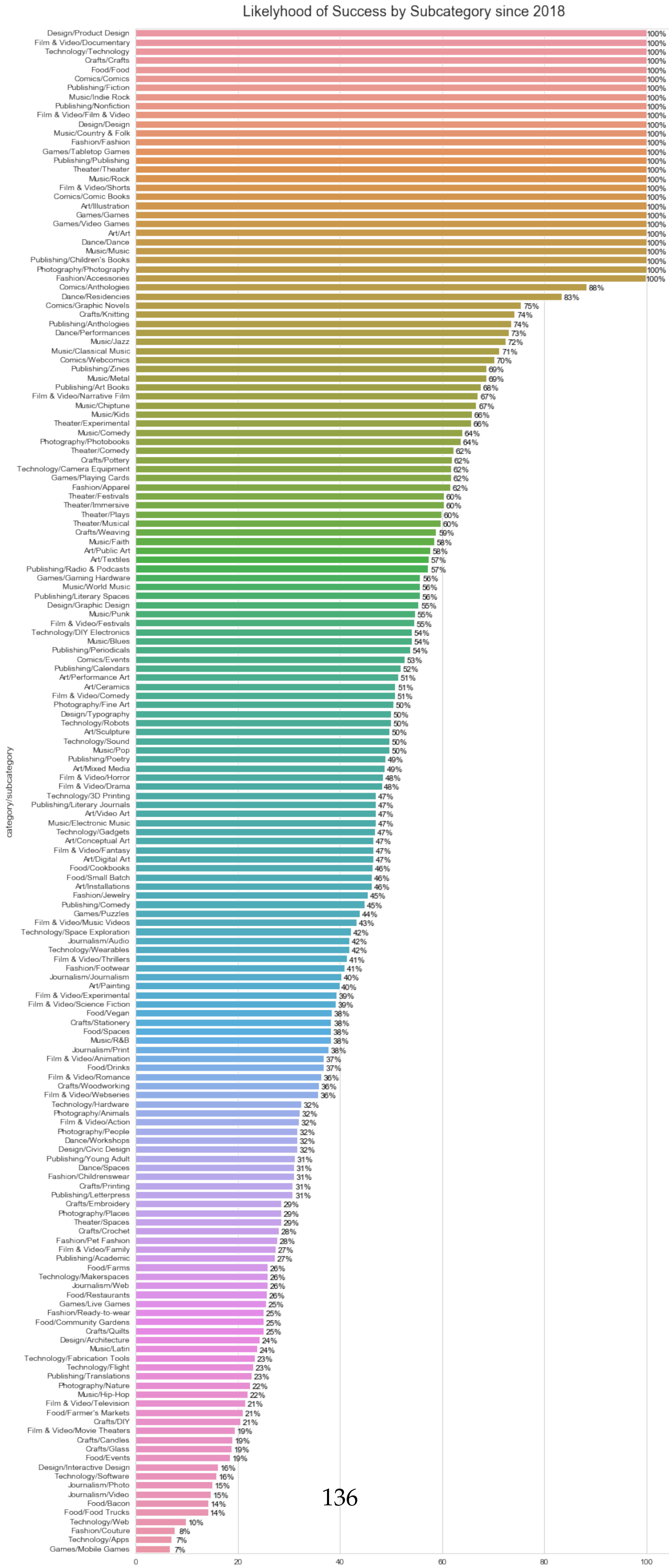
In [108]:
```
# generate data frame
comb_cats = ks_compl_18.comb_cat.value_counts().index
cat_counts = ks_compl_18.comb_cat.value_counts()

# calculate success and failure rates
def calc_rate(category, status):
    cat_df = ks_compl_18[ks_compl_18.comb_cat == category]
    if len(cat_df):
        return (len(cat_df[cat_df.status == status]) / len(cat_df)) * 100
    return 0

comb_cat_success = [calc_rate(cat,"successful") for cat in comb_cats]
comb_cat_failed = [calc_rate(cat,"failed") for cat in comb_cats]

# create a new dataframe based success and failure rates
df_comb_cat_r = pd.DataFrame({'comb_cat': comb_cats, 'success': comb_cat_success, 'fa
# order by success rates
df_comb_cat_r.sort_values(by='success', ascending=False, inplace=True)
df_comb_cat_r.reset_index(inplace=True, drop=True)
df_comb_cat_r.head()
```

Out[108]:

	comb_cat	success	failed
0	Design/Product Design	100.0	0.0
1	Film & Video/Documentary	100.0	0.0
2	Technology/Technology	100.0	0.0
3	Crafts/Crafts	100.0	0.0
4	Food/Food	100.0	0.0

In [109]:
```
# create horizontal bar chart of probability to be supported leading to success
plt.figure(figsize=[12,35])

# utility for annotations
def annotate_success(df, outcome, x_offset=0, y_offset=0):
    locs, labels = plt.yticks()
    for loc, label in zip(locs, labels):
        label = label.get_text()
        cat_p = df[df['comb_cat'] == label][outcome].values[0]
        cat_p_label = str(int(round(cat_p))) + "%"
        plt.text(cat_p+x_offset, loc+y_offset, cat_p_label, ha='center', color="blac

# plot
ax = sns.barplot(data=df_comb_cat_r, x='success', y='comb_cat', order=df_comb_cat_r.
```

```
# annotate rel. success
annotate_success(df_comb_cat_r, 'success', 2, 0.4)

# labels and titles
plt.title("Likelyhood of Success by Subcategory since 2018", fontsize=18, pad=15);
plt.xlabel("success rate by subcategory(%)", fontsize=12)
plt.ylabel("category/subcategory", fontsize=12)
plt.show()
```



Likelyhood of Success by Subcategory since 2018
Design/Product Design 100%
Film & Video/Documentary 100%
Technology/Technology 100%
Crafts/Crafts 100%
Food/Food 100%
Comics/Comics 100%
Publishing/Fiction 100%
Music/Indie Rock 100%
Publishing/Nonfiction 100%
Film & Video/Film & Video 100%
Design/Design 100%
Music/Country & Folk 100%
Fashion/Fashion 100%
Games/Tabletop Games 100%
Publishing/Publishing 100%
Theater/Theater 100%
Music/Rock 100%
Film & Video/Shorts 100%
Comics/Comic Books 100%
Art/Illustration 100%
Games/Games 100%
Games/Video Games 100%
Art/Art 100%
Dance/Dance 100%
Music/Music 100%
Publishing/Children's Books 100%
Photography/Photography 100%
Fashion/Accessories 100%
Comics/Anthologies 88%
Dance/Residencies 83%
Comics/Graphic Novels 75%
Crafts/Knitting 74%
Publishing/Anthologies 74%
Dance/Performances 73%
Music/Jazz 72%
Music/Classical Music 71%
Comics/Webcomics 70%
Publishing/Zines 69%
Music/Metal 69%
Publishing/Art Books 68%
Film & Video/Narrative Film 67%
Music/Chiptune 67%
Music/Kids 66%
Theater/Experimental 66%
Music/Comedy 64%
Photography/Photobooks 64%
Theater/Comedy 62%
Crafts/Pottery 62%
Technology/Camera Equipment 62%
Games/Playing Cards 62%
Fashion/Apparel 62%
Theater/Festivals 60%
Theater/Immersive 60%
Theater/Plays 60%
Theater/Musical 60%
Crafts/Weaving 59%
Music/Faith 58%
Art/Public Art 58%
Art/Textiles 57%
Publishing/Radio & Podcasts 57%
Games/Gaming Hardware 56%
Music/World Music 56%
Publishing/Literary Spaces 56%
Design/Graphic Design 55%
Music/Punk 55%
Film & Video/Festivals 55%
Technology/DIY Electronics 54%
Music/Blues 54%
Publishing/Periodicals 54%
Comics/Events 53%
Publishing/Calendars 52%
Art/Performance Art 51%
Art/Ceramics 51%
Film & Video/Comedy 51%
Photography/Fine Art 50%
Design/Typography 50%
Technology/Robots 50%
Art/Sculpture 50%
Technology/Sound 50%
Music/Pop 50%
Publishing/Poetry 49%
Art/Mixed Media 49%
Film & Video/Horror 48%
Film & Video/Drama 48%
Technology/3D Printing 47%
Publishing/Literary Journals 47%
Art/Video Art 47%
Music/Electronic Music 47%
Technology/Gadgets 47%
Art/Conceptual Art 47%
Film & Video/Fantasy 47%
Art/Digital Art 47%
Food/Cookbooks 46%
Food/Small Batch 46%
Art/Installations 46%
Fashion/Jewelry 45%
Publishing/Comedy 45%
Games/Puzzles 44%
Film & Video/Music Videos 43%
Technology/Space Exploration 42%
Journalism/Audio 42%
Technology/Wearables 42%
Film & Video/Thrillers 41%
Fashion/Footwear 41%
Journalism/Journalism 40%
Art/Painting 40%
Film & Video/Experimental 39%
Film & Video/Science Fiction 39%
Food/Vegan 38%
Crafts/Stationery 38%
Food/Spaces 38%
Music/R&B 38%
Journalism/Print 38%
Film & Video/Animation 37%
Food/Drinks 37%
Film & Video/Romance 36%
Crafts/Woodworking 36%
Film & Video/Webseries 36%
Technology/Hardware 32%
Photography/Animals 32%
Film & Video/Action 32%
Photography/People 32%
Dance/Workshops 32%
Design/Civic Design 32%
Publishing/Young Adult 31%
Dance/Spaces 31%
Fashion/Childrenswear 31%
Crafts/Printing 31%
Publishing/Letterpress 31%
Crafts/Embroidery 29%
Photography/Places 29%
Theater/Spaces 29%
Crafts/Crochet 28%
Fashion/Pet Fashion 28%
Film & Video/Family 27%
Publishing/Academic 27%
Food/Farms 26%
Technology/Makerspaces 26%
Journalism/Web 26%
Food/Restaurants 26%
Games/Live Games 25%
Fashion/Ready-to-wear 25%
Food/Community Gardens 25%
Crafts/Quilts 25%
Design/Architecture 24%
Music/Latin 24%
Technology/Fabrication Tools 23%
Technology/Flight 23%
Publishing/Translations 23%
Photography/Nature 22%
Music/Hip-Hop 22%
Film & Video/Television 21%
Food/Farmer's Markets 21%
Crafts/DIY 21%
Film & Video/Movie Theaters 19%
Crafts/Candles 19%
Crafts/Glass 19%
Food/Events 19%
Design/Interactive Design 16%
Technology/Software 16%
Journalism/Photo 15%
Journalism/Video 15%
Food/Bacon 14%
Food/Food Trucks 14%
Technology/Web 10%
Fashion/Couture 8%
Technology/Apps 7%
Games/Mobile Games 7%
category/subcategory
0
20
40
60
80
100
success rate by subcategory(%)

There were quite some subcategories with an incredible 100% chance for success. Among others, there were Tabletop Games, Dance, Country & Folk Music, Comics and Product Design projects.

Notice the accumulation of high-ranking projects without subcategories, e.g. Dance/Dance, Photography/Photography or Comics/Comics. We found that 12 out of 15 parent categories without any subcategory had a 100% chance to succeed. This behavior seems a bit odd to me. I wonder if this is related to search algorithms used by the platform or search behavior by users. This may be a topic to elaborate on, but I'm missing the relevant data.

Overall, the plot suggests that the type of project is correlated with success. The subcategory should be chosen carefully by checking success rates against subcategories before running a campaign. For example, Tabletop Games and Video Games had a 100% chance to succeed, but Mobile Games failed at a rate of 93%. And, while Hip-Hop Music only had a 22% success rate, Rock Music campaigns always ended successfully since 2018.

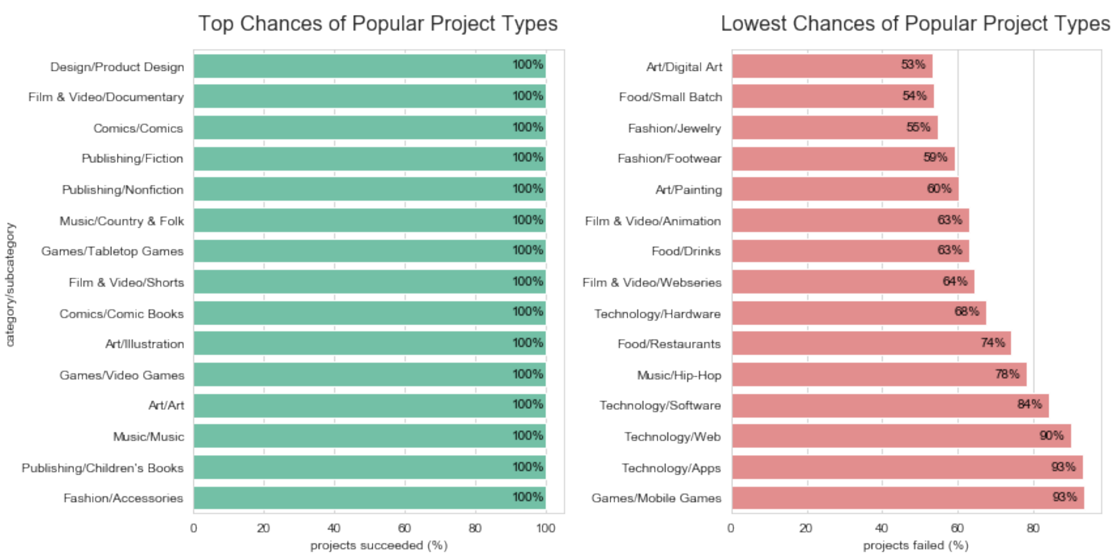
As I depicted relative numbers here, we may overestimate or underestimate the significance of the probability of success. Also, because of the high number of subcategories, the above plot is difficult to read and interpret. Thus, I'm going to plot a best-off version which only considers the most popular subcategories.

In [110]:
```
# I'm considering the upper quarter of project counts the most popular categories.
# According to the 75 quantile, popular subcategories have more 228 projects recorde
cat_counts.describe()
```

Out[110]:
```
count   168.0
mean    197.1904761904762
std     244.84121586570802
min     6.0
25%     50.75
50%     124.5
75%     226.75
max     1,721.0
Name: comb_cat, dtype: float64
```

In [111]:
```
# plot highlights
plt.figure(figsize=[12,6])

# filter top 25% of the most popular comb categories and sort by relevance
pop_cats = cat_counts.where(cat_counts > cat_counts.quantile(q=0.75)).dropna().index

# filter subcategorical counts by popular subcategories
df_comb_cat_pop = df_comb_cat_r[df_comb_cat_r.comb_cat.isin(pop_cats)]
df_comb_cat_pop.reset_index(drop=True, inplace=True)

# left plot: top 15 of poular combined categories
plt.subplot(1, 2, 1)
ax = sns.barplot(data=df_comb_cat_pop[:15], x='success', y='comb_cat', color=cust_gr
```

```
# ticks and labels
plt.title("Top Chances of Popular Project Types", fontsize=16, pad=15);
plt.xlabel("projects succeeded (%)")
plt.ylabel("category/subcategory")
annotate_success(df_comb_cat_pop, 'success', -5, 0.1)

# right plot: 15 lowest chances of popular combined categories
plt.subplot(1, 2, 2)
ax = sns.barplot(data=df_comb_cat_pop[-15:], x='failed', y='comb_cat', color=cust_re

# ticks and labels
plt.title("Lowest Chances of Popular Project Types", fontsize=16, pad=15);
plt.xlabel("projects failed (%)")
plt.ylabel("")
annotate_success(df_comb_cat_pop, 'failed', -5, 0.1)

plt.tight_layout()
plt.show()
```



7.3.2 Summary Categories

The type of project matters! Creative projects and categories seem to work best on Kickstarter. The top chances of popular project categories show a tendency to not have subcategories selected. Generally, Publishing, Comics, Film & Video, Art and Music performed well if they were not communicated in niche categories.

Written work and comics dominated the top categories. Fiction & Nonfiction Publishing Projects, Children's and Comic Books all ended in success.

We found Product Design, Documentaries and Comics at the top of the most successful projects. While Video Games were attributed with top success chances, Mobile Games have been the subcategory most likely to fail (93%). Tech or digital projects generally performed low. Gadgets, Hard- and Software, Web Projects and Apps all had very low chances of success, although being among the most popular categories.

In addition to technology ventures, we found 3 food subcategories among the projects with the lowest chances: Small Batch, Drinks and Restaurants.

Product Design and Illustrations worked in any case. In contrast, paintings had a 60% chance to fail. Generally, campaigns labeled as *Design* worked better than labeled as *Art*.

The taste in music seems to matter. While crowdfunding worked well for Country & Folk Music, Hip-Hop campaigns failed at a rate of 78%. Film & Video projects appear on both sites of success chances. Short Films and Documentaries were a guarantee for success, while Animations and Web Series were more likely to fail.

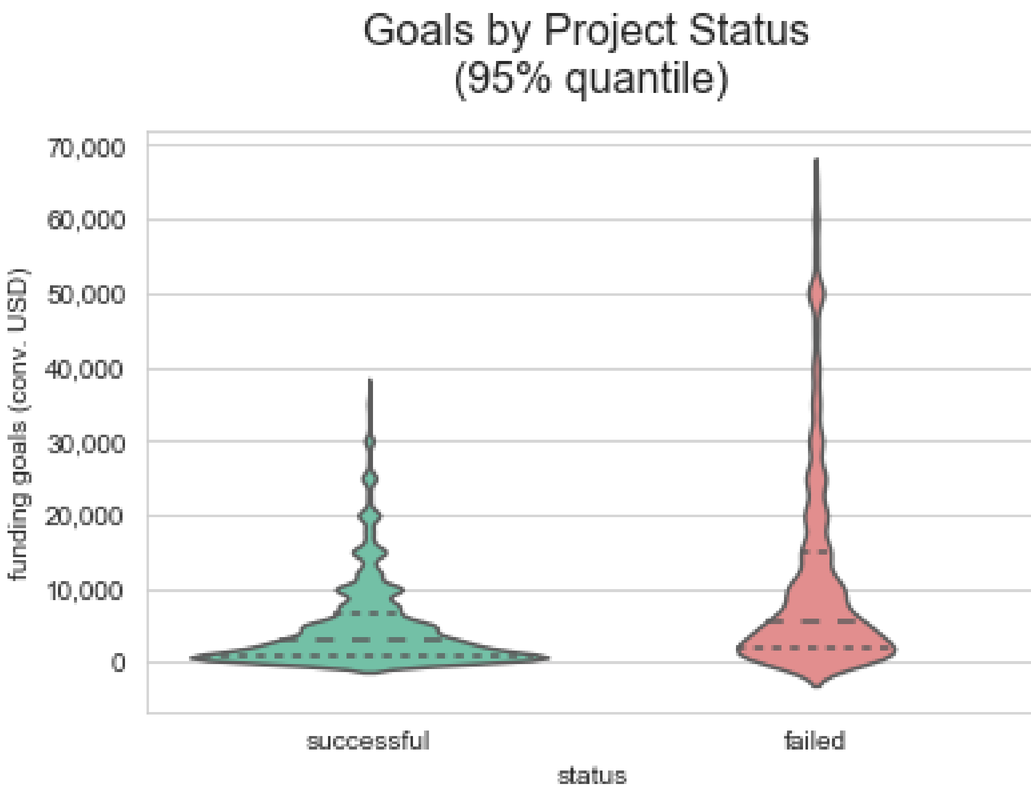
Overall, I see indications that the type of project is correlated with with the chances for success. The category and subcategory should be chosen carefully by observing popularity, success rates and current trends of subcategories before running a campaign.

7.3.3 Funding

Closely related to a campaign's funding are three variables: the goal set by a project creator, the final amount pledged and the number of supporters. I'll start by investigating how a goal may influence success, then I'll look into pledges and how much each backer contributed.

Does a campaign's funding goal affect the chances for success?

```
In [112]: # violin plots of 95 quantile data frame
          ax = sns.violinplot(data = ks_compl_95, x = 'status', y = 'goal_hist_usd',
                              order=['successful', 'failed'],
                              color=sns.set_palette([cust_green, cust_red]),
                              inner='quartile')
          #annotate
          plt.title("Goals by Project Status \n(95% quantile)", fontsize=16, pad=15 )
          ylabels = ['{:,.0f}'.format(ytick) for ytick in ax.get_yticks()]
          ax.set_yticklabels(ylabels)
          plt.ylabel('funding goals (conv. USD)')

          plt.show()
```



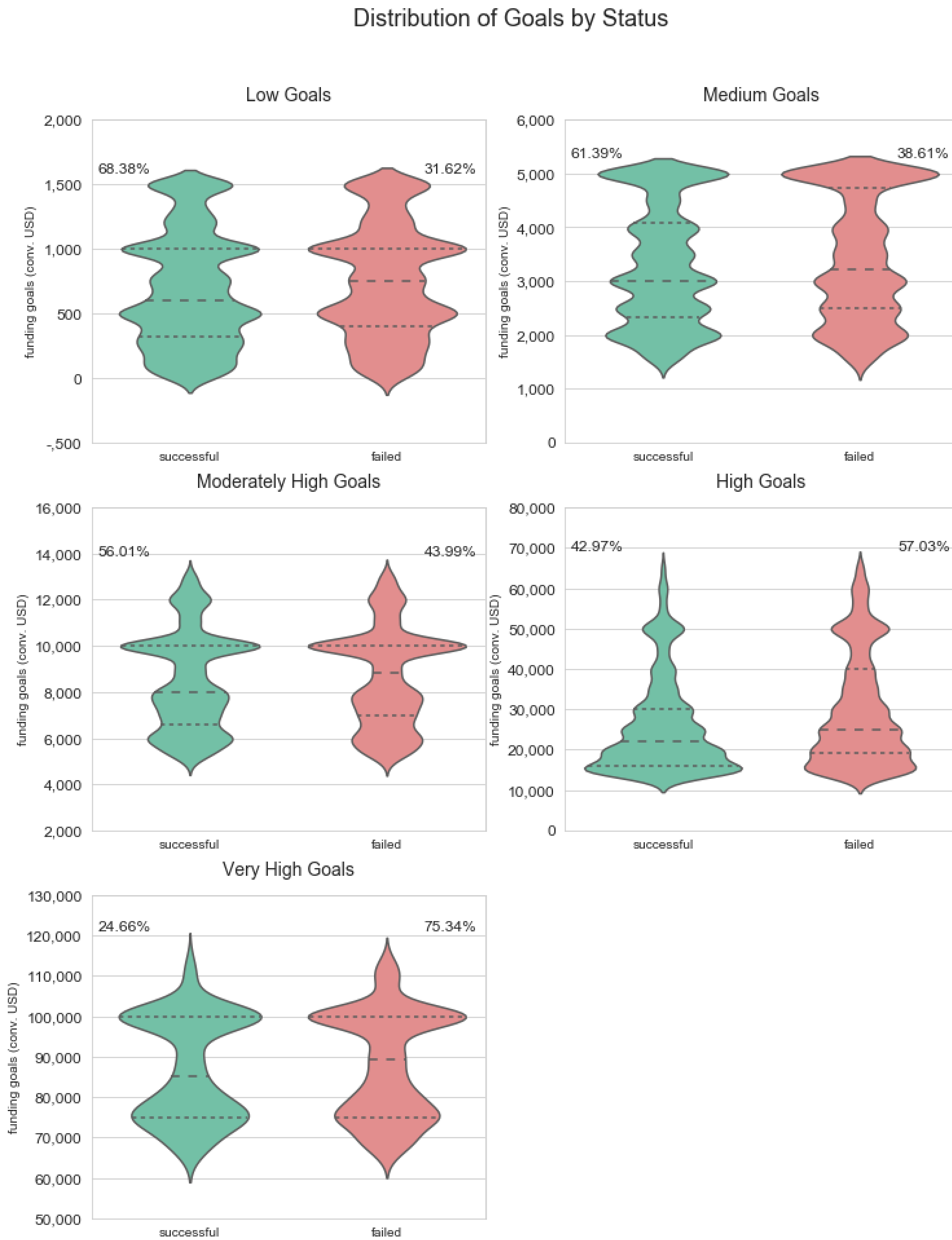
The above violin plots of the 95% quantile data suggests that successful campaigns tend to have lower funding goals compared to failed projects. Notice the comparatively wide section at the bottom of successful campaigns. It indicates that the lower the funding goal the higher is the probability of success. The median of failed campaigns is higher than of successful campaigns, the tail and the upper quartile range are much higher. While successful funding goals remained below USD 40k, failed goals range up to USD 70k.

One more interesting observation: the multi-modality of successful goals seems to be more pronounced compared to failed goals. We've already discovered that goals are more frequently set at full numbers like 5, 10, 15 or 20k. However, the plot above suggests that supporters may also have an increased preference to invest in fully numbered goals.

By using the 95% quantile data above, we removed any extreme funding goals. Nevertheless, our goal data is still highly skewed. Let's take a more detailed look on funding goals by plotting goal level categories.

```
In [113]: # settings
          plt.figure(figsize=[12,10])

          # completed projects filtered by goal level
          ks_goal_leveled = [ks_compl_goal_low, ks_compl_goal_medium,
                             ks_compl_goal_moderate, ks_compl_goal_high,
                             ks_compl_goal_very_high, ks_compl_goal_extreme]

          texts = ["Low", "Medium", "Moderately High", "High", "Very High", "Extreme"]
```

```
# faceted goal violin plots
for i, df in enumerate(ks_goal_leveled[:-1]):
    plt.subplot(3, 2, i+1)
    ax = sns.violinplot(data = df, x = 'status', y = 'goal_hist_usd',
                        order=['successful', 'failed'],
                        color =sns.set_palette([cust_green, cust_red]),
                        inner='quartile')

    # calculate success rates
    p_failed_goal = len(df[df.status == "failed"])* 100 / len(df)
    p_success_goal = 100 - p_failed_goal

    #annotate
    ax.annotate(str(round(p_failed_goal,2)) + "%", xy=(1.19, df.goal_hist_usd.max()*
    ax.annotate(str(round(p_success_goal,2)) + "%", xy=(-0.47, df.goal_hist_usd.max(

    plt.title(texts[i]+" Goals", fontsize=14, pad=15)
    locs, labels = plt.yticks()
    labels = [str(format_num(loc)) for loc in locs]
    plt.yticks(locs, labels, fontsize=12)
    plt.ylabel("funding goals (conv. USD)")

    plt.xlabel("")
    plt.subplots_adjust(bottom=-0.3)

plt.suptitle("Distribution of Goals by Status", fontsize=18, y=1)
plt.show()
```



By faceting funding goals into 5 levels, we eliminated the long tail of the previous plot. The multi-modal character of goals has become more prominent. At the same time the differences between successful and failed goals have become less apparent. If we look closely, independent from a goal category, the violin plots of successful goals tend to be wider on the lower end, while failed goals are generally wider on the upper end.

Also, the median of successful campaigns is always lower than the median of failed projects. Thus, it is reasonable to stick to the lowest goal possible to maximize the chance for success.

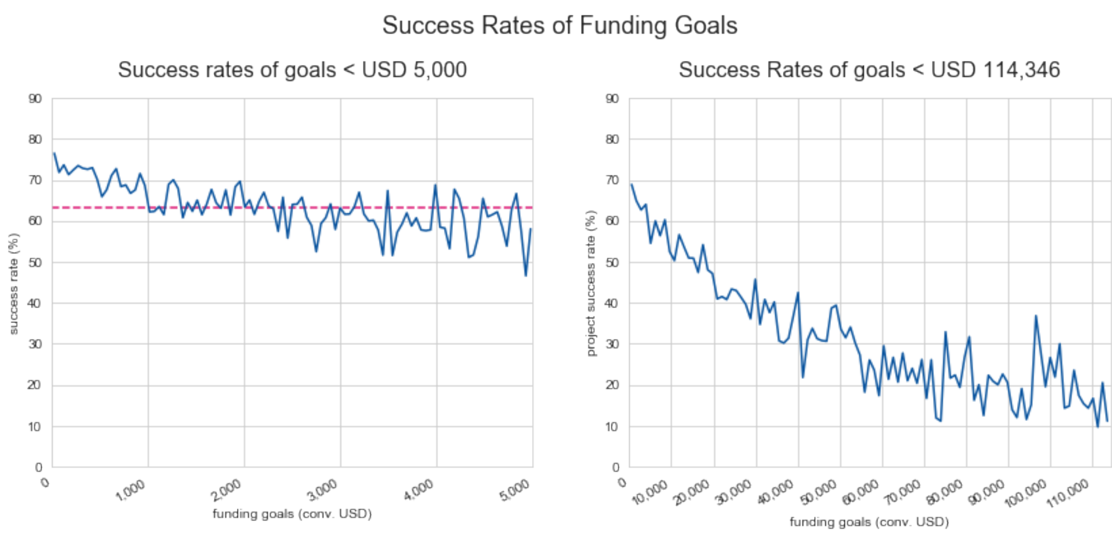
I annotated the proportion of successful and failed campaigns for each goal level. With 68%, the chances for success were highest for low goals below USD {{goal_25}}. Success rates decrease the higher the goal category. Very high goals between USD {{format_num(goal_95)}} and USD {{format_num(goal_975)}} only succeed at a rate of 24.66%. I would like to illustrate the decreasing trend clearer by clustering goals and plot respective success rates.

```
In [114]: # settings
          plt.figure(figsize=[15,8])

          # utility to bin data
          def bin_data(df):
              # create bin edges for goals
              bin_size = (df['goal_hist_usd'].max()-df['goal_hist_usd'].min()) / 101
              bins = np.arange(df['goal_hist_usd'].min(),df['goal_hist_usd'].max()+bin_size, bi
              # create bin centers to plot them in their accurate positions
              # leave out the the last value, since it doesn't correspond to an actual bin cen
              bins_c = bins[:-1] + bin_size/2
              # Use cut function to bin values into discrete intervals to segment and sort dat
              # for all goals
              goals_binned = pd.cut(df['goal_hist_usd'], bins, include_lowest = True)
              # successful goals
              goals_binned_success = pd.cut(df[df.status == 'successful']['goal_hist_usd'], bin
              return {'total': goals_binned, 'success': goals_binned_success, 'bins': bins_c}

          # utility to plot success rates
          def plot_success_r(goals_binned, mean=True):
              # calculate success rate for every bin
              success_r = (goals_binned['success'].value_counts(sort=False) / goals_binned['tot
              # plot success rates as adapted line plot to emphasize relative change
              plt.errorbar(x = goals_binned['bins'], y = success_r, color=goal_color)
              # plot success mean
              if mean:
                  plt.axhline(success_r.mean(), color='#dd1c77', linestyle='--')
          #        plt.annotate("mean:\n" + str(int(round(success_r.mean()))) + "%", xy=(goal

          # faceted goals and success rates
          for i, df in enumerate(ks_goal_leveled[:-1]):
              plt.subplot(2, 3, i+1)
              goals_binned = bin_data(df)
              plot_success_r(goals_binned)

              # ticks and labels
              plt.title(texts[i]+" Goals", fontsize=14, pad=15)

              locs, labels = plt.xticks()
              labels = [str(format_num(loc)) for loc in locs]
```

```
        plt.xticks(locs, labels, fontsize=12, rotation=30, ha='right')
        plt.xlabel("funding goals (conv. USD)")

        plt.yticks(np.arange(0, 101, 20))
        plt.ylabel("project success rate (%)")
        plt.tight_layout()

    plt.suptitle("Success Rates and Funding Goals ", fontsize=18, y=1.05)
    plt.show()
```


```
In [115]: # settings
          plt.figure(figsize=[14,5])

          plt.subplot(1,2,1)
          # plot low to moderately high goals
          goals_binned = bin_data(ks_compl[ks_compl['goal_hist_usd'] < goal_50])
          plot_success_r(goals_binned)

          # ticks and labels
          plt.title("Success rates of goals < USD " + format_num(goal_50), fontsize=16, pad=15

          locs = np.arange(0, goal_50+1, 1000)
          labels = [str(format_num(loc)) for loc in locs]
          plt.xticks(locs, labels, rotation=30, ha='right')
          plt.xlabel("funding goals (conv. USD)")
          plt.xlim(0, goal_50)
```

```
plt.yticks(np.arange(0, 91, 10))
plt.ylabel("success rate (%)")

plt.subplot(1,2,2)
# plot low to moderately high goals
goals_binned = bin_data(ks_compl[ks_compl['goal_hist_usd'] < goal_975])
plot_success_r(goals_binned, False)

# ticks and labels
plt.title("Success Rates of goals < USD " + format_num(goal_975), fontsize=16, pad=15

locs = np.arange(0, goal_975+10000, 10000)
labels = [str(format_num(loc)) for loc in locs]
plt.xticks(locs, labels, rotation=30, ha='right')
plt.xlabel("funding goals (conv. USD)")
plt.xlim(0, goal_975)

plt.yticks(np.arange(0, 91, 10))
plt.ylabel("project success rate (%)")

plt.suptitle("Success Rates of Funding Goals ", fontsize=18, y=1.05)
plt.show()
```



Success rates continuously decrease the higher the funding goal. If creators want to keep a minimum of a 50% chance, it appears advisable to stay below goals of USD 10k.

The chances of success drop from a mean 68% for low goals to 20% for very high goals. The higher the goal the more volatile the plot of success rates becomes. Creators should generally consider the most pessimistic goals possible to win investments.

Due to Kickstarter's all-or-nothing approach to funding, this result doesn't surprise. More interesting for creators is to set a realistic goal in order to gain the best chance for success and collect the maximum investment possible to start their venture.

The success rates of medium goals from USD {{format_num(goal_25)}} to USD {{format_num(goal_50)}} make the most stable impression. The mean of a success chance is at a rate of 61% and a reasonable high investment may be collected.

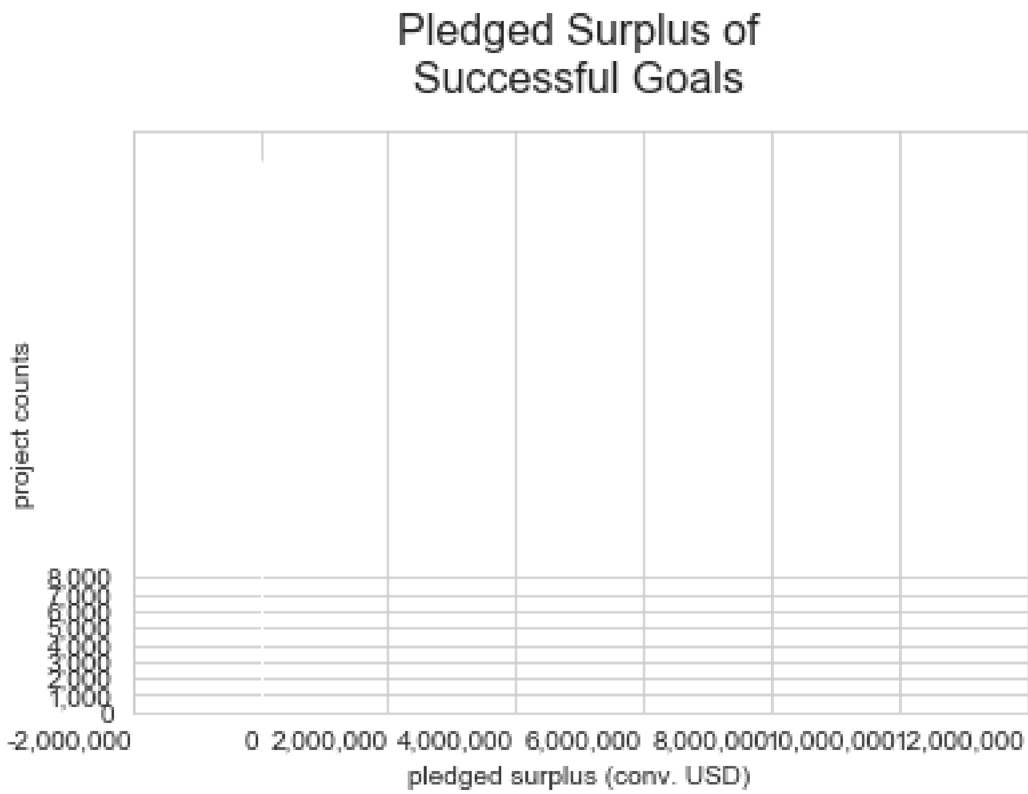
Creators who seek funding in the range of moderately high goals may be aware of decreased success rates just ahead of USD 10k. This is when the mean success rates drop under 50/50 chances for success.

High goals up to USD {format_num(goal_95)}} and to a greater degree very high goals are rather risky ventures. Success is rather unlikely, decreasing to means of 35%, respectively 20%. However, there are individual peaks in success chances at goals around USD 40k and USD 50k.

Does the scope of a funding goal affect the final collected investment?

If funding goals should be set rather low to win a crowdfunding campaign, creators may fear that a campaign doesn't result in the necessary funding needed to launch their business. Ultimately, the final amount pledged of a project determines the profitability of a campaign. Thus, I'm going to take into account pledges by calculating the surplus raised above each successful funding goal.

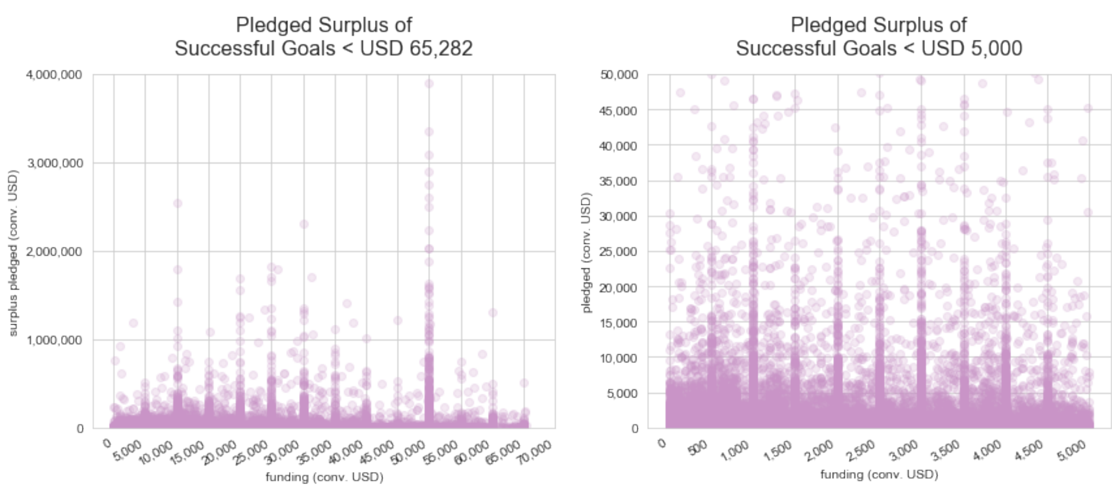
In [116]:
```
# calculate surplus of successful campaigns
ks_compl['surplus'] = ks_compl['pledged_hist_usd'] - ks_compl['goal_hist_usd']
ks_compl_95['surplus'] = ks_compl_95['pledged_hist_usd'] - ks_compl_95['goal_hist_usd
ks_compl_success= ks_compl[ks_compl.status == "successful"]

bin_edges = np.arange(0, ks_compl_success['surplus'].max()+250, 250)
sns.distplot(ks_compl_success['surplus'], bins = bin_edges, kde = False,
             hist_kws = {'alpha' : 1, 'color': pledged_color})
# plt.xlim(0, 8000)

# ticks and labels
plt.title("Pledged Surplus of\nSuccessful Goals", fontsize=16, pad=15)
# format_yticks(40000, 5000)
plt.ylabel("project counts")
format_yticks(8000, 1000)

locs, labels = plt.xticks()
labels = [str(format_num(loc)) for loc in locs]
plt.xticks(locs, labels, ha='right')
plt.xlabel("pledged surplus (conv. USD)")

plt.show()
```



Like pledges, low surpluses are more common than high surpluses and the distribution is strongly skewed. By far, most common are surpluses realized below USD 250. Now, let's depict surpluses to respective goal.

```
In [117]: # a regplot approach

          # settings
          plt.figure(figsize=[14,5])

          # left: regplot approach - 95-quantile goals only
          plt.subplot(1,2,1)
          # for successfull campaigns with goals below 95%-quantile
          ks_goal_95_s = ks_compl_success[ks_compl_success.goal_hist_usd < goal_95]
          sns.regplot(ks_goal_95_s.goal_hist_usd, ks_goal_95_s.surplus,
                      scatter_kws = {'alpha' : 1/5}, fit_reg=False, color=pledged_color);
          plt.xlabel("goals < " + format_num(int(round(goal_95))) +  " (conv. USD)")

          # ticks and labels
          plt.title("Pledged Surplus of\nSuccessful Goals < USD " + format_num(goal_95), fonts

          locs = np.arange(0, goal_95+5000, 5000)
          labels = [str(format_num(loc)) for loc in locs]
          plt.xticks(locs, labels, fontsize=10, rotation=30, ha='right')
```

```
plt.xlabel("funding (conv. USD)")

locs = np.arange(0,  4000000+1000000, 1000000)
labels = [str(format_num(loc)) for loc in locs]
plt.yticks(locs, labels, fontsize=10)
plt.ylabel("surplus pledged (conv. USD)")
plt.ylim(0, 4000000)

# right: regplot approach - 50-quantile goals only
plt.subplot(1,2,2)
ks_goal_50_s = ks_compl_success[ks_compl_success.goal_hist_usd < goal_50]
sns.regplot(ks_goal_50_s.goal_hist_usd, ks_goal_50_s.surplus,
            scatter_kws = {'alpha' : 1/5}, fit_reg=False, color=pledged_color);

# ticks and labels
plt.title("Pledged Surplus of\nSuccessful Goals < USD " + format_num(goal_50), fonts

locs = np.arange(0, goal_50+500, 500)
labels = [str(format_num(loc)) for loc in locs]
plt.xticks(locs, labels, fontsize=10, rotation=30, ha='right')
plt.xlabel("funding (conv. USD)")

format_yticks(50000, 5000)
plt.ylabel("pledged (conv. USD)")
plt.ylim(0, 50000)

plt.show()
```



The most striking feature about the relationship between the surplus pledged and a goal is the density of projects generating an array of surpluses at goals in intervals of 5,000. In goals below USD 5k, the intervals occur in steps of USD 500.

To be precise, goals of USD 5k, 10k, 15k etc., stand out in realizing high surpluses. Goals of USD 50k catch the eye by realizing the highest possible pledges within the scope of the 95 quantile goals.

Ignoring the multi-modality of goals, the realized surplus appears to be relatively evenly distributed across goals. This is true for low and high goals. This indicates that the scope of a goal does not necessarily influence the surplus of the final amount collected and that creators may increase their chances to realize higher investments by choosing goals in aforementioned intervals.

Before we draw any conclusion, it makes sense to relate the surplus to its goal.

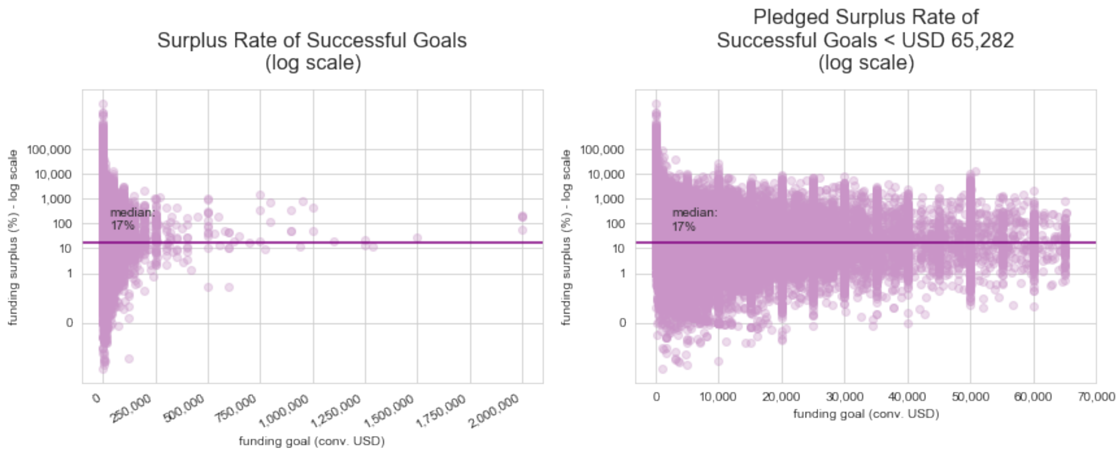
In [118]:
```
# calculate relative differences between goal and pledged of successful campaigns
ks_compl['surplus_r'] = abs(ks_compl['surplus'] / ks_compl['goal_hist_usd']) *100
ks_compl_95['surplus_r'] = abs(ks_compl_95['surplus'] / ks_compl_95['goal_hist_usd']
ks_compl_success = ks_compl[ks_compl.status == 'successful']
ks_compl_success.surplus_r.sort_values().tail(10)
```

Out[118]:
```
12846     809,951.0
10104     958,708.8607594937
82148     960,400.0
165325    999,900.0
88831     1,257,415.0
63817     2,260,200.0
148766    2,303,506.7
83782     2,758,723.0
26136     2,868,718.0
61720     6,876,310.000000001
Name: surplus_r, dtype: float64
```

We found some very high surplus rates. Thus, we are going to apply a log scale transformation on our rates.

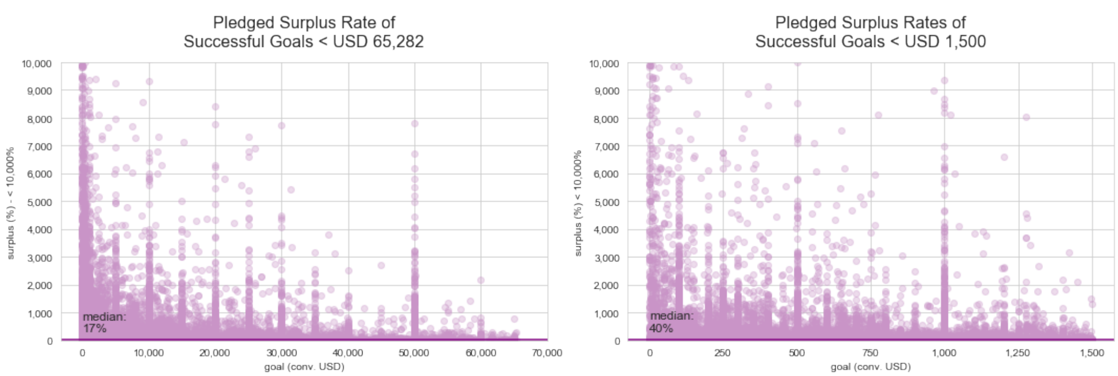
In [119]:
```
# settings
plt.figure(figsize=[14,5])

# left plot: regplot using log scale on y-axis, goals of all successful projects
plt.subplot(2,2,1)
sns.regplot(ks_compl_success.goal_hist_usd, ks_compl_success.surplus_r.apply(log_tran
            scatter_kws = {'alpha' : 1/3}, truncate=True, color=pledged_color,
            fit_reg=False);

# plot and annotate median
surplus_r_median = round(log_trans(ks_compl_success.surplus_r.median()),2)
plt.axhline(surplus_r_median, color='purple')
plt.text(35000, surplus_r_median+0.5,
         "median:\n" + str(int(round(log_trans(surplus_r_median, inverse=True)))) + '

# ticks and labels
plt.title("Surplus Rate of Successful Goals\n(log scale)", fontsize=16, pad=15)

ylocs = [0.01, 1, 10, 100, 1000, 10000, 100000]
```

```
ylabels = [str(format_num(loc)) for loc in ylocs]
plt.yticks(log_trans(ylocs), ylabels)

plt.xlabel("funding goal (conv. USD)")
plt.ylabel("funding surplus (%) - log scale")

xlocs = np.arange(0, ks_compl_success.goal_hist_usd.max()+25000, 250000)
xlabels = [str(format_num(loc)) for loc in xlocs]
plt.xticks(xlocs, xlabels, rotation=30, ha='right')

# right plot: zoom in on 95-quantile goals
plt.subplot(2,2,2)
ks_goal_95_s = ks_compl_success[ks_compl_success.goal_hist_usd < goal_95]
sns.regplot(ks_goal_95_s.goal_hist_usd, ks_goal_95_s.surplus_r.apply(log_trans),
            scatter_kws = {'alpha' : 1/3}, color=pledged_color,
            fit_reg=False);

# plot and annotate median
surplus_r_median = round(log_trans(ks_goal_95_s.surplus_r.median()), 2)
plt.axhline(surplus_r_median, color='purple')
plt.text(2500, surplus_r_median+0.5,
         "median:\n" + format_num(log_trans(surplus_r_median, inverse=True)) + "%")

# ticks and labels
plt.title("Pledged Surplus Rate of\nSuccessful Goals < USD " + format_num(goal_95) +
ylocs = [0.01, 1, 10, 100, 1000, 10000, 100000]
ylabels = [str(format_num(loc)) for loc in ylocs]
plt.yticks(log_trans(ylocs), ylabels)
plt.ylabel("funding surplus (%) - log scale")

format_xticks(70000, 10000)
plt.xlabel("funding goal (conv. USD)")
plt.subplots_adjust(bottom=-0.5)

plt.show()
```



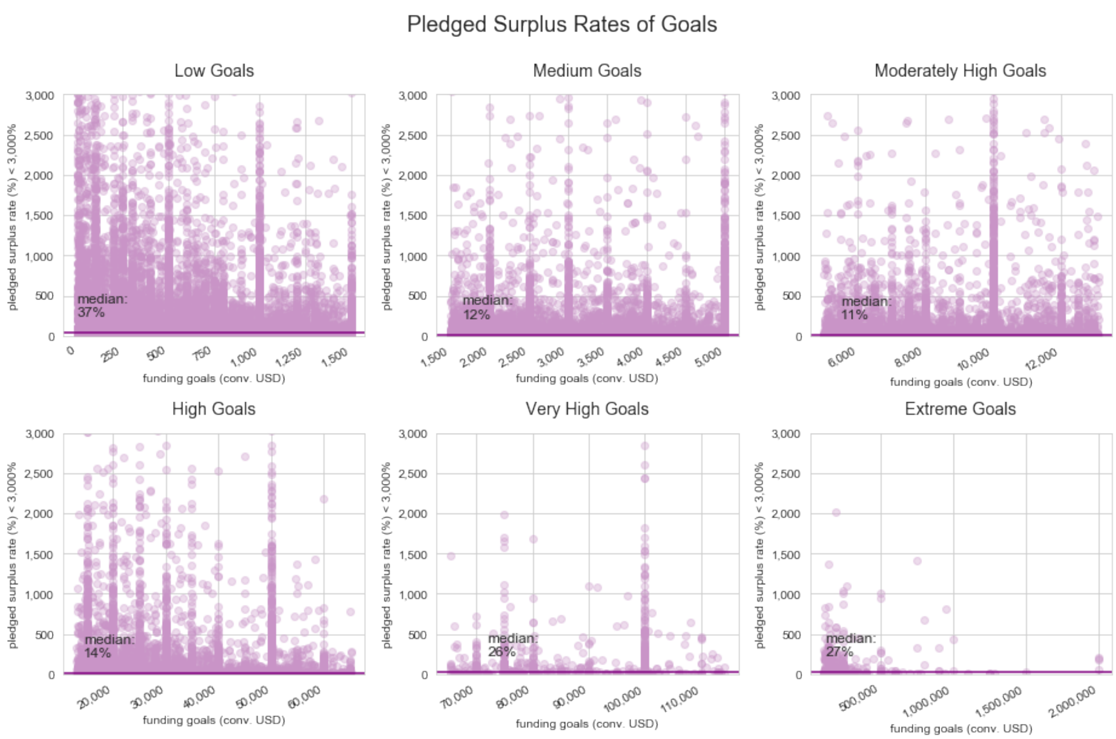

```
In [120]: # settings
          plt.figure(figsize=[15,5])

          # left: plot surplus rates of 75% quantile goals
          plt.subplot(1,2,1)
          ks_goal_95_s = ks_compl_success[ks_compl_success.goal_hist_usd < goal_95]
          sns.regplot(ks_goal_95_s.goal_hist_usd, ks_goal_95_s.surplus_r,
                      scatter_kws = {'alpha' : 1/3}, color=pledged_color,
                      fit_reg=False);
          plt.ylim(0, 10000)

          # annotate median
          surplus_r_median = round(ks_goal_95_s.surplus_r.median(),2)
          plt.axhline(surplus_r_median, color='purple')
          plt.text(ks_goal_95_s.goal_hist_usd.min()*1.2, surplus_r_median+300,
                   "median:\n" + str(int(surplus_r_median)) + "%", fontsize=12)

          # ticks and labels
          plt.title("Pledged Surplus Rate of\nSuccessful Goals < USD " + format_num(goal_95), 

          ylocs = np.arange(0, 10000+1000, 1000)
          ylabels = [str(format_num(loc)) for loc in ylocs]
          plt.yticks(ylocs, ylabels)
          plt.ylabel("surplus (%) - < 10,000%")

          xlocs = np.arange(0, goal_95+10000, 10000)
          xlabels = [str(format_num(loc)) for loc in xlocs]
          plt.xticks(xlocs, xlabels)
          plt.xlabel("goal (conv. USD)")
          plt.subplots_adjust(bottom=-0.5)
```

```
# right: plot surplus rate of 50% quantile goals
plt.subplot(1,2,2)
ks_goal_25_s = ks_compl_success[ks_compl_success.goal_hist_usd < goal_25]
sns.regplot(ks_goal_25_s.goal_hist_usd, ks_goal_25_s.surplus_r,
            scatter_kws = {'alpha' : 1/3}, color=pledged_color,
            fit_reg=False);

# annotate median
surplus_r_median = round(ks_goal_25_s.surplus_r.median(),2)
plt.axhline(surplus_r_median, color='purple')
plt.text(ks_goal_25_s.goal_hist_usd.min()*1.2, surplus_r_median+300,
         "median:\n" + str(int(surplus_r_median)) + "%", fontsize=12)

# ticks and labels
plt.title("Pledged Surplus Rates of\nSuccessful Goals < USD " + format_num(goal_25),
format_yticks(100000, 1000)
plt.ylabel("surplus (%) < 10,000%")
plt.ylim(0, 10000)
format_xticks(goal_25, 250)
plt.xlabel("goal (conv. USD)")
plt.subplots_adjust(bottom=-0.5)

plt.tight_layout()
plt.show()
```




```
In [121]: # settings
plt.figure(figsize=[13,8])

# facet goals
for i, goal_level in enumerate([goal_level.lower() for goal_level in texts]):
    plt.subplot(2, 3, i+1)
    df = ks_compl[ks_compl['goal_level'] == goal_level]
    df = df[df.status == 'successful']
    sns.regplot(df.goal_hist_usd, df.surplus_r,
```

```
                scatter_kws = {'alpha' : 1/3}, color=pledged_color,
                fit_reg=False);

        # annotate median
        surplus_r_median = round(df.surplus_r.median(),2)
        plt.axhline(surplus_r_median, color='purple')
        plt.text(df.goal_hist_usd.min()*1.1, surplus_r_median+200,
             "median:\n" + str(int(surplus_r_median)) + "%", fontsize=12)

        # ticks and labels
        plt.title(texts[i]+" Goals", fontsize=14, pad=15)
        locs, labels = plt.xticks()
        labels = [str(format_num(loc)) for loc in locs]
        plt.xticks(locs[1:-1], labels[1:-1], rotation=30, ha='right')
        plt.xlabel("funding goals (conv. USD)")
        format_yticks(3000, 500)
        plt.ylabel("pledged surplus rate (%) < 3,000%")
        plt.ylim(0,3000)
        plt.tight_layout()
    plt.suptitle("Pledged Surplus Rates of Goals", fontsize=18, y=1.05)
    plt.show()
```



The relative surplus creators realize, can be best interpreted by depicted surplus rates under USD {{format_num(goal_95)}}.

Regardless of the chosen funding goal, on average, creators may expect a surplus of 17% above their successful funding goal. The higher a campaign goal, the lower the relative surplus. As a matter of fact the possible surplus decreases sharpest for low goals.

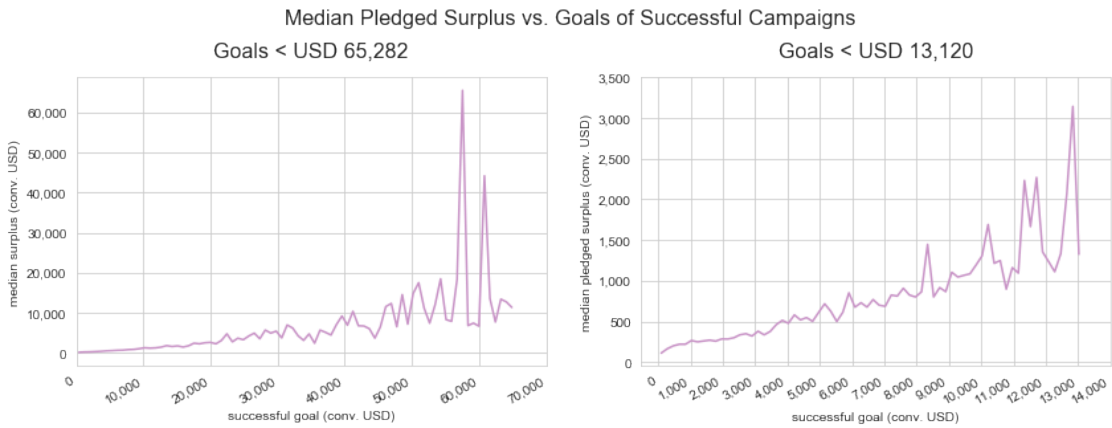
If creators set low goals below USD {{format_num(goal_25)}}, they can expect a median surplus of 37%. After the initial decay, medium, moderately high and high goals generate relatively constant median surplus rates of 11-14%.

The median surplus drops down to 11% for moderately high goals. Notice a slight upward trend for goals above USD 65k. Ultimately, very high goals realize median surplus rates of 27%.

Despite relative surplus rates, there still is a high density of surplus rates at full numbers, which may distort the interpretation of pledged funding. This is why we are going to bin goals according to the detected intervals. Then, we calculate the median of the surplus of each binned goal. This will allow us to depict the relationship in an adapted line plot.

In [122]:
```
# settings
plt.figure(figsize=[14,4])

def binned_pledges(df, bin_count):
    # cluster goals
    bin_size = (df['goal_hist_usd'].max()-df['goal_hist_usd'].min()) / bin_count
    bin_edges = np.arange(df['goal_hist_usd'].min(), df['goal_hist_usd'].max()+bin_s
    bin_centers = bin_edges[:-1] + bin_size/2
    pd.set_option('mode.chained_assignment', None) # turn off warning
    df['goal_bin'] = pd.cut(df['goal_hist_usd'], bin_edges, labels=bin_centers)
    # calculate pledged median for every goal
    df_binned = df['surplus'].groupby([df.goal_bin]).median().reset_index()
    return df_binned

# left plot: binned median pledges and respective binned goals
plt.subplot(1,2,1)
# for successfull campaigns with goals below 95%-quantile
df_binned = binned_pledges(ks_goal_95_s, 80)
plt.errorbar(x = df_binned['goal_bin'], y = df_binned['surplus'], color=pledged_colo
plt.title("Goals < USD " + format_num(int(goal_95)), fontsize=16, pad=15)

locs = np.arange(0, 65000+10000, 10000)
labels = [str(format_num(loc)) for loc in locs]
plt.xticks(locs, labels,  rotation=30, ha='right')
plt.xlabel("successful goal (conv. USD)")
plt.xlim(0, 70000)

format_yticks(60000, 10000)
plt.ylabel("median surplus (conv. USD)")

# right plot: binned median pledges vs. respective binned goals: moderately high goa
plt.subplot(1,2,2)
df_binned = binned_pledges(ks_compl_success[ks_compl_success.goal_hist_usd < goal_75]
plt.errorbar(x = df_binned['goal_bin'], y = df_binned['surplus'], color=pledged_colo
plt.title("Goals < USD " + format_num(goal_75), fontsize=16, pad=15)
```

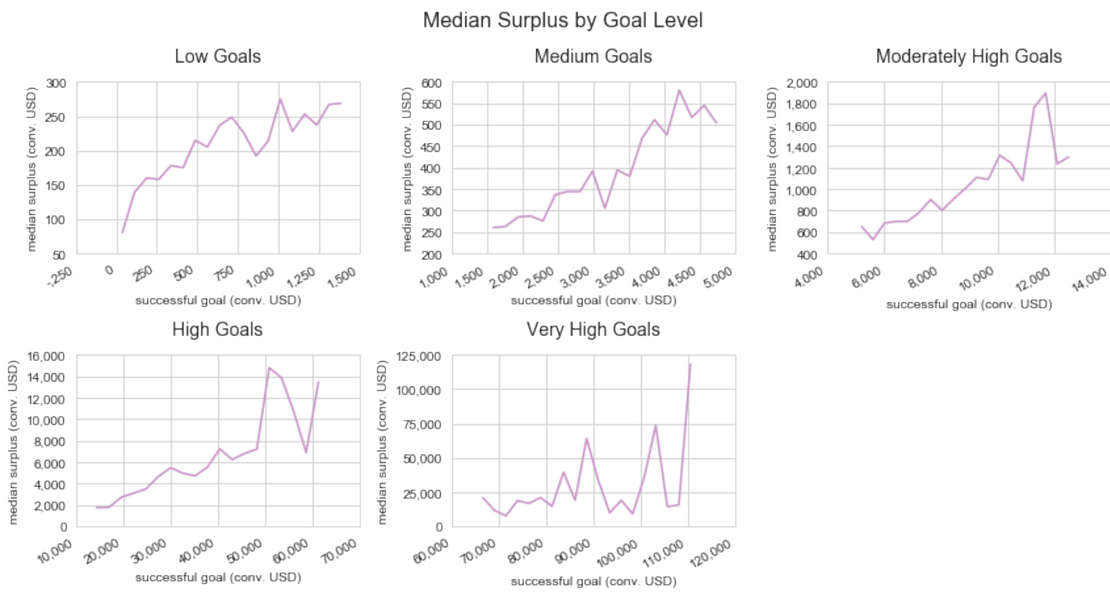
```
locs = np.arange(0, goal_75+1000, 1000)
labels = [str(format_num(loc)) for loc in locs]
plt.xticks(locs, labels, fontsize=10, rotation=30, ha='right')
plt.xlabel("successful goal (conv. USD)")

format_yticks(3500, 500)
plt.ylabel("median pledged surplus (conv. USD)")

plt.suptitle("Median Pledged Surplus vs. Goals of Successful Campaigns  ", fontsize=1
plt.show()
```



The surplus pledged above goal increases linearly up to goals of USD 10k at rate below 1. Beyond USD 10k goals, the surplus grows much faster. The median surplus of very high goals becomes more and more volatile and therefore less reliable.

```
In [123]: # settings
          plt.figure(figsize=[12,6])

          # facet by binned goals
          for i, goal_level in enumerate([goal_level.lower() for goal_level in texts][:-1]):
              plt.subplot(2, 3, i+1)
              df = ks_compl_success[ks_compl_success['goal_level'] == goal_level]
              df_binned = binned_pledges(df, 20)
              plt.errorbar(x = df_binned['goal_bin'][:-1], y = df_binned['surplus'][:-1], colo

              # ticks and labels
              plt.title(texts[i]+" Goals", fontsize=14, pad=15)

              locs, labels = plt.xticks()
              labels = [format_num(loc) for loc in locs]
              plt.xticks(locs, labels, rotation=30, ha='right')
              plt.xlabel("successful goal (conv. USD)")
```

```
        locs, labels = plt.yticks()
        labels = [format_num(loc) for loc in locs]
        plt.yticks(locs, labels)
        plt.ylabel("median surplus (conv. USD)")
        plt.tight_layout()

    plt.suptitle("Median Surplus by Goal Level", fontsize=16, y=1.04)
    plt.show()
```

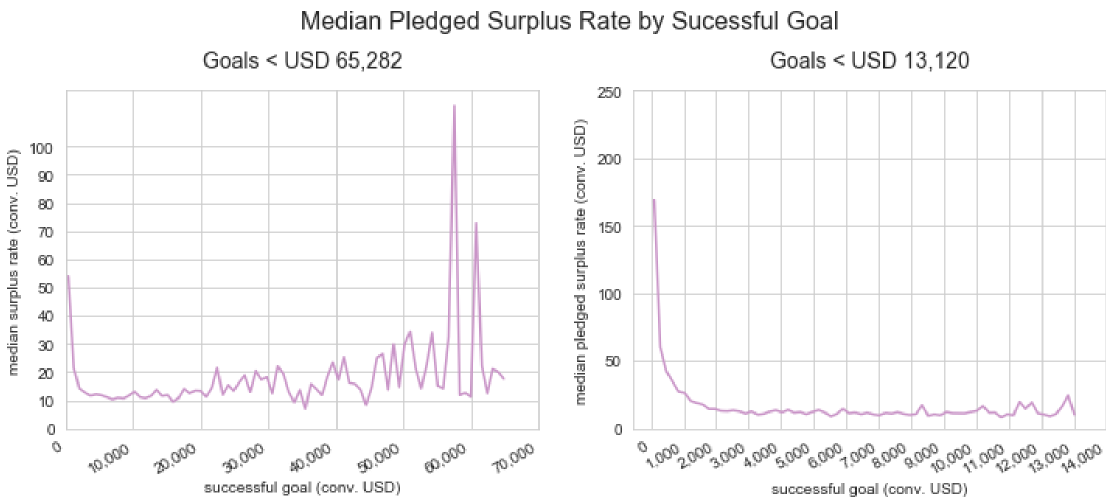


By working with the median surplus of binned goals, we smoothed the curve to eliminate the multi-modal character of funding. Accordingly, the best chances to generate a high surplus are at:

- Low goals: USD 1k - 1.5k,
- Medium goals: USD 3k - 5k,
- Moderately high goals: USD 11k - 12k,
- High goals: USD 50k - 60k.

In [124]:
```
# settings
plt.figure(figsize=[12,4])

def binned_pledges(df, bin_count):
    # cluster goals
    bin_size = (df['goal_hist_usd'].max()-df['goal_hist_usd'].min()) / bin_count
    bin_edges = np.arange(df['goal_hist_usd'].min(), df['goal_hist_usd'].max()+bin_s
    bin_centers = bin_edges[:-1] + bin_size/2
    pd.set_option('mode.chained_assignment', None) # turn off warning
    df['goal_bin'] = pd.cut(df['goal_hist_usd'], bin_edges, labels=bin_centers)
    # calculate median surplus rate for every goal
```

```
    df_binned = df['surplus_r'].groupby([df.goal_bin]).median().reset_index()
    return df_binned

# left plot: binned median pledges and respective binned goals
plt.subplot(1,2,1)
# for successfull campaigns with goals below 95%-quantile
df_binned = binned_pledges(ks_goal_95_s, 80)
plt.errorbar(x = df_binned['goal_bin'], y = df_binned['surplus_r'], color=pledged_co
plt.title("Goals < USD " + format_num(int(goal_95)), fontsize=14, pad=15)

locs = np.arange(0, 65000+10000, 10000)
labels = [str(format_num(loc)) for loc in locs]
plt.xticks(locs, labels, rotation=30, ha='right')
plt.xlabel("successful goal (conv. USD)")
plt.xlim(0, 70000)

plt.yticks(np.arange(0, 100+10, 10))
plt.ylabel("median surplus rate (conv. USD)")

# right plot: binned median pledges vs. respective binned goals: moderately high goa
plt.subplot(1,2,2)
df_binned = binned_pledges(ks_compl_success[ks_compl_success.goal_hist_usd < goal_75]
plt.errorbar(x = df_binned['goal_bin'], y = df_binned['surplus_r'], color=pledged_co
plt.title("Goals < USD " + format_num(goal_75), fontsize=14, pad=15)

locs = np.arange(0, goal_75+1000, 1000)
labels = [str(format_num(loc)) for loc in locs]
plt.xticks(locs, labels, rotation=30, ha='right')
plt.xlabel("successful goal (conv. USD)")

format_yticks(250, 50)
plt.ylabel("median pledged surplus rate (conv. USD)")

plt.suptitle("Median Pledged Surplus Rate by Sucessful Goal", fontsize=16, y=1.06)
plt.show()
```



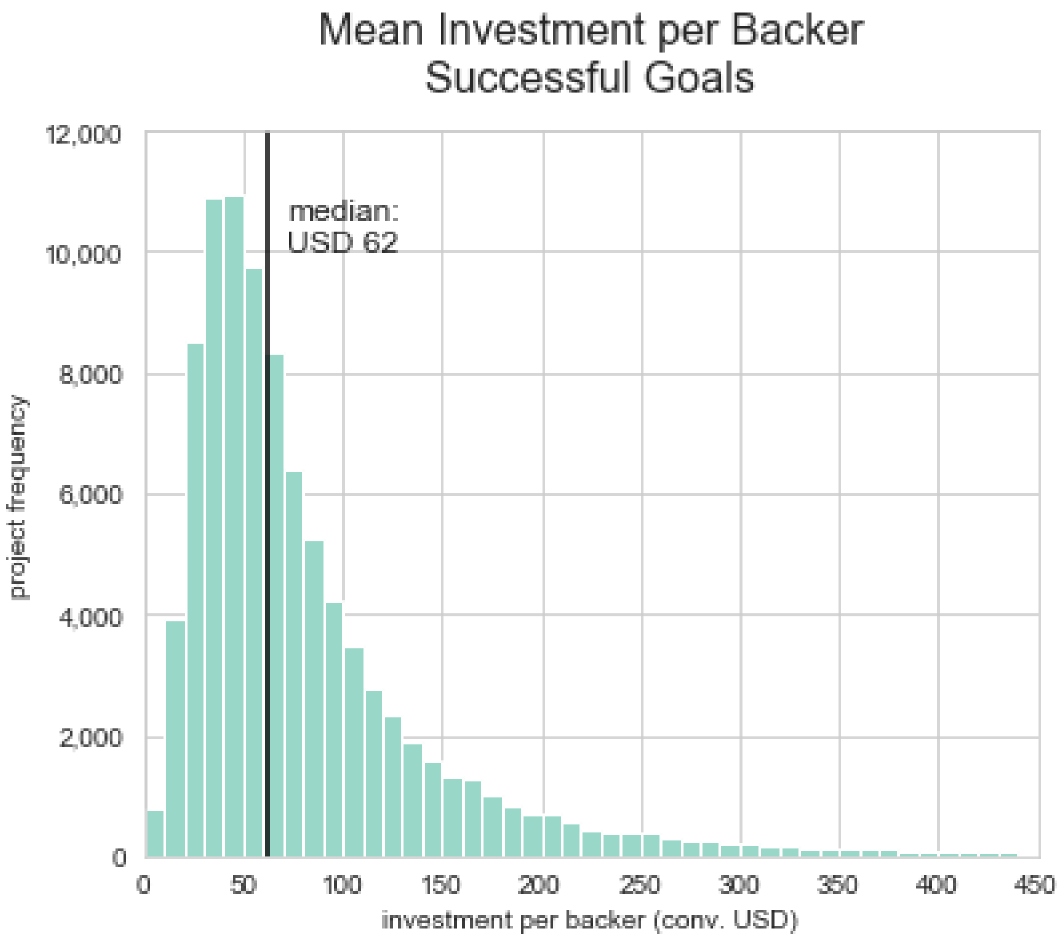
The plots illustrate that the surplus creators may generate depends on the chosen goal. Roughly, the surplus rate describes a u-form. For goals below USD 3k the surplus rate declines exponentially. The lower the goal chosen, the higher the surplus rate.

Thereafter, the median surplus rate remains relatively constant at 11%. The surplus rates increase for goals beyond USD 18k. Towards high goals above USD 44k, the pledged surplus rates sharply increase. At the same time, the plot becomes more volatile with anomalous peaks getting extremer. However, this is hardly relevant, since 3 quarters of creators stick to goals below USD 13,000.

Does a goal affect the pledged amount of individual backers?

In [125]:
```
# settings
plt.figure(figsize=[6,5])

# calculate the pledged investment per backer
ks_compl['pledged_backer_r'] = ks_compl['pledged_hist_usd'] / ks_compl['backers_coun
ks_compl_95['pledged_backer_r'] = ks_compl_95['pledged_hist_usd'] / ks_compl_95['bac
ks_compl_success = ks_compl[ks_compl.status == "successful"]

bin_edges = np.arange(0, ks_compl_success['pledged_backer_r'].max()+10, 10)
sns.distplot(ks_compl_success['pledged_backer_r'], bins = bin_edges, kde = False,
             hist_kws = {'alpha' : 1, 'color': '#99d8c9'})
plt.xlim(0, 450)

# annotate median
median_pledged = ks_compl_success['pledged_backer_r'].median()
plt.axvline(x=median_pledged, color='black')
plt.annotate("median:\nUSD " + format_num(median_pledged), xy=(median_pledged+10, 10(


# ticks and labels
plt.title("Mean Investment per Backer\nSuccessful Goals", fontsize=16, pad=15)
```

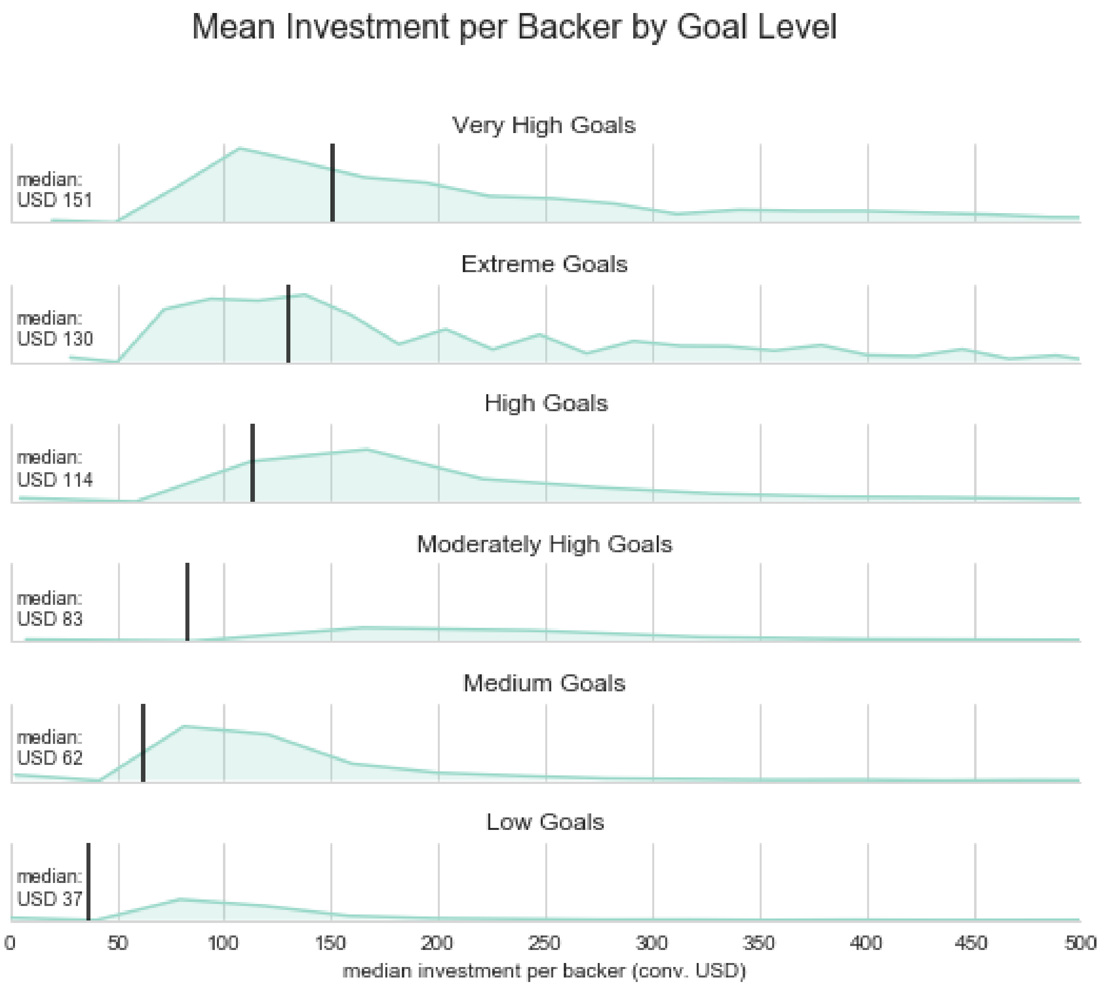
```
format_yticks(12000, 2000)
plt.ylabel("project frequency")
plt.xlabel("investment per backer (conv. USD)")

plt.show()
```



Only considering successful projects, backers pledged a median of USD 62. The investment per backer is strongly skewed towards higher pledges. Most individual pledges cluster between USD 25-50. Let's see how the scope of a goal affected how much each supporter invested.

```
In [126]: # calculate median per goal level
          group_means = ks_compl_success.groupby(['goal_level']).median()
          group_order = group_means.sort_values(['pledged_backer_r'], ascending = False).index

          # facet plots per goal levels
          g = sns.FacetGrid(data = ks_compl_success, row = 'goal_level', height = 1, aspect = 8
                            row_order = group_order)

          # plot distribution as kernel density estimate
```

```
g.map(sns.kdeplot, 'pledged_backer_r', shade = True, bw=0.1, color='#99d8c9')
plt.xlim(0, 500)

# annotate median per goal level
def vertical_mean_line(data, **kwargs):
    plt.axvline(data.median(),**kwargs)
    plt.text(3, 0.001, "median:\nUSD " + format_num(data.median()), fontsize=9)
g.map(vertical_mean_line, 'pledged_backer_r',  color='black' )

# labels and ticks
for ax, title in zip(g.axes.flat, group_order):
    ax.set_title(title.title() + " Goals")

# remove the y-axes
g.set(yticks=[])
g.despine(left=True)

format_xticks(500, 50)
plt.xlabel("median investment per backer (conv. USD)")

plt.suptitle("Mean Investment per Backer by Goal Level", fontsize=16, y=1.09)
plt.show()
```



The higher the goal the higher was the average amount each supporter invested. For successful low goal projects (below USD 1.5k) the median pledged per backer was USD 37. Moderately high goals generate a median of USD 83. Successful very high goal projects generated the highest median funding per backer: USD 151.

Do project funding opportunities depend on the project type?

It makes only sense that the wide variety of projects on Kickstarter require different scopes of funding. A card game surely plays in a different investment league than a space mission.

The question is whether different project categories are typically attributed with different scopes of funding. More importantly, I would like to know if supporters were willing to invest higher amounts if a project type typically required high funding.

To depict the relationship, we are going to work on median numbers instead of funding ranges. We want to keep the plot neat to improve readability.

```
In [127]: # calculate median goals and create dataframe
          def calc_med_goals_by(category):
              ks_cat_median = ks_compl.groupby(['status', category]).median()['goal_hist_usd']
              ks_cat_median = ks_cat_median.reset_index(name = 'goal_median')
```

```
    ks_cat_median = ks_cat_median.pivot(index = category, columns = 'status',
                            values = 'goal_median')
    ks_cat_median.rename(index=str,
                     columns={'failed': 'med_goal_fail', 'successful': 'med_goal_succ
                     inplace=True)
    # calculate median pledged
    med_cat_pledged = ks_compl.groupby(['status', category]).median()['pledged_hist_
    med_cat_pledged = med_cat_pledged.reset_index(name = 'med_pledged')
    med_cat_pledged = med_cat_pledged.pivot(index = category, columns = 'status',
                            values = 'med_pledged')

    # add to dataframe
    ks_cat_median['med_pledged_fail'] = med_cat_pledged['failed']
    ks_cat_median['med_pledged_success'] = med_cat_pledged['successful']
    ks_cat_median = ks_cat_median.fillna(0).sort_values(by='med_pledged_success', asc
    return  ks_cat_median
ks_cat_median = calc_med_goals_by('category')
ks_cat_median.head()
```

Out[127]:

```
status category  med_goal_fail  med_goal_success  med_pledged_fail  \
0       Crafts  3,000.0        1,000.0           34.2834193923985
1       Art     4,000.0        1,500.0           53.6904677640449
2       Theater 5,000.0        3,000.0           85.0
3       Dance   5,000.0        3,000.0           60.0
4       Comics  5,000.0        2,500.0           227.0

status  med_pledged_success
0      1,957.5894006210215
1      2,443.840216200004
2      3,225.0
3      3,526.0
4      3,781.912748502413
```

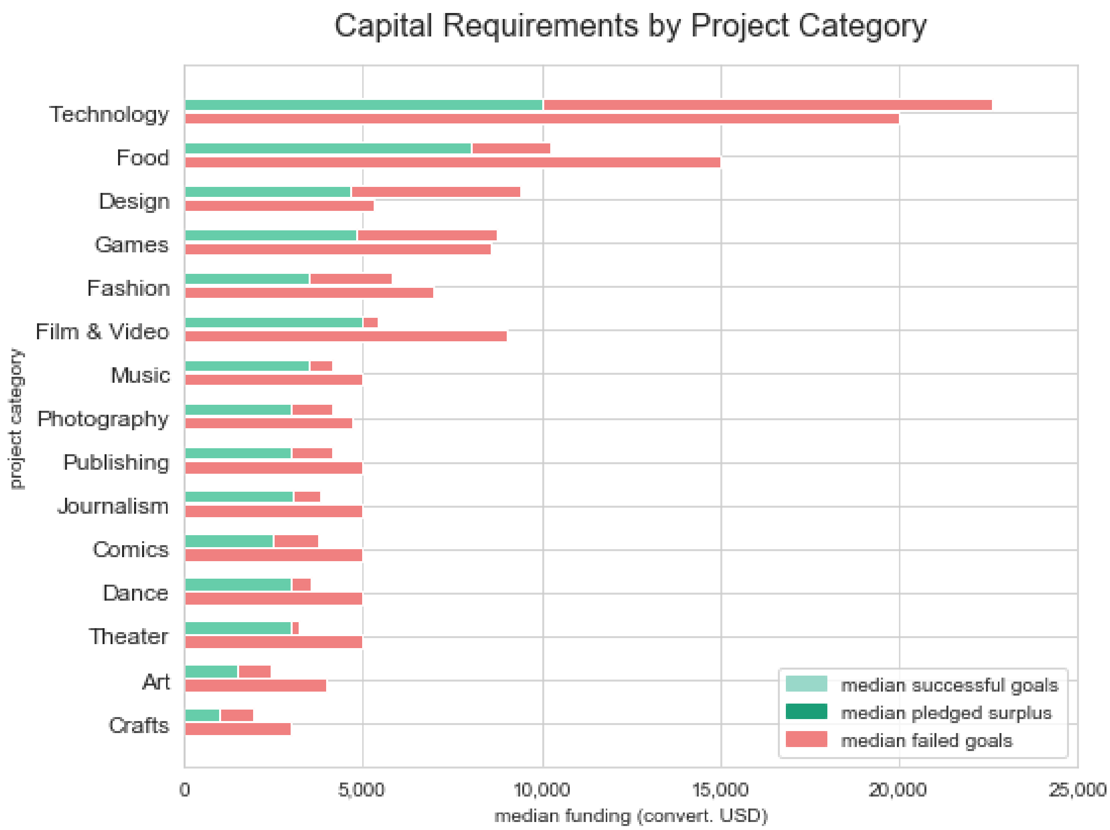
Plot each category's median funding using a stacked bars. Compare the successful values to the values of failed projects by clustering the bars.

In [128]:

```
# utility to plot clusterd/stacked bars of funding opportunities by category
def plot_funding_by(df, category, order):
    # settings
    funding = ['med_goal_success', 'med_pledged_success']
    color_greens = ['#99d8c9', '#1b9e77']
    baselines = np.zeros(len(order)) # set baseline of every barplot to zero
    bars = []

    # horizontally plot goal by category first, then plot pledged surplus on top of 
    ax = plt.subplot(111)
    for i in range(2):
        amount = df[funding[i]]
```

```
            amount = list(amount - baselines) # subtract goal from pledges to calculate 
            bars += ax.barh(y=np.arange(0.2, len(order)+0.2),
                     width=amount, left=baselines,
                     color=sns.set_palette(color_greens), height=0.3)

            # add goal to baseline to plot next stack of bar
            baselines += amount

        # add median failed goals as horizontal bars
        bars += ax.barh(y=np.arange(-0.12, len(order)-0.12),
                     width=df['med_goal_fail'],
                     color=cust_red, height=0.3)

        # ticks and labels
        ylocs = np.arange(0, len(order), 1)
        plt.yticks(ylocs, order, fontsize=12)
        plt.ylabel("project category")
        format_xticks(df['med_pledged_success'].max(), 5000)
        plt.xlabel("median funding (convert. USD)")

        leg = plt.legend([bars[0], bars[1], bars[3]],
                          ['median successful goals',
                           'median pledged surplus',
                           'median failed goals'],
                          frameon=True, fontsize=10)
        leg.legendHandles[0].set_color(color_greens[0])
        leg.legendHandles[1].set_color(color_greens[1])
        leg.legendHandles[2].set_color(cust_red)
```

```
In [129]: # settings
          fig = plt.figure(figsize = [8, 6])
          cat_order_asc = ks_cat_median.category.values

          # plot median funding by project category
          plot_funding_by(ks_cat_median, 'category', cat_order_asc)
          plt.title("Capital Requirements by Project Category", fontsize=16, pad=15)
          plt.tight_layout()
          plt.show()
```



Technology, Food and Design projects on average require the highest funding: between USD 5k to 10k. Theater, Art and Crafts usually require low funding below USD 3k.

Technology projects stand out with the highest median funding requirements of USD 10k. Failed Technology campaigns requested on average double. Even so, Technology projects seeking lower goals ultimately outbid failed goals. They collected median funding of USD 22.5k.

Most apparent for Food campaigns is the deficit of investments compared to the required funding goals. The median goal of failed projects was much higher than the average collected funding. Similarly, Film & Video productions tend to require funding capital above the supplied capital investment.

Design projects makes the most balanced impression between failed and successful goals. The high pledged surplus over design goals presages a high demand of backers, resulting in a high median surplus.

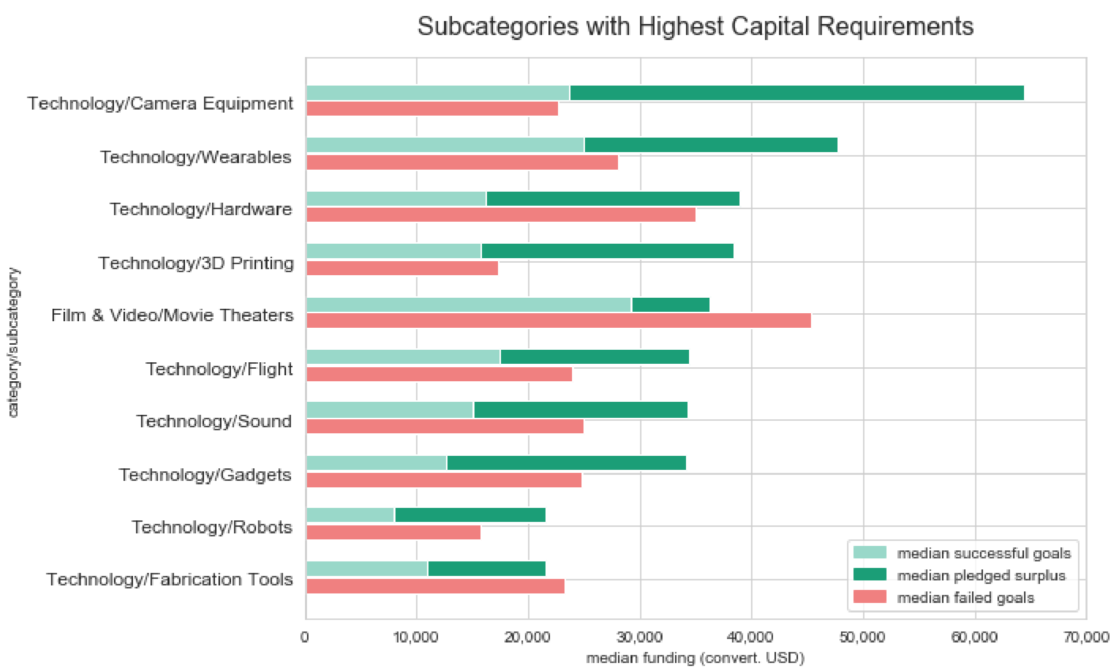
The high investment requirements of Tech and Food projects may be one explanation for their low success rates.

```
In [130]: # calulate median funding values of combined categories
          ks_comb_cat_median = calc_med_goals_by('comb_cat')
          ks_comb_cat_median.tail()
```

```
Out[130]: status                     comb_cat       med_goal_fail     med_goal_success  \
          164     Film & Video/Movie Theaters 45,337.601077732215 29,129.516163050368
          165     Technology/3D Printing      17,265.957195821975 15,740.0
```

```
166     Technology/Hardware          35,000.0            16,192.0
167     Technology/Wearables         28,000.0            24,999.5
168     Technology/Camera Equipment  22,722.526532318174 23,610.32930009085

status     med_pledged_fail   med_pledged_success
164     31.084500000531914  36,262.600000000006
165     520.5115652981099   38,358.24200426369
166     597.0304999825659   38,885.445
167     664.9058966036991   47,789.0
168     1,941.2260000275564 64,417.0
```

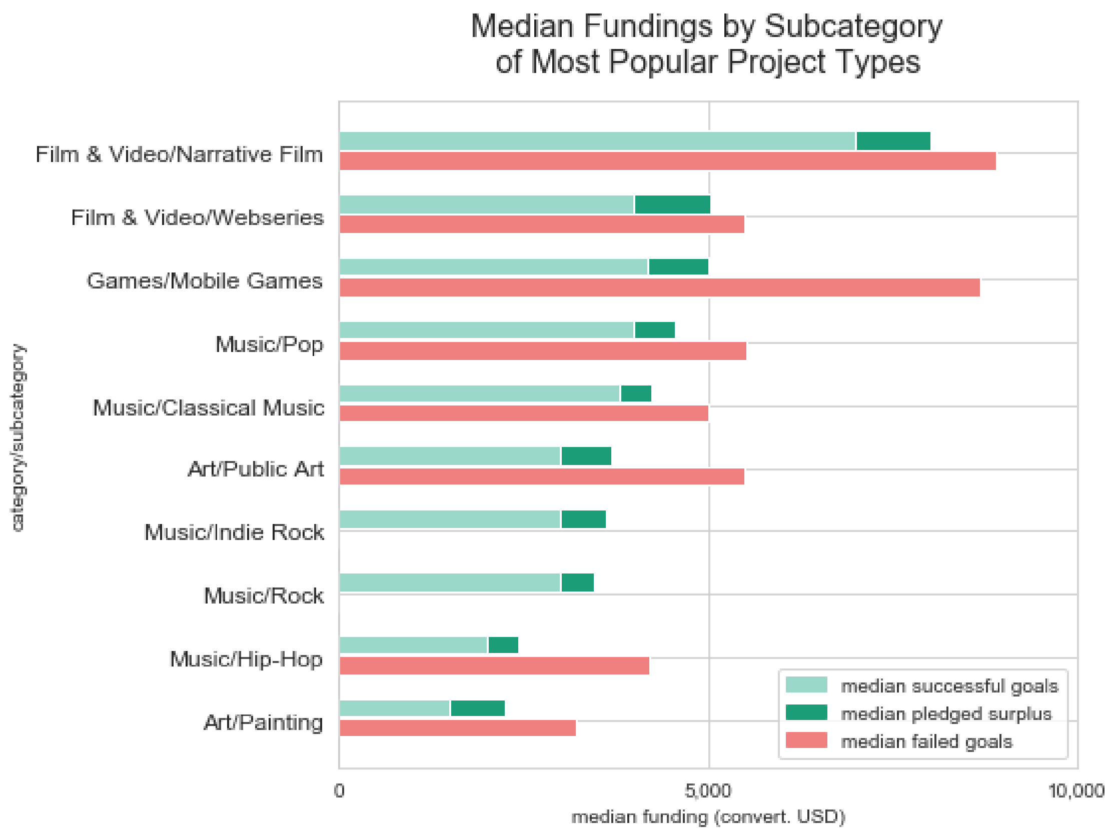
In [131]:
```
# settings
fig = plt.figure(figsize = [10, 6])
top_subcats = ks_comb_cat_median['comb_cat'].values[-10:]

# plot median funding by combined category
plot_funding_by(ks_comb_cat_median[-10:], 'comb_cat', top_subcats)

# labels and ticks
plt.title("Subcategories with Highest Capital Requirements", fontsize=16, pad=15)
plt.ylabel("category/subcategory")
format_xticks(ks_comb_cat_median['med_pledged_success'].max(), 10000)
plt.tight_layout()
plt.show()
```



Tech projects dominate in the top categories of high capital requirements. Camera Equipment by far attracted the highest median pledges, followed by Wearables. Both types of projects realized a strong surplus above goals. On average camera equipment campaigns collected the most impressive funding of USD 65k.

It's remarkable that mostly hardware appliances are among projects with the highest capital requirements. Movie Theaters seem to regularly require the highest median capital requirements, but stay behind tech projects in terms of the total collected funding.

```
In [132]: # settings
          fig = plt.figure(figsize = [8, 6])
          df_pop_subcats = ks_comb_cat_median[ks_comb_cat_median.comb_cat.isin(pop_subcats)].re
          order = df_pop_subcats['comb_cat'].values

          # plot median funding by combined category
          plot_funding_by(df_pop_subcats, 'comb_cat', order)

          # labels and ticks
          plt.title("Median Fundings by Subcategory\n of Most Popular Project Types ", fontsize
          plt.ylabel("category/subcategory")
          plt.tight_layout()
          plt.show()
```



Apart Narrative Films, the most popular Kickstarter projects sought relatively low funding goals below USD 5k.

Which project categories were worthwhile to run?

I previously analyzed the popularity of project types, their funding requirements and success rates. Now, I am prepared to evaluate how well categories performed.

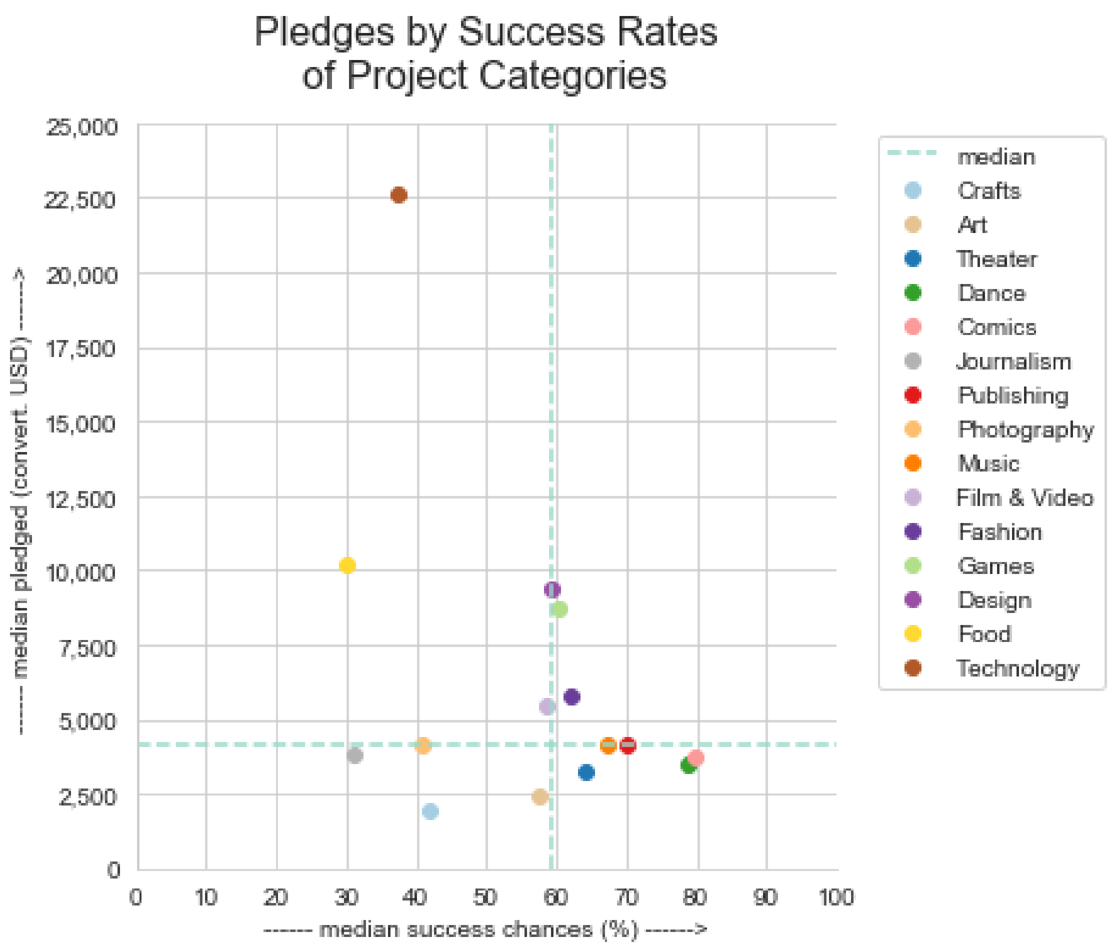
For investment seekers success rates of categories and the potential funding opportunities are important. Thus, I am going to depict the pledged median funding against the success rate for each category.

```
In [133]: # utility to add success rates to data frame
          def calc_cat_success(cat, df=ks_compl):
              success = df.groupby([cat,'status']).count()['project_id']
              success = success.reset_index(name='count')
              success = success.pivot(index=cat, columns='status', values='count')
              success = success.reset_index()
              # divide failed and success columns by category counts
              for status in ['failed', 'successful']:
                  success[status] = (success[status] / df.groupby([cat]).count()['project_id']
              return success
```

```
In [134]: # add success rates to our data frame
          df_cat_success = calc_cat_success('category')
          ks_cat_median = ks_cat_median.merge(df_cat_success, on='category')
```

```
In [135]: # utility function to plot multivariate plot of 2 numerical and 1 quantitative varia
          def plot_facet_scatter_by(df, cat, headline, quadrants=True):
              g = sns.FacetGrid(data = df, hue = cat, height = 5, palette=category_colors)
              g.map(plt.scatter, 'successful', 'med_pledged_success')
              success_median = ks_cat_median['successful'].median()
              pledged_median = ks_cat_median['med_pledged_success'].median()

              ax = g.axes[0]
              if quadrants:
              # divide axis into 4 squares using a median
                  ax[0].axvline(success_median, ls='--', label='median')
                  ax[0].axhline(pledged_median, ls='--')

              # labels and ticks
              plt.title("Pledges by Success Rates\n" + headline, fontsize=16, pad=15)
              xlocs = np.arange(0, 100+10, 10)
              plt.xticks(xlocs)
              plt.xlabel("------ median success chances (%) ------>")
              format_yticks(df['med_pledged_success'].max(),2500)
              plt.ylabel("------ median pledged (convert. USD) ------>")

              leg = ax[0].legend(loc=1, bbox_to_anchor=(1.4, 1))
              leg.set_title('')
              plt.show()
              return g
```

```
In [136]: # plot pledged investment and success chance in a faceted scatterplot for each categ
          plot_facet_scatter_by(ks_cat_median, 'category', "of Project Categories");
```



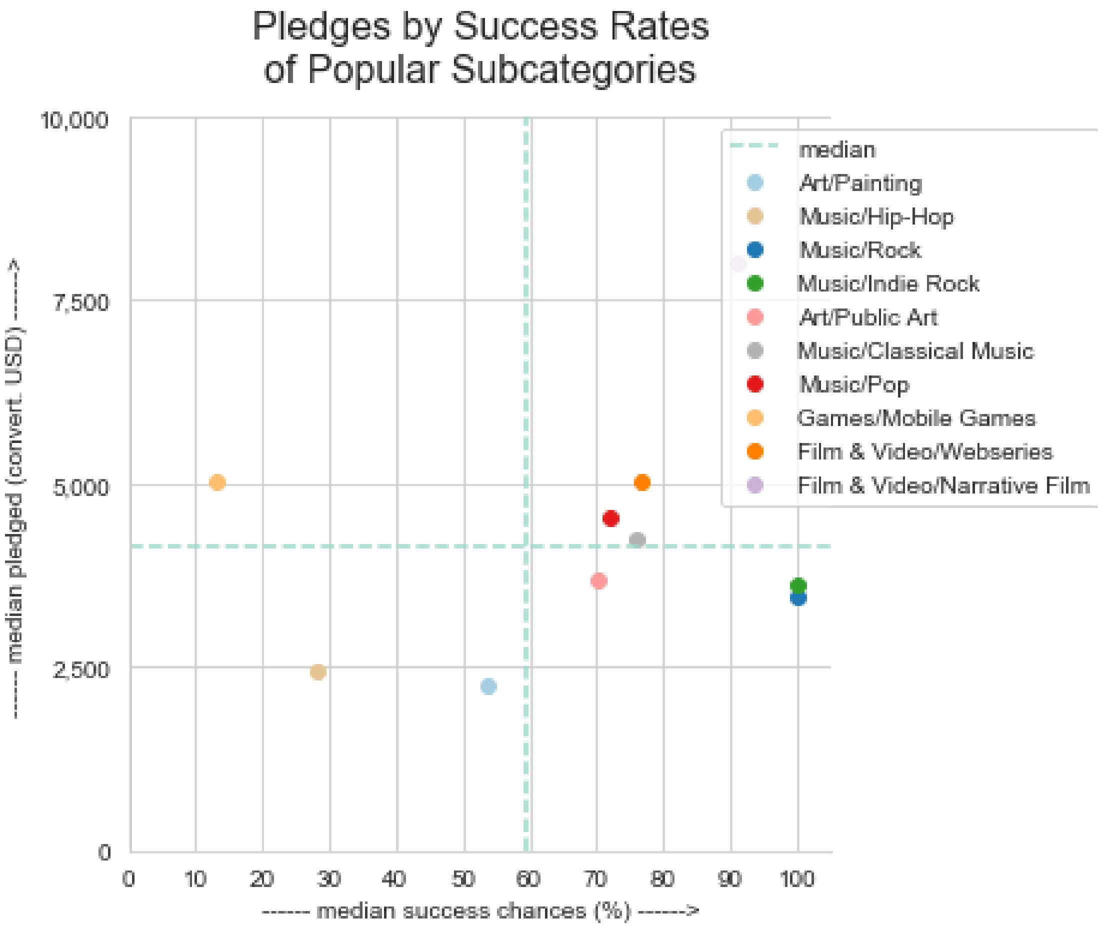
The categories located in the upper right square imply the best chances for creators. Design and Game projects have high chances of success and realize a comparatively high median funding. Tech and food projects usually collected the highest investments, yet success chances were among the lowest.

Projects categories found in the lower right quadrant have high chances to run successfully, but usually don't collect large investments. This is especially true for Comics and Dance ventures. However, creators may judge themselves how much funding they required to launch a project successfully.

Journalism, Crafts and Photography perform weakest in terms of chances and the collected funding. Let's plot a similar scatter plot for the most popular subcategories.

In [137]:
```
# add success rates to our data frame
df_comb_cat_success = calc_cat_success('comb_cat')
ks_comb_cat_median = ks_comb_cat_median.merge(df_comb_cat_success, on='comb_cat')
```

In [138]:
```
# filter by popular categories
df_pop_subcats = ks_comb_cat_median[ks_comb_cat_median.comb_cat.isin(pop_subcats)].r
# analyse most popular subcategories by median pledges and success rates
plot_facet_scatter_by(df_pop_subcats, 'comb_cat', "of Popular Subcategories");
```



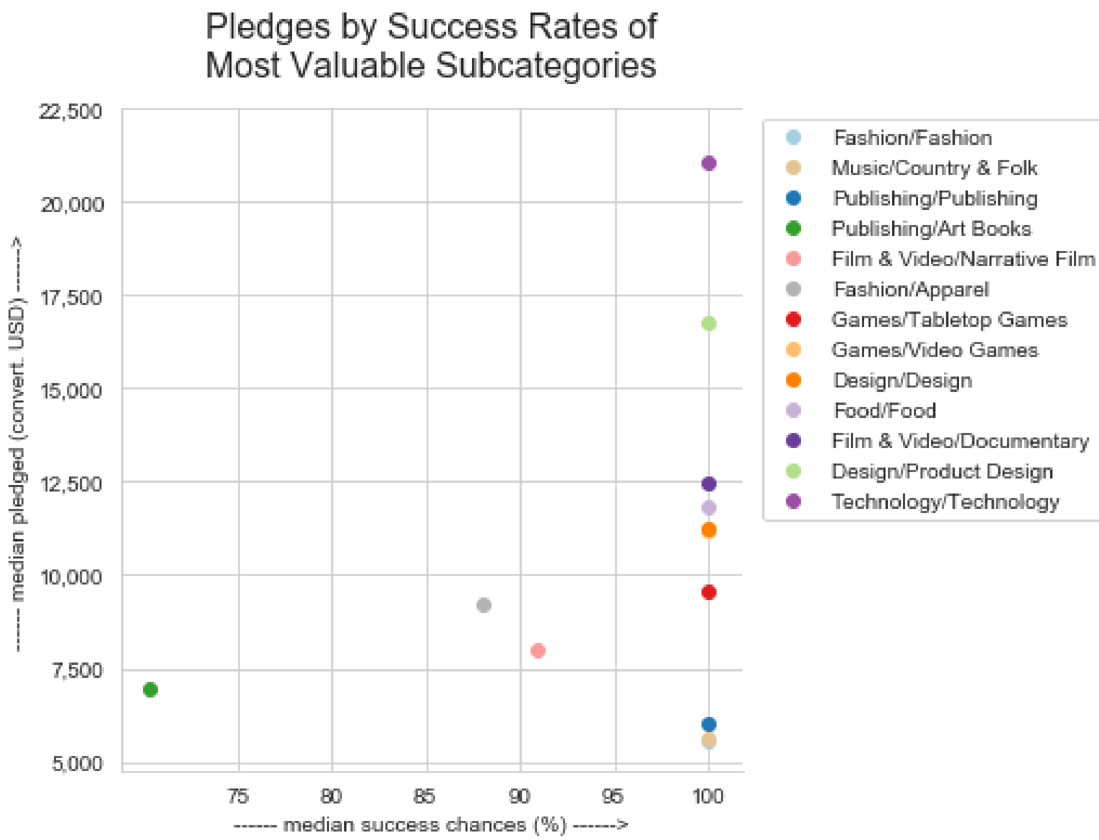
The 10 most popular subcategories performed comparatively weak. Webseries, Pop Music and Classical Music fall into the upper right quadrant. They on average realize funding of just below USD 5k.

Indie Rock and Rock Musik were the safest bets with 100% success chances.

Mobile Games and Hip-Hop Music were among the most popular categories. Nevertheless, both categories were usually not rewarding the creator with high success chances, nor high funding.

```
In [139]: # filter by best conditions
          df_best_types = ks_comb_cat_median[ks_comb_cat_median['med_pledged_success'] >= 5500]
          df_best_types = df_best_types[df_best_types.successful > 70]
          # identify best subcategories by median pledges and success rates
          g = sns.FacetGrid(data = df_best_types, hue = 'comb_cat', height = 5, palette=catego
          g.map(plt.scatter, 'successful', 'med_pledged_success')

          # labels and ticks
          plt.title("Pledges by Success Rates of\nMost Valuable Subcategories", fontsize=16, pa
          format_xticks(100, 5, 75)
          plt.xlabel("------ median success chances (%) ------>")
```

```
format_yticks(df_best_types['med_pledged_success'].max(), 2500, 5000)
plt.ylabel("------ median pledged (convert. USD) ------>")

plt.legend(loc=1, bbox_to_anchor=(1.6, 1))
plt.show()
```



7.3.4 Summary Funding

When creators decide on a goal, they generally have to consider whether to maximize their chances to successfully finish a campaign or to generate the maximum funding possible. Both targets oppose each other diametrically. Increasing the goal typically decreases the chances for success. Simultaneously, creators risk insufficient funding by aiming for low goals.

If creators want to keep at least a 50% chance, it appears to be advisable to stay below goals of USD 10k. On average goals below 5k had a chance of above 60%.

Very risk averse creators may stick to low goals below USD 1,5k. Interestingly, low goal projects typically generated a surplus of 37% above goal. At the same time goals between USD {{format_num(goal_25)}} to USD {{format_num(goal_75)}} only generate a median surplus of 11/12%. Therefore, the loss in the total funding by setting low goals may be tolerable in exchange for better chances of success.

The function of the surplus rate of the pledged investment above goal describes a slow growing trend. However, there are two significant anomalies. First of all, up until USD 3k the surplus rate describes is sharply decreasing. This explains the relatively high surplus generated by low goals. Second, goals above USD 18k have increasing surplus rates. Towards high goals above USD 45k, the pledged surplus rate grows steeper. At the same time, the plot becomes more volatile with anomalous peaks.

The goal not only influenced success chances, but also how much every supporter was contributing. The higher the goal, the higher was the amount pledged per backer. On average supporters pledged USD 37 for goals below USD {{format_num(pledged_95)}}, but invested a fourfold for very high goals. Creators may consider this behavior when defining the rewards for pledges.

Creators seeking high funding may consider alternative investment possibilities to Kickstarter. 95% of all successful projects kept below contributions of USD {{format_num(pledged_95)}}. At the same time success chances were very low for very high goal projects of USD {{format_num(goal_95)}} to {{format_num(goal_975)}} : only 20% of campaigns ended in success. For even higher goals, success chances dropped to nearly zero.

The investment capacity was strongly determined by the project type. Generally, tech and food projects required the highest average funding of USD 15k. Tech projects realized the highest median pledges of plus USD 22k. The lowest capital requirements had Art and Craft project, which realized a median USD 2.5k.

Tech and food projects realized the high investments and were the most likely to fail.

By filtering subcategories by the highest success rates and pledges, we found the most valuable categories were:

1) technology projects without defined subcategory,

2) product design projects and

3) documentary films.

The most disappointing projects were of the type:

1) mobile games,

2) Hip-Hop music and

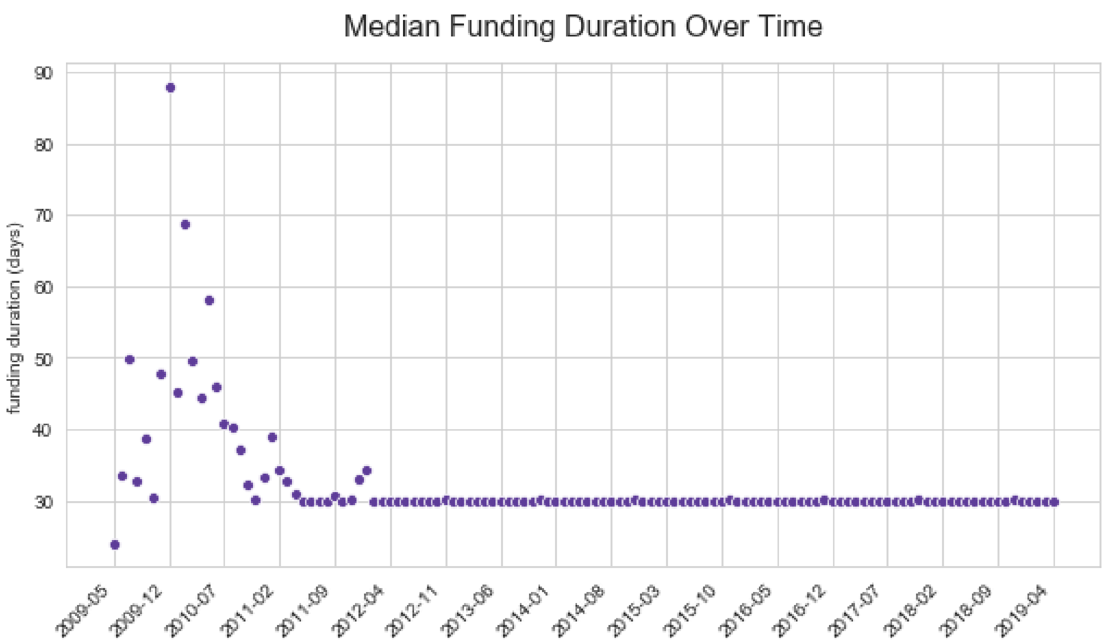
3) generally journalistic projects.

7.3.5 Duration

The univariate plot of duration above tells us that a funding duration of 30 days was most common. Let's see if 30 days has always been the standard.

```
In [140]: # calculate monthly median duration of completed projects
          # total
          duration_grouped = ks_compl.groupby([ks_compl.deadline.dt.year,
                                               ks_compl.deadline.dt.month])['duration_days'].mec
          # success
          duration_grouped_s = ks_compl_success.groupby([ks_compl_success.deadline.dt.year,
                                               ks_compl_success.deadline.dt.month])['duration_da
          # failed
          duration_grouped_f= ks_compl_failed.groupby([ks_compl_failed.deadline.dt.year,
```

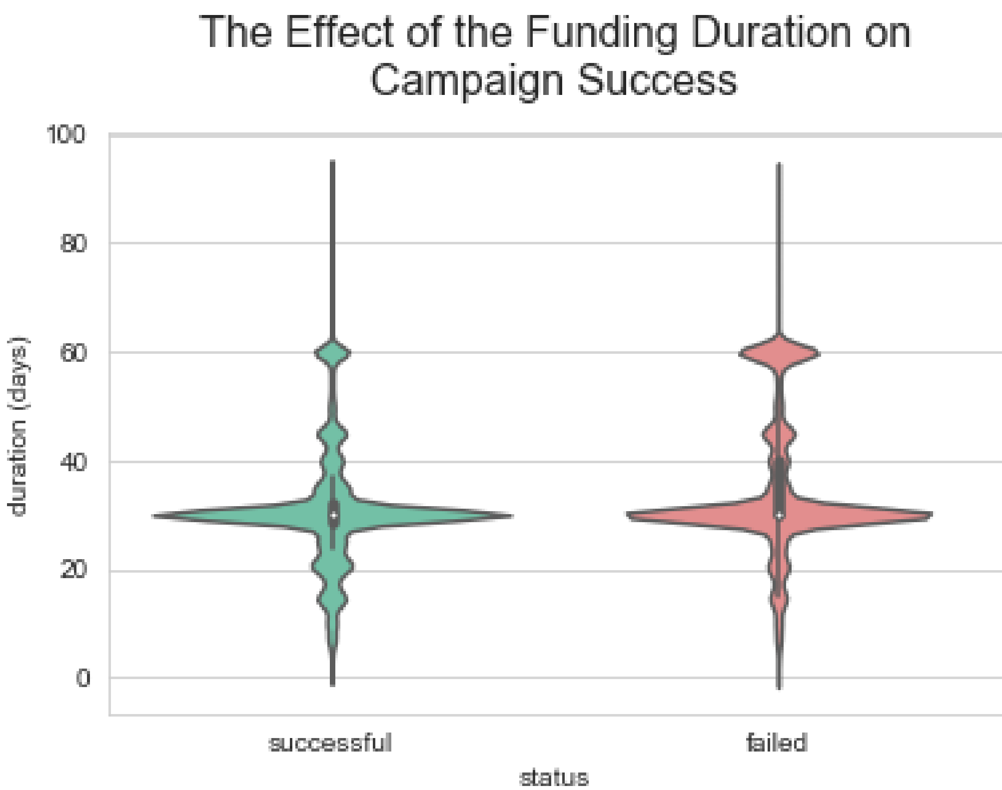
```
                                          ks_compl_failed.deadline.dt.month])['duration_day
# insert 0 occurence for 2009-6
duration_grouped_f = np.insert(duration_grouped_f,1,0)

# create dataframe
df_duration = pd.DataFrame(data={'total': duration_grouped,
                                 'success':duration_grouped_s,
                                 'failed': duration_grouped_f,
                                 'date': np.arange(0, len(duration_grouped), 1)})
# settings
plt.figure(figsize=[10,5])

# scatterplot of median duration over days
ax = sns.scatterplot(x=df_duration['date'], y=df_duration['total'],
                     color='#5e3c99');

# ticks and labels
timeline_ticks(df_duration)
plt.ylabel("funding duration (days)")
plt.title("Median Funding Duration Over Time", fontsize=16, pad=15)
plt.xlabel("")

plt.show()
```



Obviously, there was not much discrepancy in the funding duration over time. Only in the first two years creators were experimenting with the length of a funding durations. Two years after Kickstarter's launch, it became general practice to run the funding within 30 days. Nevertheless, it would make sense that a longer period may result in improved chances of success, especially for founders who require high investments.

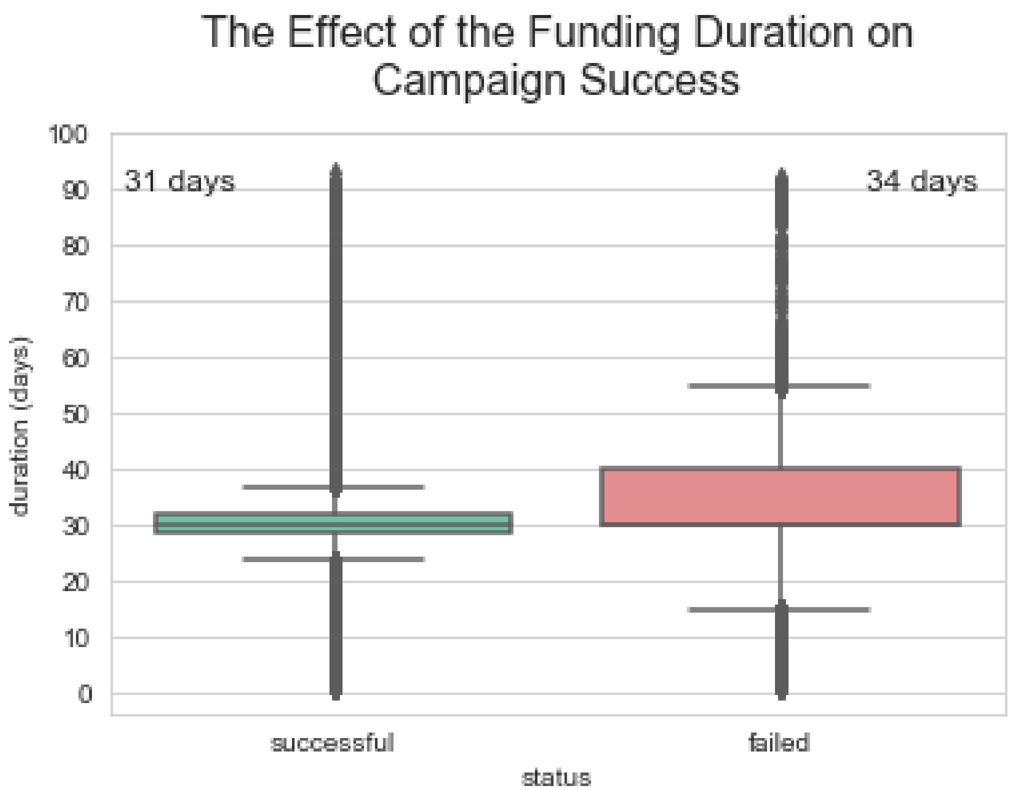
Does a longer funding period increase the chances of success?

In [141]:
```
# settings
color=sns.set_palette(status_colors[1:])

# Use violinplots to depict duration converted days. Separate completed projects by 
ax = sns.violinplot(ks_compl.status, (ks_compl.duration.astype('timedelta64[h]') / 24
                    order=['successful', 'failed'], color = color)
# labels and titles
plt.title("The Effect of the Funding Duration on\nCampaign Success", fontsize=16, pad
plt.ylabel('duration (days)')

plt.show()
```



The above distribution of the duration of the funding shows that there is generally not a big difference between successful and failed campaigns. The median duration and most occurrences are around 30 days. For successful campaigns, the distribution below 30 days is a little wider than for failed campaigns. The distribution of failed campaigns reveals comparatively more occurrences of longer durations, especially at 60 days. Also, the inner quartiles and whiskers of failed campaigns seem to be skewed upward. Let's plot this relationship in a boxplot separately next.

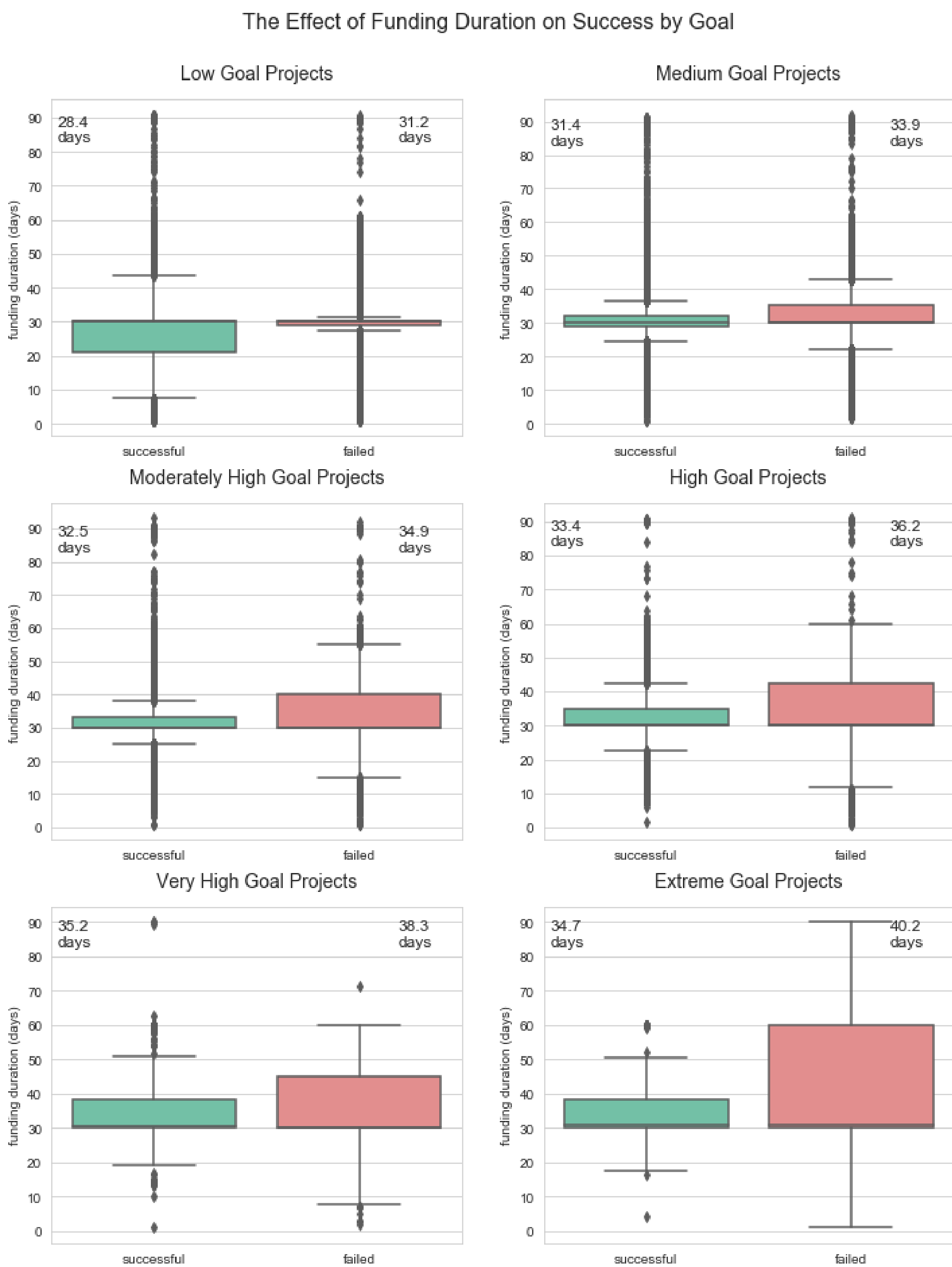
```
In [142]: # Use violinplot to depict duration converted days. Separate completed projects by s
          ax = sns.boxplot(ks_compl.status, (ks_compl.duration.astype('timedelta64[h]') / 24),
                          order=['successful', 'failed'], color = color)

          # calculate means
          dur_mean_fail  = (ks_compl[ks_compl.status == "failed"]['duration'].astype('timedelta
          dur_mean_success  = (ks_compl[ks_compl.status == "successful"]['duration'].astype('ti

          # annotate
          ax.annotate(str(int(dur_mean_fail)) + " days", xy=(1.19, 90), fontsize=12)
          ax.annotate(str(int(dur_mean_success)) + " days", xy=(-0.47, 90), fontsize=12)

          # labels and titles
          plt.title("The Effect of the Funding Duration on\nCampaign Success", fontsize=16, pad
          plt.ylabel('duration (days)')
          format_yticks(100, 10)
          plt.show()
```



The box plot approach appears to be a better choice to answer if a longer funding period may increase success chances of campaigns. While the median funding of both successful and failed campaigns, was 30 days, the mean of successful was 31 days, while failed campaigns ran 3 days longer. Particularly, the upper interquartile goes up to 40 days and the tail up to 55 days. At the same time, funding periods of successful campaigns above 38 days were a rarity.

However, we already found that creators seeking higher goals were less likely to succeed. Let's factor in goals next to find out whether high goal projects have a better chance to succeed if they add time to their campaign.

In [143]:
```
# settings
plt.figure(figsize=[12,10])

# facet plot by goals to depict the effect of duration on projects
for i, df in enumerate(ks_goal_leveled):
    # faceted boxplots
    plt.subplot(3, 2, i+1)
    ax = sns.boxplot(df.status, (df.duration.astype('timedelta64[h]') / 24),
                order=['successful', 'failed'], color = color)
    # calculate mean
    dur_mean_fail  = (df[df.status == "failed"]['duration'].astype('timedelta64[h]')
    dur_mean_success  = (df[df.status == "successful"]['duration'].astype('timedelta6

    #annotate
    ax.annotate(str(round(dur_mean_fail, 1))+ "\ndays", xy=(1.19, 83), fontsize=12)
    ax.annotate(str(round(dur_mean_success, 1))+ "\ndays", xy=(-0.47, 83), fontsize=1
    plt.title(texts[i]+" Goal Projects", fontsize=14, pad=15 )

    # labels and ticks
    plt.ylabel('funding duration (days)')
    plt.xlabel('')
    plt.subplots_adjust(bottom=-0.3)
    format_yticks(90, 10)
plt.suptitle("The Effect of Funding Duration on Success by Goal", fontsize=16, y=0.9
plt.show()
```



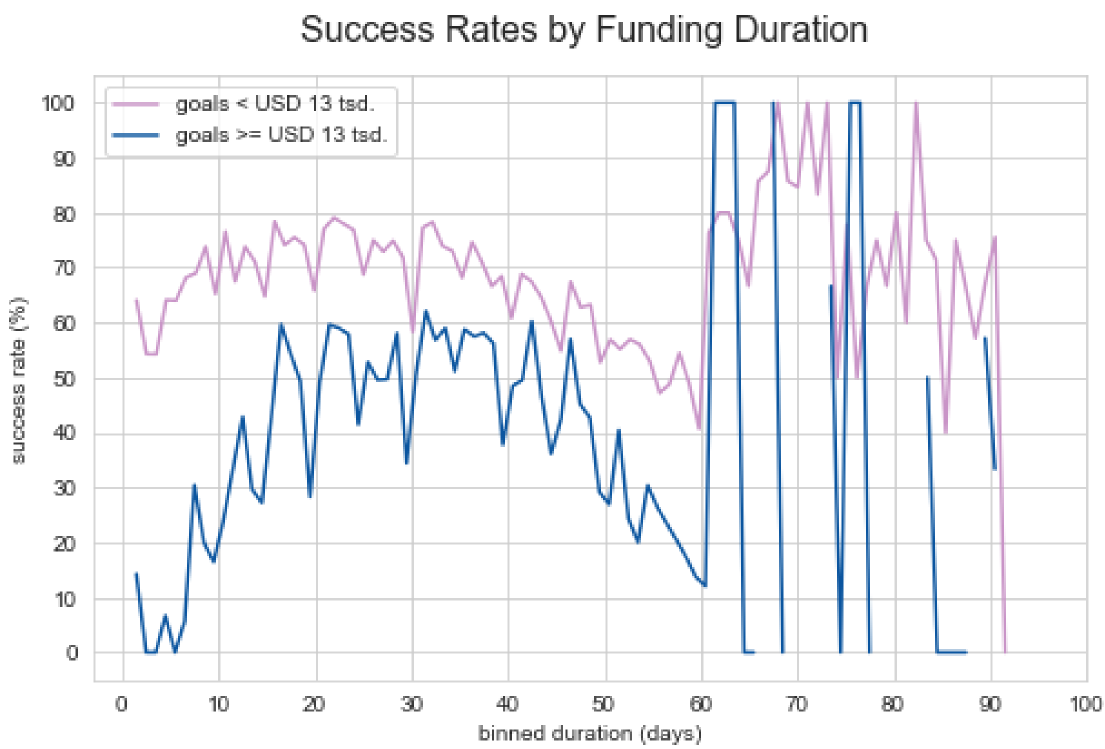
Clearly, the funding duration changed according to the goal. The higher the goal, the longer was the mean funding duration. The most occurrences, however, remain around 30 days independently from the funding ambitions and result of the campaign.

No matter how high the funding goal, successful projects on average scheduled shorter funding periods.

The duration difference between projects seeking below USD {{goal_25}} and above USD {{format_num(goal_95)}} was surprisingly short. Successful low goal projects on average sought funding within 28 days, while very high goal projects only took a week longer: 35 days.

While the above boxplots give us a general notion about duration and success, I am curious if we find more meaningful information about success rates for each funding duration. Below, I'm going to choose a line plot approach by binning duration periods and calculating their success rates. To balance out the success differences caused by the scope of a goal, I'm going to divide the plot in projects with goals above and below the 75% quantile.

```
In [144]: # settings
          plt.figure(figsize=[8,5])

          # utility to cluster duration
          def binned_duration(df, bin_count):
              # cluster duration
              bin_size = (df['duration_days'].max()-df['duration_days'].min()) / bin_count
              bin_edges = np.arange(df['duration_days'].min(), df['duration_days'].max()+bin_s
              bin_centers = bin_edges[:-1] + bin_size/2
              pd.set_option('mode.chained_assignment', None) # turn off warning
              df['duration_bin'] = pd.cut(df['duration_days'], bin_edges, labels=bin_centers)
              return df

          # calculate success rate for every bin and plot
          def plot_success_r(df_binned):
              # calculate success rate for every bin
              success_r = (df_binned[df_binned.status == 'successful']['duration_bin'].value_c
                           / df_binned['duration_bin'].value_counts(sort=False)*100).values
              plt.errorbar(x = df_binned['duration_bin'].value_counts(sort=False).index,
                           y = success_r, color=sns.set_palette([pledged_color, goal_color]))

          # plot low to moderately high goals
          df_duration_binned = binned_duration(ks_compl[ks_compl.goal_hist_usd < goal_75], 90)
          plot_success_r(df_duration_binned)

          # plot rate above moderately high goals
          df_duration_binned = binned_duration(ks_compl[ks_compl.goal_hist_usd >= goal_75], 90
          plot_success_r(df_duration_binned)

          # ticks and labels
          plt.title("Success Rates by Funding Duration ", fontsize=16, pad=15)
          plt.xticks(np.arange(0, 100+1, 10))
          plt.xlabel("binned duration (days)")
          plt.yticks(np.arange(0, 100+1, 10))
          plt.ylabel("success rate (%)")
          plt.legend(['goals < USD 13 tsd.', 'goals >= USD 13 tsd.'])
          plt.show()
```



7.3.6 Summary Duration

I cannot confirm that higher funding durations are generally rewarded with higher success rates. No matter if a campaign was successful or failed, the median period was generally around 30 days. We found that success rates generally peaked for a period of 30 days.

Adding the level of the goal to my investigation revealed that average funding durations appear to be a little longer when the goals were higher. Successful low goals under USD {{format_num(goal_25)}} had a mean funding duration of 28 days. Successful very high goal projects between USD {{format_num(goal_75)}} to {{format_num(goal_95)}} ran on average a week longer (35 days).

We found that the highest and most constant success chances were between 15 to 35 days for projects below USD {{format_num(goal_75)}}. We know that success chances are generally lower for higher goals. Nevertheless, we observe that creators of higher goal projects can extend their funding duration up to 48 days without losing significant success chances.

There is a severe dent in success rates at the duration of 30 days. Despite using relative numbers, this may be attributed to the unequivocal popularity of 30 day periods. This assumption is supported by the regular recessions that appear in duration intervals of 5 (e.g. 15, 20, 25 periods). Those periods appear to be most common. It may be worthwhile to further investigate whether creators can increase their success chances by shortening or prolonging the 30 days period by roughly 1-2 days. However, this would go beyond this visual analysis.

60 days funding durations were also quite popular. Unfortunately, they were attributed with the highest failure rates, especially for higher goal projects. Interestingly, for periods longer than 60 days, success rates increase up to roughly 90-100%. However, keep in mind that the project

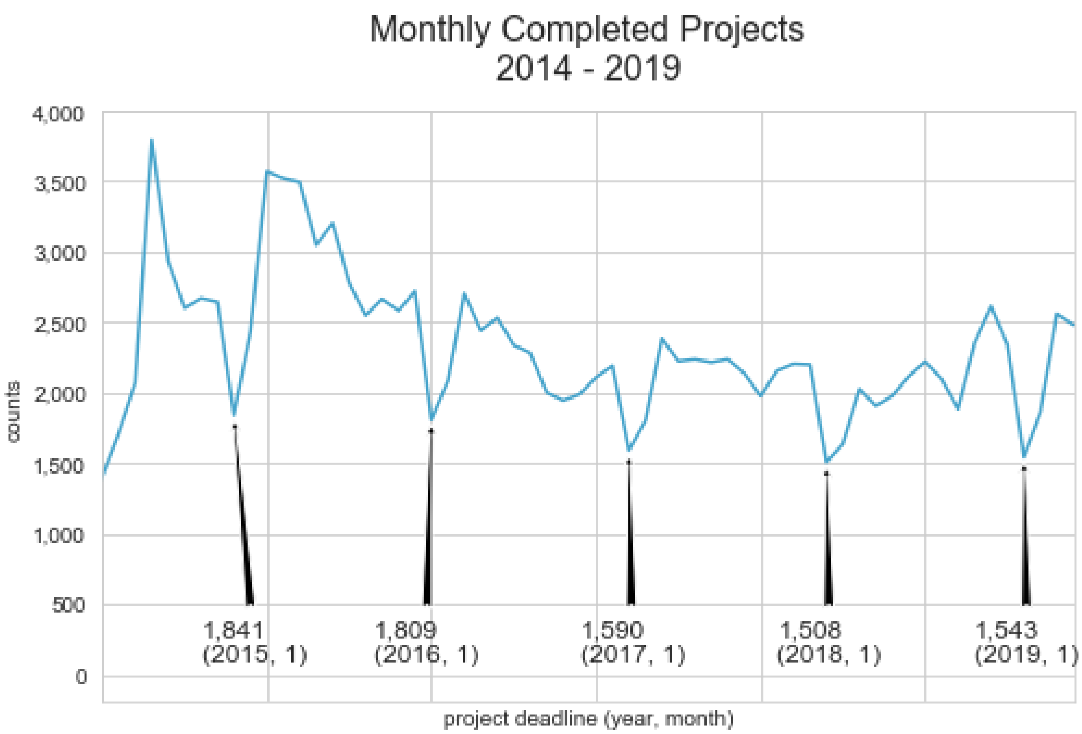
counts of long funding durations were very uncommon: only 24 projects had a funding duration of 70 days.

7.4 Seasons

Throughout this investigation, we came again and again across seasonal fluctuations. The plot below highlights the differences in absolute project counts throughout the past years 2014 - 2019.

In [145]:
```
# settings
plt.figure(figsize=[8,5])

# count projects ending by month
df = ks_compl.project_id.groupby([ks_compl.deadline.dt.year, ks_compl.deadline.dt.mon

# line plot of project counts
ax = df.plot(color=cust_blue)

#zoom into year
plt.xlim(60, 119)

# find minima
ymins = [df.xs(year).values.min() for year in range (2014, 2020)]
xmins = [df.iloc[df.values == ymin].index[0] for ymin in ymins]

# annotate minima
ax.annotate(format_num(ymins[0]) + "\n" + str(xmins[0]), xy=(56, ymins[0]),
            xytext=(53,100), fontsize=12,
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))

ax.annotate(format_num(ymins[1]) + "\n" + str(xmins[1]), xy=(68, ymins[1]-10),
            xytext=(66,100), fontsize=12,
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))

ax.annotate(format_num(ymins[2]) + "\n" + str(xmins[2]), xy=(80, ymins[2]-10),
            xytext=(76.5,100), fontsize=12,
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))

ax.annotate(format_num(ymins[3]) + "\n" + str(xmins[3]), xy=(92, ymins[3]-10),
            xytext=(89,100), fontsize=12,
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))

ax.annotate(format_num(ymins[4]) + "\n" + str(xmins[4]), xy=(104, ymins[4]-10),
            xytext=(101,100),  fontsize=12,
            arrowprops=dict(facecolor='black', arrowstyle="fancy"))

# In the year 2019, we found April to be the minima. Since, I want to depict the Jan
ax.annotate(format_num(df.xs(2019).values[0]) + "\n(2019, 1)", xy=(116, df.xs(2019).v
            xytext=(113,100), fontsize=12,
```

```
                arrowprops=dict(facecolor='black', arrowstyle="fancy"))

# labels and titles
plt.title("Monthly Completed Projects\n2014 - 2019", fontsize=16, pad=15)
plt.xlabel('project deadline (year, month)')

# turn off ticks
plt.tick_params(axis='x', which='both', bottom=False, top=False, labelbottom=False)

format_yticks(4000, 500)
plt.ylabel("counts")

plt.show()
```



The project counts dropped dramatically, every year in January by roughly 500 campaigns. This may be caused by the behavior of project creators by not running campaigns or creating campaigns which do not appeal to the audience. Additionally, potential supporters may be less willing to pledge in January.

I'm going to start the analysis of seasonal effects by investigating success and failure rates. Than, I'm going into detail about the general user behavior throughout the year to find out whether seasonal changes affected the final collected funding.

With project numbers stabilizing by the end of 2014, I'm going to consider for the following analysis only values after 2015.

What time of the year is related with the best chances for success?

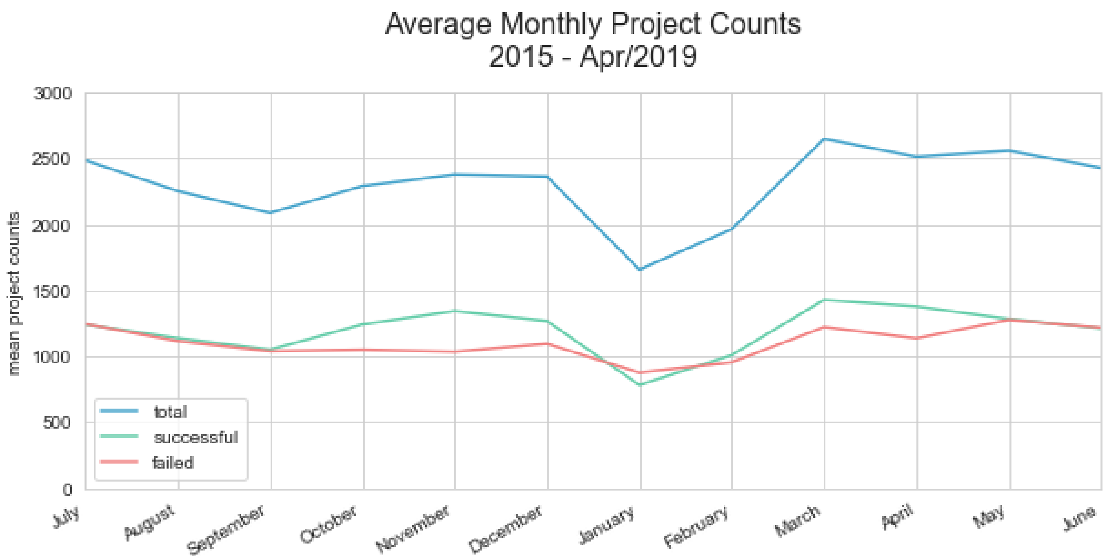
In [146]:
```
# Investigate failure and success rates on a monthly bases

# only consider data after 2015 to today - April 2019
ks_15_19  = ks_compl[ks_compl.deadline.dt.year > 2014 ]

# count projects ending each month
counts =  ks_15_19.deadline.groupby([ks_15_19.deadline.dt.month]).count()

# get average by dividing Jan-Apr months by 5 other months by 4
proj_counts = [count / 5 for count in counts[:4]] + [count / 4 for count in counts[4

# calculate average monthly project counts of successful and failed projects
df_success_15  = ks_15_19[ks_15_19.status == "successful"]
counts =  df_success_15.deadline.groupby([df_success_15.deadline.dt.month]).count()
success_proj_counts = [count / 5 for count in counts[:4]] + [count / 4 for count in c

df_fail_15  = ks_15_19[ks_15_19.status == "failed"]
counts =  df_fail_15.deadline.groupby([df_fail_15.deadline.dt.month]).count()
failed_proj_counts = [count / 5 for count in counts[:4]] + [count / 4 for count in co

# create combined dataframe
ks_months = pd.DataFrame({'avg_total': proj_counts, 'avg_success': success_proj_coun

# As the interesting behavior is happening in January, I want to shift January to th
# Rearange ordering so that July is at the frst place
ks_months_sorted = ks_months[6:].append(ks_months[:6]).reset_index(drop=True)
ks_months_sorted.head()
```

Out[146]:

	avg_total	avg_success	avg_failed
0	2,486.25	1,241.0	1,245.25
1	2,253.75	1,138.25	1,115.5
2	2,087.75	1,050.0	1,037.75
3	2,291.0	1,242.0	1,049.0
4	2,377.75	1,343.5	1,034.25

In [147]:
```
# plot
ax = ks_months_sorted.plot(color=sns.set_palette(status_colors));

# figure settings
fig = plt.gcf();
fig.set_size_inches(10, 4);

# ticks and labels
xlocs = np.arange(0,12)
plt.xticks(xlocs, months, rotation=30, ha='right');

ylocs = np.arange(0, 3000+500, 500)
ylabels = [format_num(yloc) for yloc in ylocs]
```

```
ax.set_yticks(ylocs, ylabels)

plt.ylabel("mean project counts");
plt.title("Average Monthly Project Counts\n2015 - Apr/2019", fontsize=16, pad=15)

plt.legend(['total', 'successful', 'failed'], loc=3)
plt.show()
```

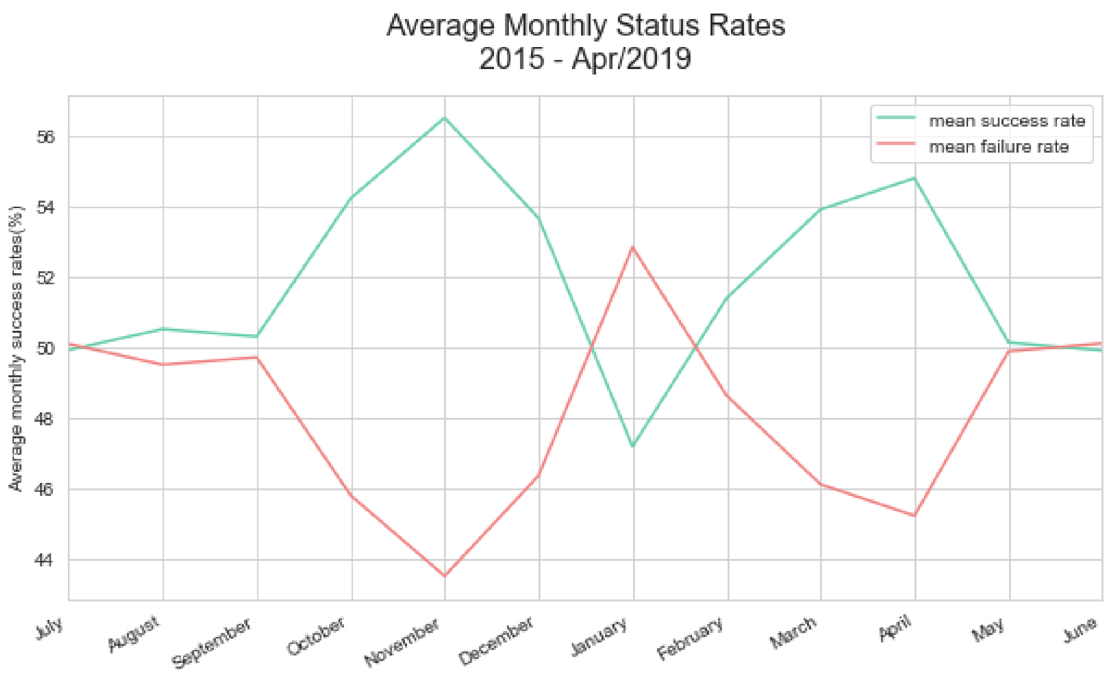


In terms of absolute counts by month, in January successful campaigns on average dropped below the number of failed campaigns. In September project counts were also lower than usual. In contrast to January, successful and failed campaigns uniformly decreased.

In March, we find the highest mean counts of successful campaigns. November, October, December and May were also popular months to launch projects. March and November seem to be have the widest gap between successful and failed campaigns. To prove this, we are going to calculate the proportion of successful and failed campaigns of the total of all campaigns.

In [148]:
```
# create new columns of avg monthly avg success and failure rates
ks_months_sorted['success_r'] = [ks_months_sorted.iloc[i][1] *100/ ks_months_sorted.i
ks_months_sorted['failure_r'] = [ks_months_sorted.iloc[i][2] *100/ ks_months_sorted.i

# plot
ax = ks_months_sorted[['success_r', 'failure_r']].plot(color=sns.set_palette(status_c

# figure settings
fig = plt.gcf();
fig.set_size_inches(10, 5);

plt.xticks(xlocs, months, rotation=30, ha='right');
```

```
plt.ylabel("Average monthly success rates(%)");
plt.title("Average Monthly Status Rates\n2015 - Apr/2019", fontsize=16, pad=15);
plt.legend(['mean success rate', 'mean failure rate'])
plt.show();
```



The plot above proves that November was attributed with the best chances. 56% of campaigns ended in success. April and March followed with success rates around 54%.

January was definitely the least successful month to end a campaign. On average, more than every second campaign failed (53%). September, February, May, June and July were not the best months to end a campaign, but the success chances were still above 50%.

In addition to the chances for success, a campaign creator's main goal is to seek the highest amount possible to start their venture. Hence, I am going to determine whether the amount of investments creators collected changed according to the time of year.

Are supporters more likely to pledge in a certain time of year?

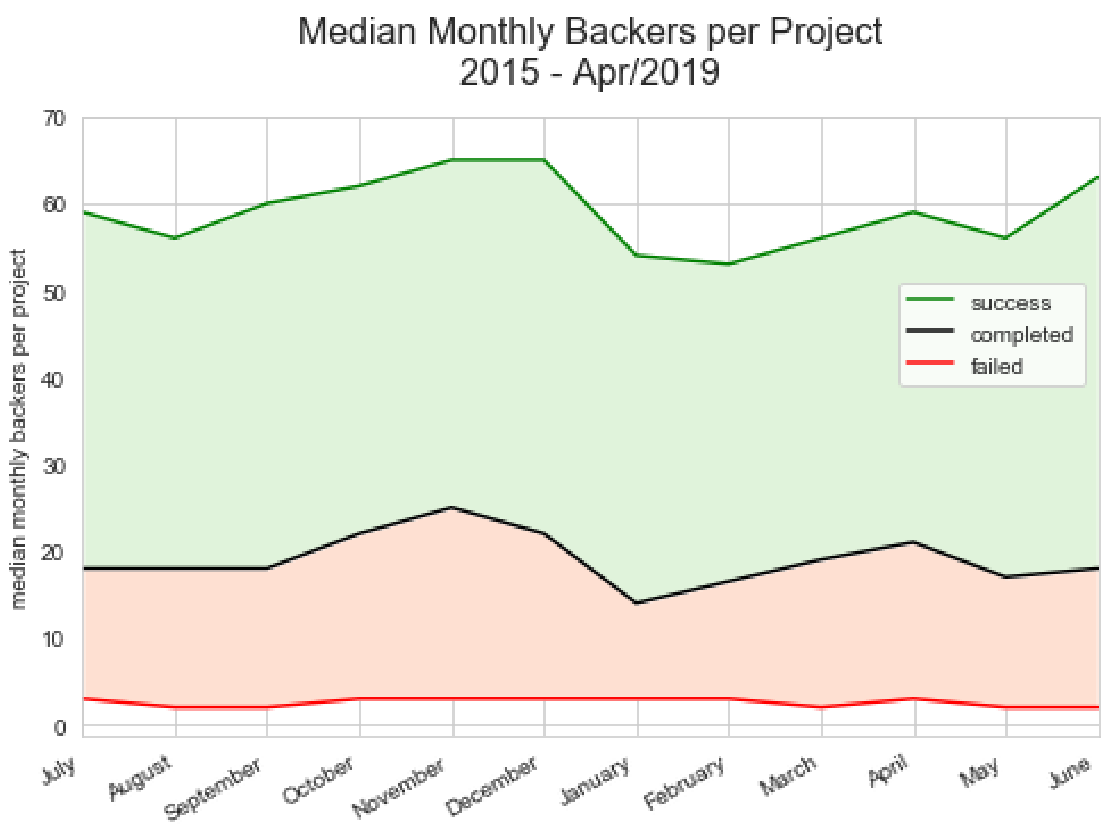
```
In [149]: # we are going to work with our 95-quantile data to allow reasonable interpretation

          # select only projects from 2015 on
          ks_compl_95_latest   = ks_compl_95[ks_compl_95.deadline.dt.year > 2014 ]
          ks_compl_95_latest_s  = ks_compl_95_latest[ks_compl_95_latest.status == "successful"]
          ks_compl_95_latest_f  = ks_compl_95_latest[ks_compl_95_latest.status == "failed"]
          print(f"After 2014:\n\
          Project count total: {format_num(len(ks_compl_95_latest))}\n\
          Project count success: {format_num(len(ks_compl_95_latest_s))}\n\
          Project count failed: {format_num(len(ks_compl_95_latest_f))}")
```

```
After 2014:
Project count total: 105,438
Project count success: 54,041
Project count failed: 51,397
```

```
In [150]: # utility function to create a median values of specific features grouped by months
          def group_data(df, feature):
              # select by successful and failed projects
              df_s  = df[df.status == "successful"]
              df_f  = df[df.status == "failed"]

              # Due to strong skew, I use median instead of average to calculate the number of
              feat_total = df[feature].groupby([df.deadline.dt.month]).median()
              feat_success = df_s[feature].groupby([df_s.deadline.dt.month]).median()
              feat_fail = df_f[feature].groupby([df_f.deadline.dt.month]).median()

              # create data frame
              df_months_95 = pd.DataFrame({'total': feat_total.values,
                                           'successful': feat_success.values,
                                           'failed': feat_fail.values})

              # change order of data, bring January to center position
              return df_months_95[6:].append(df_months_95[:6]).reset_index(drop=True)

          # utility function to plot features grouped by months
          def plot_monthly(df):
              # color settings
              cust_color = ['green', 'black', 'red']

              # plot
              ax = df[['successful', 'total', 'failed']].plot(color=sns.set_palette(cust_color)

              # highlight differences
              x_ticks = np.arange(0, len(ks_months_95_sorted))
              y1 = df['successful']
              y2 = df['total']
              y3 = df['failed']
              ax.fill_between(x_ticks, y1, y2 , where=y1 >= y2, facecolor=fill_green, interpola
              ax.fill_between(x_ticks, y2, y3 , where=y2 >= y3, facecolor=fill_red, interpolate

              # figure settings
              fig = plt.gcf();
              fig.set_size_inches(8, 5);

              # ticks and labels
              plt.xticks(xlocs, months, rotation=30, ha='right');
```

```
        return ax
```

```
In [151]: # plot median backers counts per projects for each month
          ks_months_95_sorted = group_data(ks_compl_95_latest, 'backers_count')
          ax = plot_monthly(ks_months_95_sorted)

          # ticks and labels
          plt.yticks(np.arange(0, 70+10, 10))
          plt.ylabel("median monthly backers per project");
          plt.title("Median Monthly Backers per Project\n2015 - Apr/2019", fontsize=16, pad=15
          plt.legend(["success", "completed", "failed" ], loc=1,  bbox_to_anchor=(0.999, 0.75)
          plt.show();
```

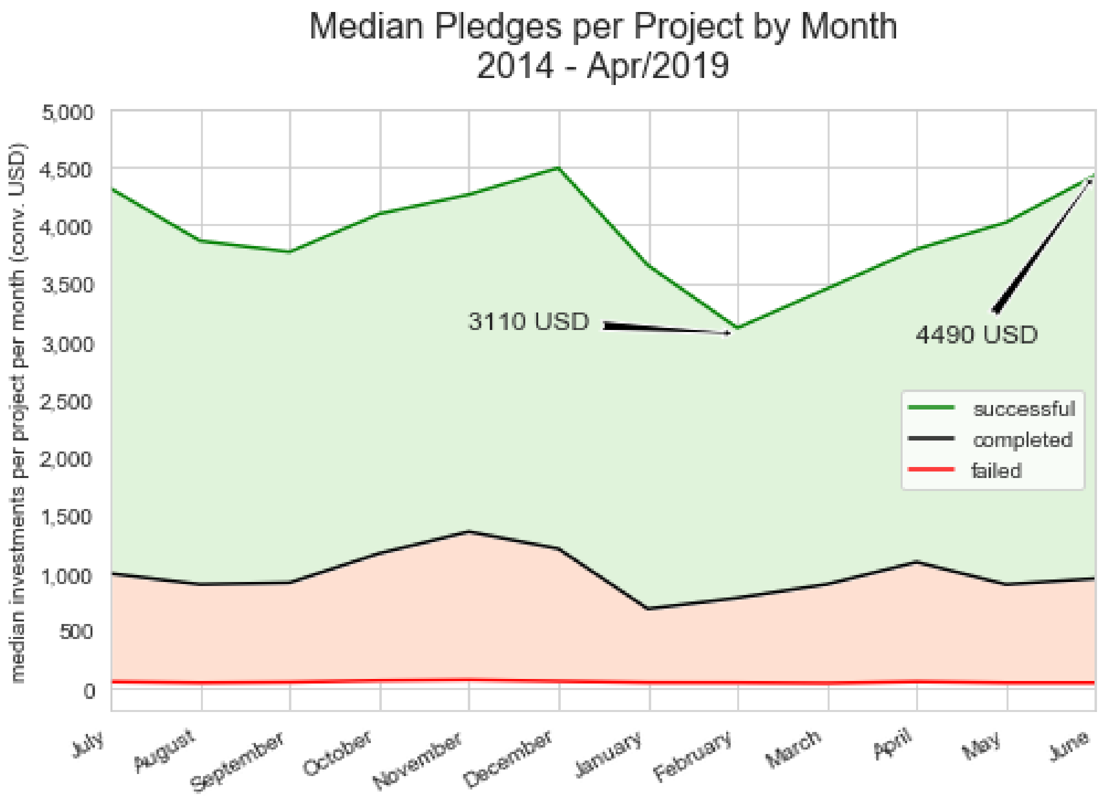


To start, I plotted the relative amount of backers per completed project, grouped by months. The median amount of backers peaked in November for all completed projects. Only considering successful projects resulted in November, December and June as the months with increased chances. The lowest number of supporters per project were commonly in February and January.

Unlike success rates, we don't find strong peaks in March/April, but in June/July. Also, having the strongest recession of backers in February, contradicts the increased success rates in February.

Insofar the success of projects is further determined by the amount every individual supporter invests and by the amount a creator seeks for funding.

```
In [152]: # plot median amount pledged per project by month
          ks_months_95_sorted = group_data(ks_compl_95_latest, 'pledged_hist_usd')
          ax = plot_monthly(ks_months_95_sorted)

          # annotate
          # maximum success
          max_success = int(round(ks_months_95_sorted.successful.values.max()))
          ax.annotate(str(max_success) + " USD", fontsize=12, xy=(11 , max_success - 50),
                      xytext=(9, max_success-1500), arrowprops=dict(facecolor='black', arrowsty

          # min success
          min_success =int(round(ks_months_95_sorted.successful.values.min()))
          ax.annotate(str(min_success) + " USD", fontsize=12, xy=(7, min_success - 50),
                      xytext=(4, min_success), arrowprops=dict(facecolor='black', arrowstyle="

          # ticks and labels
          format_yticks(5000, 500)
          plt.ylabel("median investments per project per month (conv. USD)");
          plt.title("Median Pledges per Project by Month\n2014 - Apr/2019", fontsize=16, pad=1
          plt.legend(["successful", "completed", "failed" ], loc=1,  bbox_to_anchor=(1, 0.55))
          plt.show();
```



The pledged funding per project seems to be lagging by one month compared to success rates. On average, creators collected the lowest amount of funding in February (USD {{min_success}}), whereas the success rates were lowest in January.

The highest median investments were collected in June: USD {{max_success}}. Creators who ran a campaign ending in June on average collected {{round((4507-3112) / 3112 * 100)}} % more compared to February. In absolute numbers, this is USD {{max_success-min_success}}. At the same time, chances of success in June were comparatively low.

December was the second best month to collect high funding. Again, pledges are lagging behind success rates, which peaked in November.

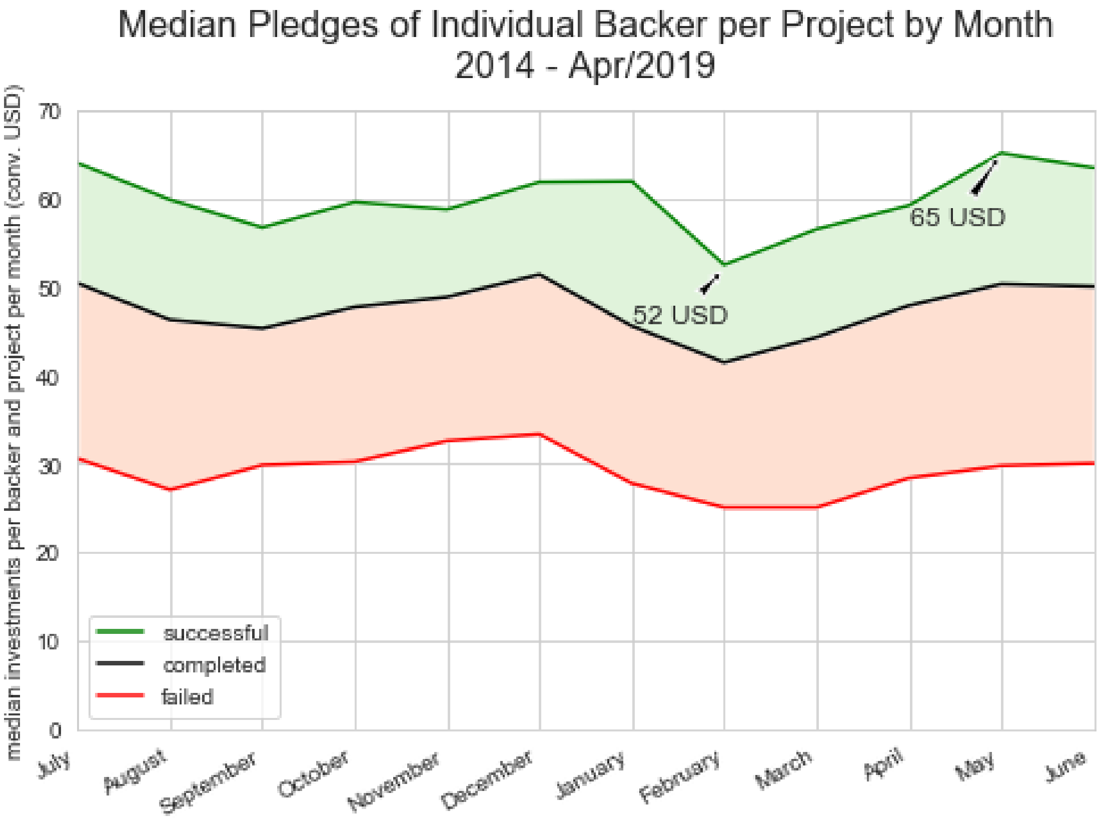
Whereas March had quite high success rates, the collected funding was even lower than in January.

Considering both, success rates and the total investment collected, we see most potential in the months October/November/December. On the other hand, January, February and September performed worst.

Absolute counts, success rates, pledges and backers show similarities, but their behavior does not fully coincide. Therefore, we suspect multiple factors to influence seasonal fluctuations.

One assumption is that an individual backer's willingness to pledge changes over a year. Let's plot the median pledged per backer for each project.

```
In [153]: # Investigate pledges per backer and project per each month
          ks_months_95_sorted = group_data(ks_compl_95_latest, 'pledged_backer_r')
          ax = plot_monthly(ks_months_95_sorted)

          # annotate
          # maximum success
          max_success = int(round(ks_months_95_sorted.successful.values.max()))
          ax.annotate(str(max_success) + " USD", fontsize=12, xy=(10 , max_success),
                      xytext=(9, max_success-8), arrowprops=dict(facecolor='black', arrowstyle=

          # min success
          min_success =int(round(ks_months_95_sorted.successful.values.min()))
          ax.annotate(str(min_success) + " USD", fontsize=12, xy=(7, min_success),
                      xytext=(6, min_success-6), arrowprops=dict(facecolor='black', arrowstyle=

          # ticks and labels
          ylocs = np.arange(0, 70+10, 10)
          ylabels = [format_num(yloc) for yloc in ylocs]
          plt.yticks(ylocs, ylabels)
          plt.ylabel("median investments per backer and project per month (conv. USD)");

          plt.title("Median Pledges of Individual Backer per Project by Month\n2014 - Apr/2019
          plt.legend(["successful", "completed", "failed"])
          plt.show();
```



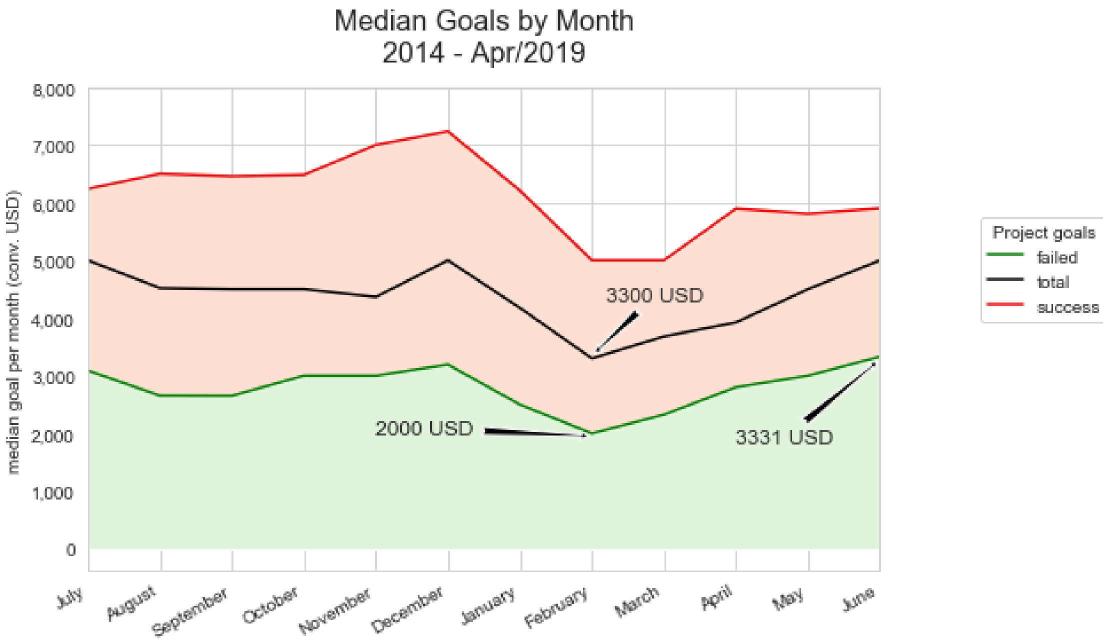
Individual supporters backed the highest amounts per project in May and the lowest amounts in February. The difference between both months was USD 13 per pledge. In September the individual median pledges were also quite low.

Roughly the best times to seek high amounts per supporter were April-July and October-January. Since success rates and median pledged per project were low in January, the tendency to pledge high at the beginning of the year comes with a surprise.

However, the individual pledges also depend on how a creator designed rewards and the scope of the funding goal.

```
In [154]: # Investigate goals per project each month
          ks_months_95_sorted = group_data(ks_compl_95_latest, 'goal_hist_usd')
          ax = plot_monthly(ks_months_95_sorted)

          # highly differences
          y1 = ks_months_95_sorted['failed']
          y2 = ks_months_95_sorted['total']
          y3 = ks_months_95_sorted['successful']
          ax.fill_between(xlocs, y1, y3 , where=y1 >= y3, facecolor=fill_red, interpolate=True)
          ax.fill_between(xlocs, y3 , where=y3 >= xlocs, facecolor=fill_green, interpolate=True)

          # annotate
          # minimum total
```

```
min_total = int(ks_months_95_sorted.total.values.min())
ax.annotate(str(min_total) + " USD", fontsize=12, xy=(7 ,min_total + 50),
            xytext=(7.2, min_total+1000), arrowprops=dict(facecolor='black', arrowst

# maximum success
max_success =int(round(ks_months_95_sorted.successful.values.max()))
ax.annotate(str(max_success) + " USD", fontsize=12, xy=(11 , max_success - 50),
            xytext=(9, max_success-1500), arrowprops=dict(facecolor='black', arrowst

# min success
min_success =int(round(ks_months_95_sorted.successful.values.min()))
ax.annotate(str(min_success) + " USD", fontsize=12, xy=(7, min_success - 50),
            xytext=(4, min_success), arrowprops=dict(facecolor='black', arrowstyle="

# ticks and labels
format_yticks(8000,1000)
plt.ylabel("median goal per month (conv. USD)");
plt.title("Median Goals by Month\n2014 - Apr/2019", fontsize=16, pad=15);
plt.legend(["failed", "total", "success" ], title="Project goals", loc=1,  bbox_to_a
plt.show();
```



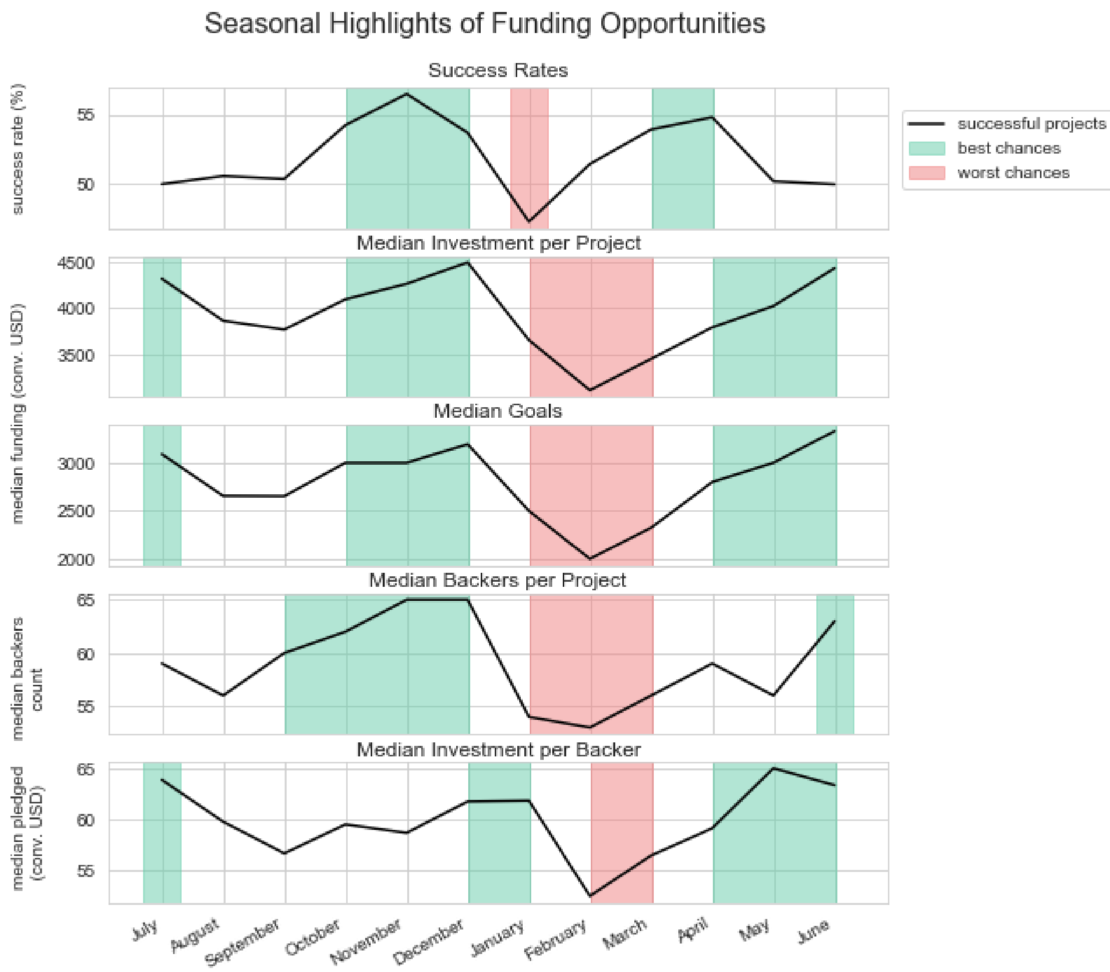
The graph shows that pessimistic project goals were more successful across the entire year. There is a significant dent of median project goals in February at USD 2k. In February low-goal-projects seem to be more common.

The most ambitious successful goal projects are typically ending in June/July and December.

The above plots demonstrate that the success rates and user behavior changes according to the season of the year. We found some commonalities, but also contradicting behavior. To keep it neatly arranged, let's put it all in one plot.

```
In [155]: # bring them all in one plot
          fig, ax = plt.subplots(5, 1, sharex=True)

          # plot success rates
          ax[0].plot(xlocs, ks_months_sorted['success_r'], color='black')

          # data
          features = ['pledged_hist_usd', 'goal_hist_usd', 'backers_count', 'pledged_backer_r']

          # plot features
          for i, feature in enumerate(features):
              ks_months_95_sorted = group_data(ks_compl_95_latest, feature)
              ax[i+1].plot(xlocs, ks_months_95_sorted['successful'], color='black', label="succ
              plt.subplots_adjust(bottom=-0.2)

          # highlight best months
          # success rates: highlight positively Oct-Dec and March/April
          ax[0].axvspan(3, 5,color=cust_green, alpha=0.5, label="best chances")
          ax[0].axvspan(8, 9, color=cust_green, alpha=0.5)

          # pledged_hist_usd: highlight positively May, June, July and Oct-Dec
          ax[1].axvspan(3, 5,  color=cust_green, alpha=0.5)
          ax[1].axvspan(9, 11, color=cust_green, alpha=0.5)
          ax[1].axvspan(-0.3, 0.3,  color=cust_green, alpha=0.5)

          # goal_hist_usd: highlight positively Apr-July and Oct-Dec
          ax[2].axvspan(9, 11, color=cust_green, alpha=0.5)
          ax[2].axvspan(-0.3, 0.3,  color=cust_green, alpha=0.5)
          ax[2].axvspan(3, 5, color=cust_green, alpha=0.5)

          # backers counts: highlight positively June/July and Sept-Dec
          ax[3].axvspan(10.7, 11.3,  color=cust_green, alpha=0.5)
          ax[3].axvspan(2, 5, color=cust_green, alpha=0.5)

          # pledged per backer: highlight positively Apr-July and Dec/Jan
          ax[4].axvspan(9, 11, color=cust_green, alpha=0.5)
          ax[4].axvspan(-0.3, 0.3,  color=cust_green, alpha=0.5)
          ax[4].axvspan(5, 6, color=cust_green, alpha=0.5)

          # highlight worst months
          ax[0].axvspan(5.7, 6.3,  color=cust_red, alpha=0.5, label="worst chances")  # success
          ax[1].axvspan(6, 8, color=cust_red, alpha=0.5) # pledged hist usd - Jan-Mar
          ax[2].axvspan(6, 8, color=cust_red, alpha=0.5) # goals hist usd - Jan-Mar
          ax[3].axvspan(6, 8, color=cust_red, alpha=0.5) # backers count - Jan-Mar
          ax[4].axvspan(7, 8, color=cust_red, alpha=0.5) # pledged per backer - Feb-Mar
```

```
# figure size
fig.set_size_inches(8, 6);

# ticks and labels
fig.text(0.03, 0.8, "success rate (%)", va='center', rotation='vertical')
fig.text(0.03, 0.45, "median funding (conv. USD)", va='center', rotation='vertical')
fig.text(0.03, 0.1, "median backers\n      count", va='center', rotation='vertical')
fig.text(0.03, -0.1, "median pledged\n  (conv. USD)", va='center', rotation='vertica

fig.suptitle('Monthly Funding Behavior\n2014 - Apr/2019', y=1.05, fontsize=16 )
ax[0].set_title('Success Rates', fontsize=12)
ax[1].set_title('Median Investment per Project', pad=4, fontsize=12)
ax[2].set_title('Median Goals', pad=4, fontsize=12)
ax[3].set_title('Median Backers per Project', pad=4, fontsize=12)
ax[4].set_title('Median Investment per Backer', pad=4, fontsize=12)
plt.suptitle("Seasonal Highlights of Funding Opportunities", fontsize=16)

plt.xticks(xlocs, months, rotation=30, ha='right');
plt.legend(["successful projects", "best chances", "worst chances"], loc=1,  bbox_to_

plt.show()
```



7.4.1 Summary Seasons

We do find seasonal changes of success rates and the collected funding throughout a year. It's advisable for creators to carefully choose the month in which they plan to end a campaign. By optimizing the season, creators may be able to increase success chances or to increase the total funding.

Above, I highlighted the months with the best and lowest chances over the year. I separated successful campaigns by features that may determine a campaign's success. We can differentiate a campaign's success in general success chances, number of backers and the amount of funding collected, e.g. goals, total investment and the individual pledged amount per backer.

Generally, we found an overlap of best chances in December. Ignoring some inconsistencies, I identified October to December and April to July as the most promising months to run a campaign. January to March performed suboptimal. However, the best month for a creator may depend on the individual campaign objectives. Some creators may prefer the best possible success chances, while others may prefer to increase their reach by addressing a maximum of possible backers or to collect the maximum funding possible.

I noticed that success rates behaved slightly different from funding attributes. The success chances were best from October to January and March and April. November was the safest bet for creators with the primary goal to end a campaign successfully. Those creators should avoid to run a campaign in January since success rates were roughly 10% lower.

Creators seeking high funding had the best chances in December or June. They should avoid launching January to March.

If the focus was to attract a maximum amount of backers, a creator's best chances were in November and December. In contrast, January to March were not advisable to seek a maximum of backers.

7.5 Featured

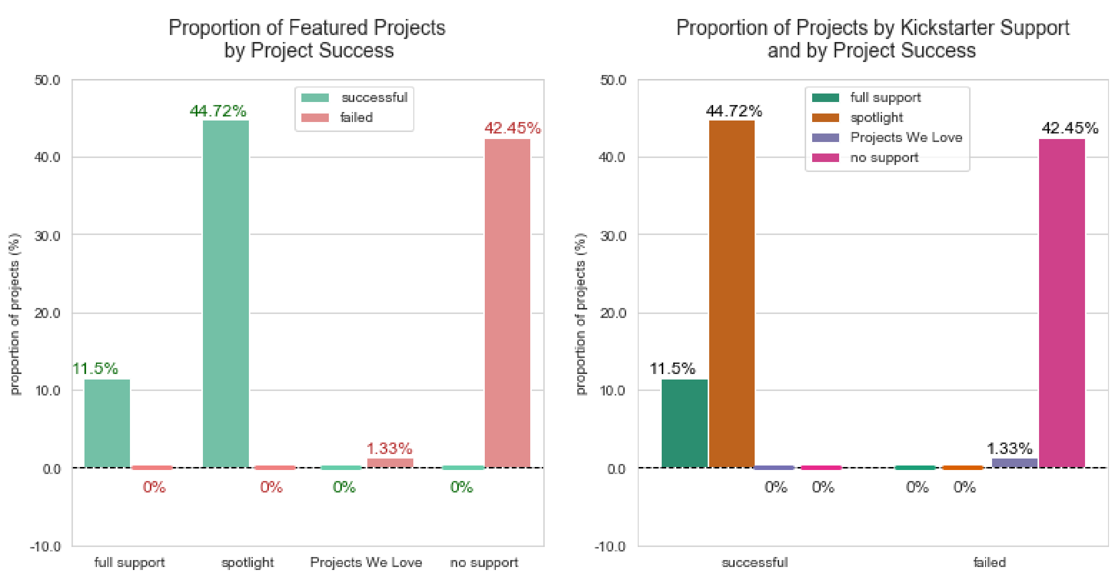
Kickstarter has the tools to actively support a project by rewarding a badge or introducing a project on their landing page or other digital channels. The support offered by Kickstarter may affect a campaign's success by increasing success chances or increasing the total of the collected investment.

Does Kickstarter's promotional support increase the chances of a campaign's success?

```
In [156]: # relative values
          # settings
          plt.figure(figsize = [13, 6])
          # cust_color = [cust_green, cust_red]
          color=sns.set_palette(status_colors[1:])
          dark_colors = ['#7570b3', '#e7298a', '#1b9e77', '#d95f02']

          # order
          status_order = ks_compl.status.value_counts().index
          feat_order = ['full support', 'spotlight', 'Projects We Love', 'no support']

          # get proportion of most common group - successful projects
          # - relative values
          n_points = ks_compl.shape[0]
          max_feat = ks_compl['featured'].value_counts().max()
          max_feat_prop = max_feat / n_points
          max_status = ks_compl['status'].value_counts().max()
          max_status_prop = max_status / n_points

          # left plot: clustered bar chart featured categories vs. project status
          plt.subplot(1, 2, 1)
          sns.countplot(data = ks_compl, x = 'featured', hue = 'status',
                        order = feat_order, hue_order = status_order, color=color)

          # add zero line
          ax1 = plt.gca()
          ax1.axhline(linewidth=1, color='black', y=0.1, ls="--")

          # annotate percentages and add empty categories
          i = -0.5
```

```
xmin=0.13
k=-0.1
annot_color = ['darkgreen', 'darkgreen', 'firebrick', 'firebrick']
bar_color = [ cust_green, cust_green, cust_red, cust_red]
for j, feat in enumerate(feat_order):
    if j == 2:
        i += 0.5
        color_i = 'firebrick'
        xmin -= 0.12
        k = 0.29
    rate = (ks_compl.featured.value_counts()[feat] / n_points) * 100
    plt.text(i, ks_compl.featured.value_counts()[feat]+1000, str(round(rate, 2)) + "%
    fontsize=12, color=annot_color[j])
    ax1.axhline(linewidth=3, color=bar_color[::-1][j], y=0.1, xmin=xmin, xmax=xmin+0
    plt.text(j-k, -5000, "0%", fontsize=12, color=annot_color[::-1][j])
    xmin+=0.26
    i+=1

#label and title
plt.legend(loc=9, bbox_to_anchor=(0.6, 1))
plt.title("Proportion of Featured Projects\n by Project Success", fontsize=14, pad=15
plt.xlabel("")

# generate proportion tick marks
ylocs = np.arange(-0.1, 0.5+0.1, 0.1)
ylabels = ['{:0.1f}'.format(yloc*100) for yloc in ylocs]
plt.yticks(ylocs * n_points,ylabels )
plt.ylabel("proportion of projects (%)")

# right plot: clustered bar chart status counts categories related to Kickstarter su
# - relative values
plt.subplot(1, 2, 2)
color=sns.set_palette(sns.color_palette("Dark2"))
sns.countplot(data = ks_compl, x = 'status', hue = 'featured',
             order = status_order, hue_order = feat_order, color=color)

# add zero line
ax2 = plt.gca()
ax2.axhline(linewidth=1, color='black', y=0.1, ls="--")

# annotate rates
i = -0.45
for j, feat in enumerate(feat_order):
    if j == 2:
        i += 0.95
    rate = (ks_compl.featured.value_counts()[feat] / n_points) * 100
    plt.text(i, ks_compl.featured.value_counts()[feat]+1000, str(round(rate, 2)) + "%
    fontsize=12, color="black")
```

```
    i+=0.24

# add empty categories
xmin= 0.25
pos = 0.04
for i,c in enumerate(dark_colors):
    if i == 2:
        xmin += 0.1
        pos+=0.2
    ax2.axhline(linewidth=3, y=0.1, xmin=xmin, xmax=xmin+0.08, color=dark_colors[i])
    ax2.annotate("0%", fontsize=12, xy=(pos ,-5000))
    xmin +=0.1
    pos+=0.2

# generate proportion tick marks
ylocs = np.arange(-0.1, 0.5+0.1, 0.1)
ylabels = ['{:0.1f}'.format(yloc*100) for yloc in ylocs]
plt.yticks(ylocs * n_points,ylabels )
plt.ylabel("proportion of projects (%)")
plt.title("Proportion of Projects by Kickstarter Support\nand by Project Success", f
plt.legend(loc=9, bbox_to_anchor=(0.53, 1))
plt.xlabel("")

plt.show()
```

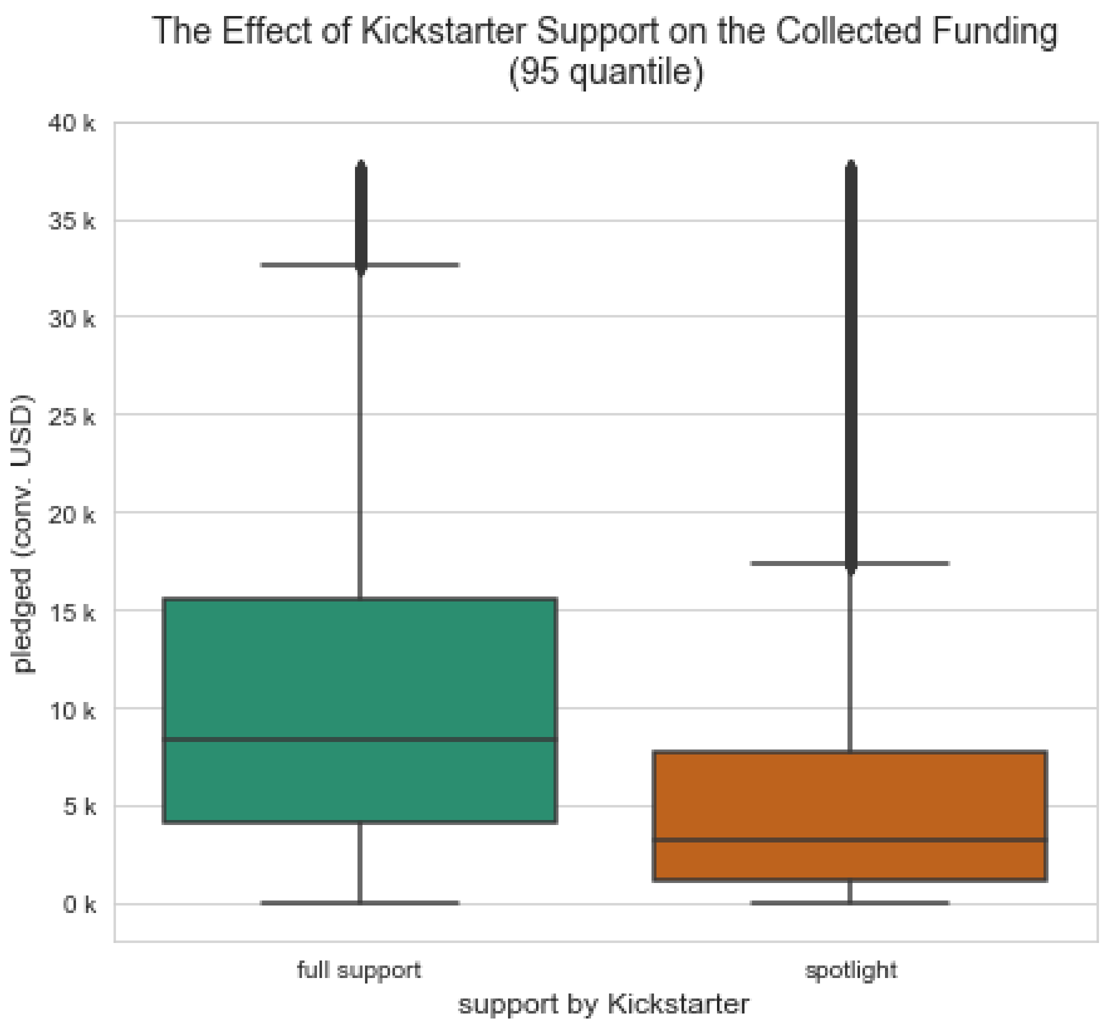


According to our data the support offered by Kickstarter was extremely relevant to win a campaign. Only projects that were supported by Kickstarter ended successfully. 45% of the projects were spotlighted on Kickstarter's channels and 12% of completed projects got full support. Unsupported projects or projects only receiving a Projects We Love badge did not succeed.

Since fully supported projects were awarded the badge in addition of being spotlighted by Kickstarter, I wonder if the badge affected the chances of a higher funding.

Does Kickstarter's "Projects We Love" badge increase the chances for a higher funding?

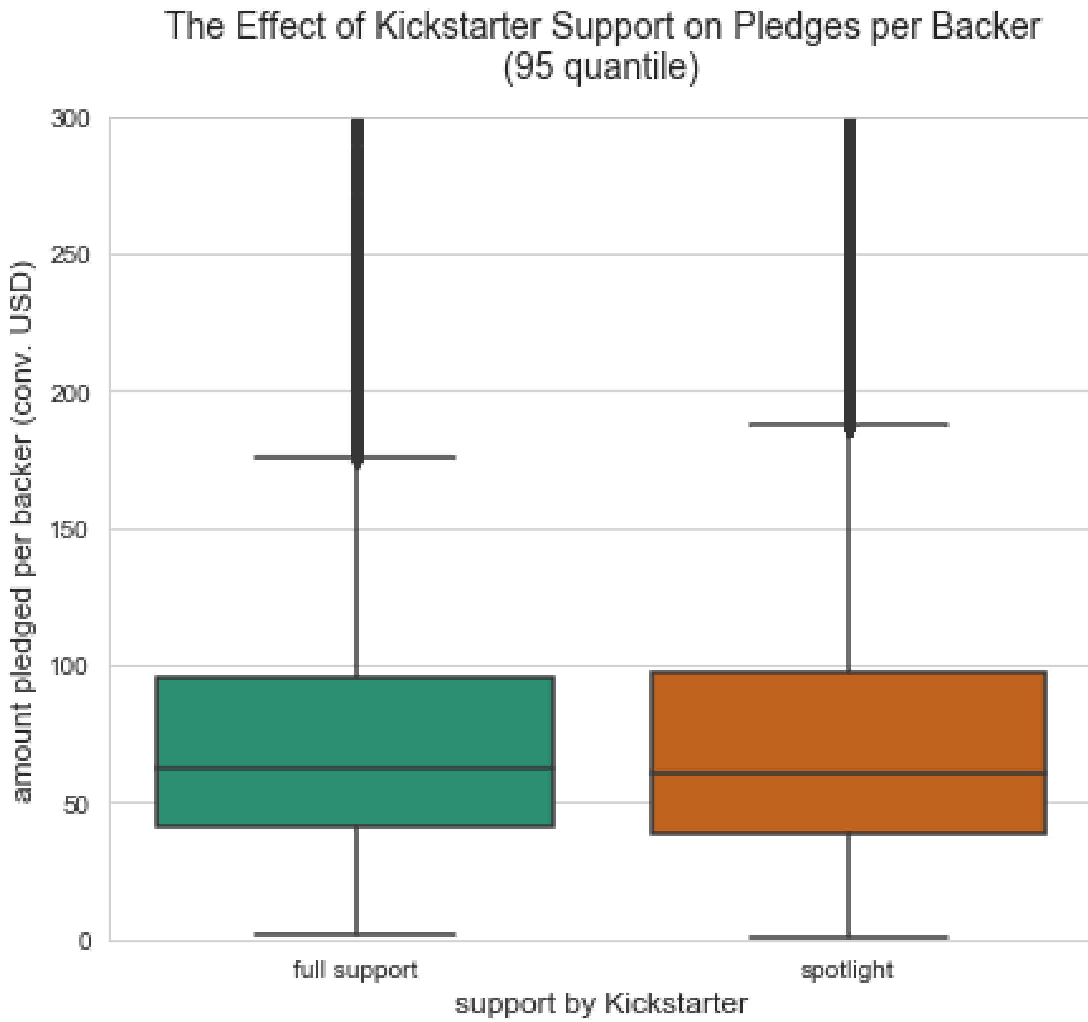
```
In [157]: # settings
          plt.figure(figsize = [7, 6])

          # violinplot of 95 quantile data to reduce strong skew caused by outliers
          ax = sns.boxplot(data = ks_compl_95_latest, x = 'featured', y = 'pledged_hist_usd', c

          # ticks and labels
          ylocs = np.arange(0, pledged_95+5000, 5000)
          ylabels = [str(int(yloc/1000)) + " k" for yloc in ylocs]
          plt.yticks(ylocs, ylabels)
          plt.xlabel("support by Kickstarter", fontsize=12)
          plt.ylabel("pledged (conv. USD)", fontsize=12)
          plt.title("The Effect of Kickstarter Support on the Collected Funding\n(95 quantile)"
          plt.show()
```



The “Projects We Love” badge clearly helped to increase the collected funding of successful campaigns. The median of campaigns that were only spotlighted was USD {{format_num(ks_compl_95_latest[ks_compl_95_latest.featured == “spotlight”][‘pledged_hist_usd’].median())}}, whereas campaigns which were awarded the badge sought USD {{format_num(ks_compl_95_latest[ks_compl_95_latest.featured == “full support”][‘pledged_hist_usd’].median())}}. This enhanced the median pledged funding by {{ format_num((ks_compl_95_latest[ks_compl_95_latest.featured == “full support”][‘pledged_hist_usd’].median()/ ks_compl_95_latest[ks_compl_95_latest.featured == “spotlight”][‘pledged_hist_usd’].median())*100)}}%.

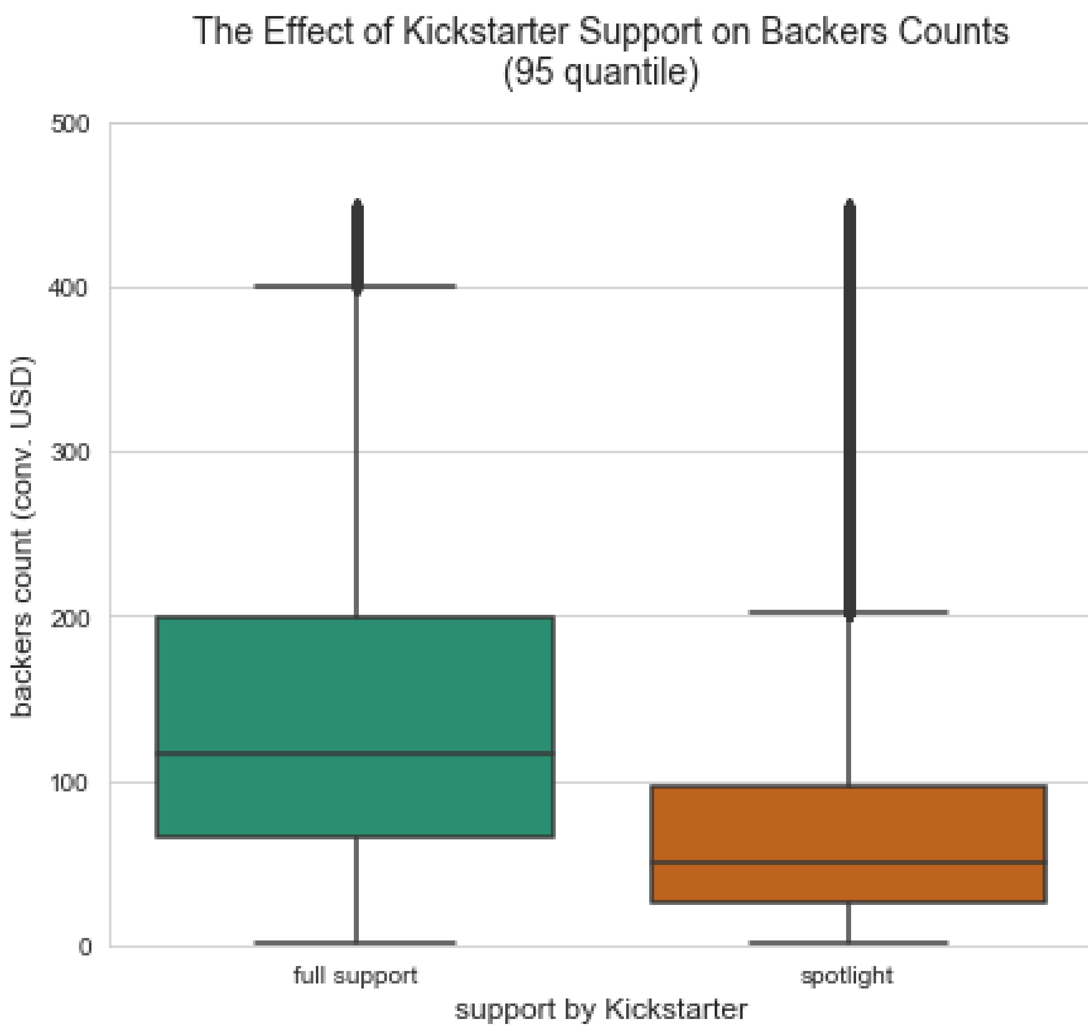
Not only the median pledges were higher. We notice that the entire interquartile range and the upper whisker increased by a factor of 2.

```
In [158]: # settings
          plt.figure(figsize = [7, 6])

          # violinplot 95 quantile data
          ax = sns.boxplot(data = ks_compl_95, x = 'featured', y = 'pledged_backer_r', order=fe

          # ticks and labels
          plt.ylim(0,300)
          plt.xlabel("support by Kickstarter", fontsize=12)
          plt.ylabel("amount pledged per backer (conv. USD)", fontsize=12)
          plt.title("The Effect of Kickstarter Support on Pledges per Backer\n(95 quantile)", f
          plt.show()
```



Interestingly, the “Projects We Love” badge didn’t influence the decision how much each backer was willing to pledge. Only the total amount of pledges was affected. Consequently, a higher number of supporters must have been attracted by the award.

```
In [159]: # settings
          plt.figure(figsize = [7, 6])

          # violinplot 95 quantile data
          ax = sns.boxplot(data = ks_compl_95, x = 'featured', y = 'backers_count', order=feat_

          # ticks and labels
          plt.ylim(0,500)
          plt.xlabel("support by Kickstarter", fontsize=12)
          plt.ylabel("backers count (conv. USD)", fontsize=12)
          plt.title("The Effect of Kickstarter Support on Backers Counts\n(95 quantile)", fonts
          plt.show()
```



The above plot confirms that being awarded "Projects We Love" in addition to being spotlighted drives the number of investors. Whereas the median number of supporters of spotlighted projects was {{format_num(ks_compl_95[ks_compl_95.featured == "spotlight"]['backers_count'].median())}}, fully supported campaigns convinced {{format_num(ks_compl_95[ks_compl_95.featured == "full support"]['backers_count'].median())}} supporters. Beyond the median in the boxplot, we can clearly see that backers counts doubled for the upper 50% of backers counts.

As a result of the strong effect of Kickstarter support on success rates, the number of investors and the total collected funding, it is important to understand what kind of projects Kickstarter was most likely to support.

Did the funding goal affect Kickstarter's decision to promote a campaign?

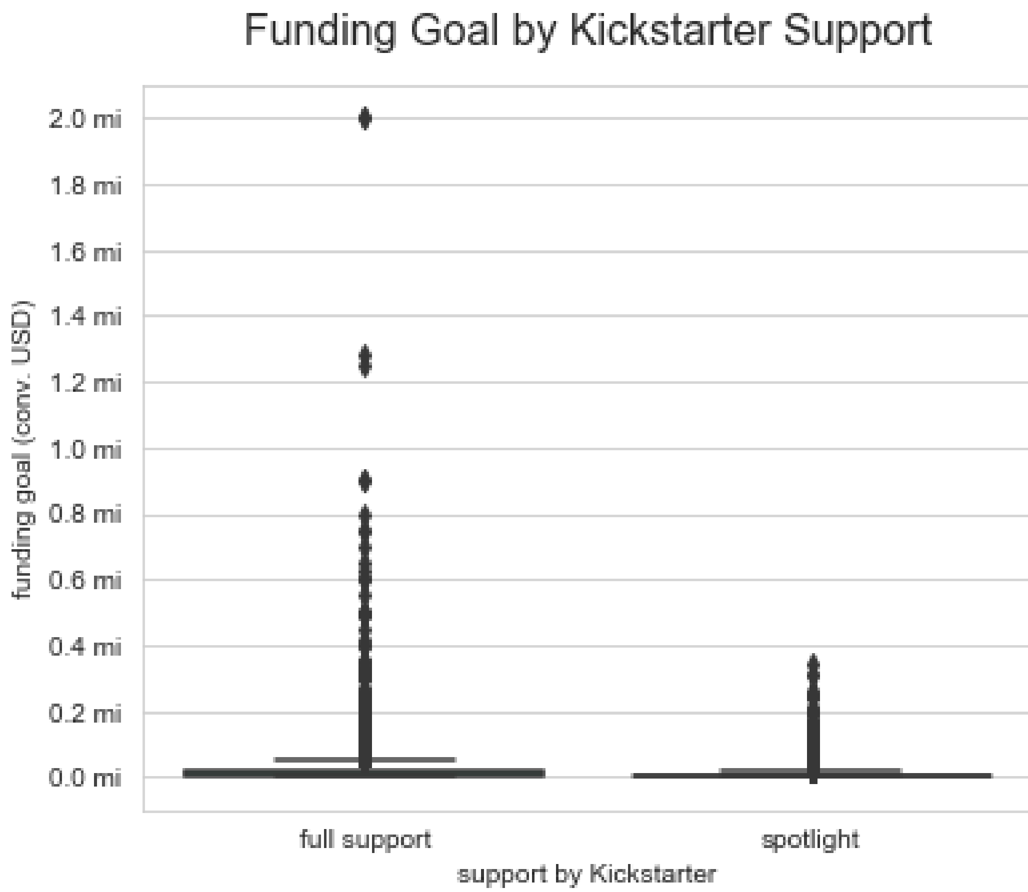
As we want to eliminate trends affecting our data, we are going to analyze data since the year 2015.

```
In [160]: # descriptive statistics of support groups
          ks_15_19.groupby(['featured'])['goal_hist_usd'].describe().transpose()
```

```
Out[160]: featured    Projects We Love        full support           no support  \
          count    1,422.0             12,266.0             55,807.0
          mean     43,842.37839515853  20,809.806981082067 90,470.01514541254
          std      274,400.2376835397  49,497.26123464968  1,792,385.981874966
          min      100.0               1.0                  1.0
          25%      6,500.0             4,000.0              2,500.0
          50%      16,205.211202952167 10,000.0             7,558.42599386768
          75%      38,214.87500076296  22,443.000000097807 25,000.0
          max      10,000,000.0        2,000,000.0          150,099,318.94817606

          featured           spotlight
          count    49,831.0
          mean     6,496.956562017776
          std      11,952.951055269472
          min      0.7110381409261841
          25%      800.0
          50%      2,781.0167909539778
          75%      7,443.543403463912
          max      347,000.0
```

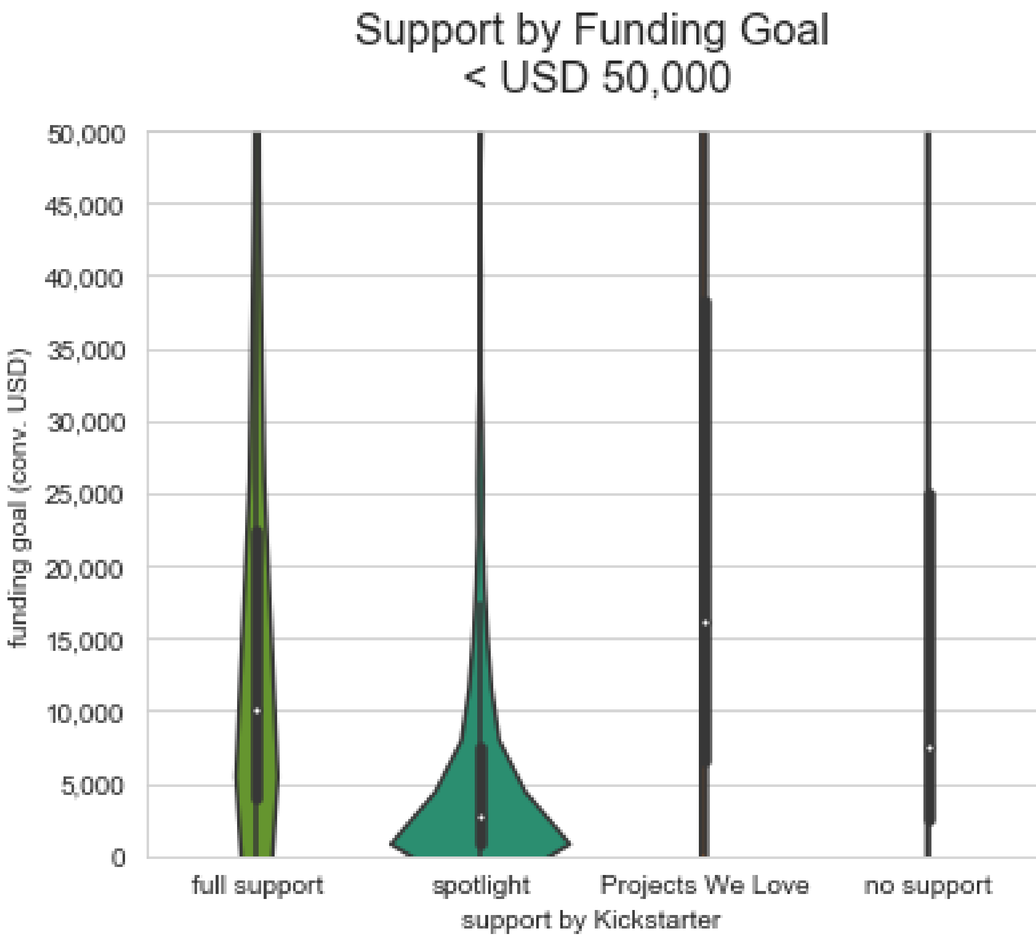
The above statistics show that goals above USD 2mi had no chance to be fully supported or spotlighted.

```
In [161]: # settings
          plt.figure(figsize = [6, 5])

          # boxplot of goals, clustered by featured
          ax = sns.boxplot(data = ks_15_19, x = 'featured', y = 'goal_hist_usd', order=feat_ord

          y_ticks = np.arange(0, 2000000+20000, 200000)
          y_labels = [str(y_tick / 1000000) + " mi" for y_tick in y_ticks]
          plt.yticks(y_ticks, y_labels)
          plt.xlabel("support by Kickstarter")
          plt.ylabel("funding goal (conv. USD)")
          plt.title("Funding Goal by Kickstarter Support", fontsize=16, pad=15)
          plt.show()
```



Apparently, Kickstarter preferred to fully support projects if the funding goal was more ambitious. The highest goal of full support was USD 2mi, whereas spotlighted projects reached a maximum goal of USD 347k. Because of the strong skew of goals, we basically only see the outliers of above boxplots. Let's examine more realistic goals en detail.

```
In [162]: # settings
          plt.figure(figsize = [6, 5])

          # change to violinplot to emphasize the distribution
          ax = sns.violinplot(data = ks_15_19, x = 'featured', y = 'goal_hist_usd',
                              order=feat_order, palette = success_colors)
          plt.ylim(0, 50000) # zoom in to goals under USD 50000,

          # ticks and labels
          format_yticks(50000,5000)
          plt.ylabel("funding goal (conv. USD)")
          plt.xlabel("support by Kickstarter")
          plt.title("Support by Funding Goal\n < USD 50,000", fontsize=16, pad=15)

          plt.show()
```



The violin plots demonstrate that projects which were fully supported or spotlighted generally had lower goals than projects without support or which got only the badge.

Again, it is obvious that Kickstarter preferred to reward full support to projects seeking higher funding compared to projects which were spotlighted. The interquartile range of fully supported projects and the upper tail is longer than the features of spotlighted projects. Fully supported projects realized a median goal of USD {{format_num(ks_15_19[ks_15_19.featured == "full support"]['goal_hist_usd'].median())}}, whereas spotlighted projects only aimed for a goal of USD {{format_num(ks_15_19[ks_15_19.featured == "spotlight"]['goal_hist_usd'].median())}}.

While the Kickstarter team generally preferred to support projects with lower goals, they encouraged projects of high, but reasonable funding in some cases with the badge. In contrast to successful projects, the violin plots of goals of non-supported projects and Projects We Love-projects are extremely lengthy.

If the goal would have been the only determination, we would have expected a wider distribution toward high goals. As this is not the case, we may assume additional factors to determine whether Kickstarter supports a project.

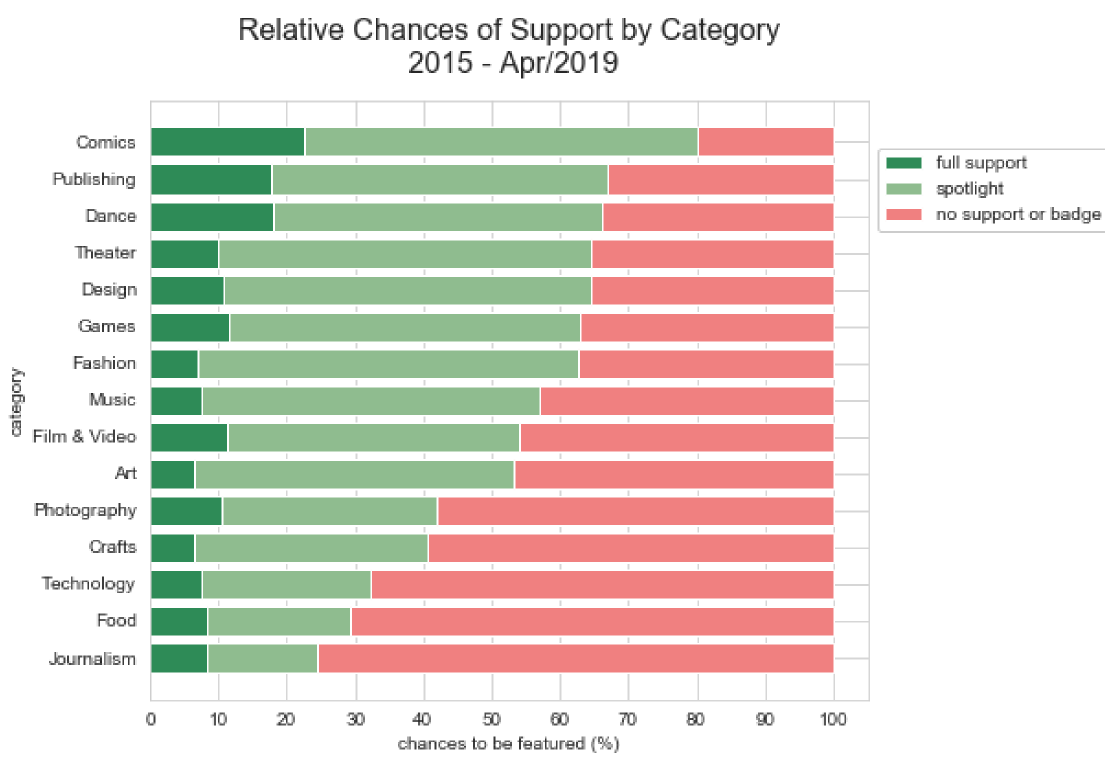
Did the project type affect Kickstarter supporting a campaign?

I'm going to analyze whether there were categories that were more likely chosen for support than others. To start, I'm going to calculate the chances of being supported given the category.

```
In [163]: # utility to calculate success chances by category

          def calc_support_chance(category):
              # summarize project counts per category into a matrix
              cat_counts = ks_15_19.groupby(['featured', category]).size()
              cat_counts = cat_counts.reset_index(name = 'count')
              cat_counts = cat_counts.pivot(index = category,
                                            columns = 'featured',
                                            values = 'count').reset_index()
              # fill zero counts
              cat_counts.fillna(0, inplace=True)

              # add column to sum up project counts by category
              cat_counts['cat_count'] = ks_15_19.groupby([category]).project_id.count().values

              # calculate the proportion of each category of all projects and add to datafarme
              cat_counts['cat_prop'] = cat_counts['cat_count'] / (cat_counts['cat_count'].sum()

              # calculate the proportion to be selected for support out of all completed proje
              cat_r = cat_counts.copy()
              for col in ['full support', 'spotlight', 'Projects We Love', 'no support']:
                  cat_r[col] = cat_r[col] / (cat_r['cat_count'].sum())

              # according to the rules of conditional probability,
              # calculate the probability to be featured given the chances that a category was
              for col in ['full support', 'spotlight', 'Projects We Love', 'no support']:
                  cat_r[col] = (cat_r[col] / cat_counts['cat_prop'])*100

              # add up failed proportion and the successfull proportion
              cat_r['featured_successful'] = round(cat_r['full support'] + cat_r['spotlight'],
              cat_r['featured_failed'] = round(cat_r['Projects We Love'] + cat_r['no support']

              cat_r.sort_values(by=['featured_successful', 'full support'], ascending=True, inp
              cat_r.reset_index(drop=True, inplace=True)
              return cat_r

In [164]: # utility to plot stacked bars for categorical success rates by category

          def plot_support_by_cat(cat_rates, cat_type):
              baselines = np.zeros(len(cat_rates)) # initital baseline
              artists = [] # for storing references to plot elements
              cat_order = cat_rates[cat_type].values

              # horizontally plot relative full support
              for feature in ['full support','spotlight', 'featured_failed']:
                  bars = plt.barh(y = np.arange(len(cat_order)), width = cat_rates[feature],
                                  left = baselines, color=sns.set_palette(['seagreen', 'darksea
                  artists.append(bars)
```

```
        # add values of full support to baseline
        baselines += cat_rates[feature].values

    # labels and ticks
    plt.yticks(np.arange(len(cat_order)), cat_order)
    plt.xticks(np.arange(0, 100+10, 10))
    plt.legend(artists, ['full support', 'spotlight', 'no support or badge'],
               framealpha = 1, bbox_to_anchor = (1, 0.85), loc = 6);
```

In [165]:
```
# settings
plt.figure(figsize = [7, 6])

cat_r = calc_support_chance("category")

# plot categories
plot_support_by_cat(cat_r, 'category')

# labels and ticks
plt.title("Relative Chances of Support by Category\n 2015 - Apr/2019", fontsize=16,
plt.ylabel("category")
plt.xlabel("chances to be featured (%)")

plt.show()
```



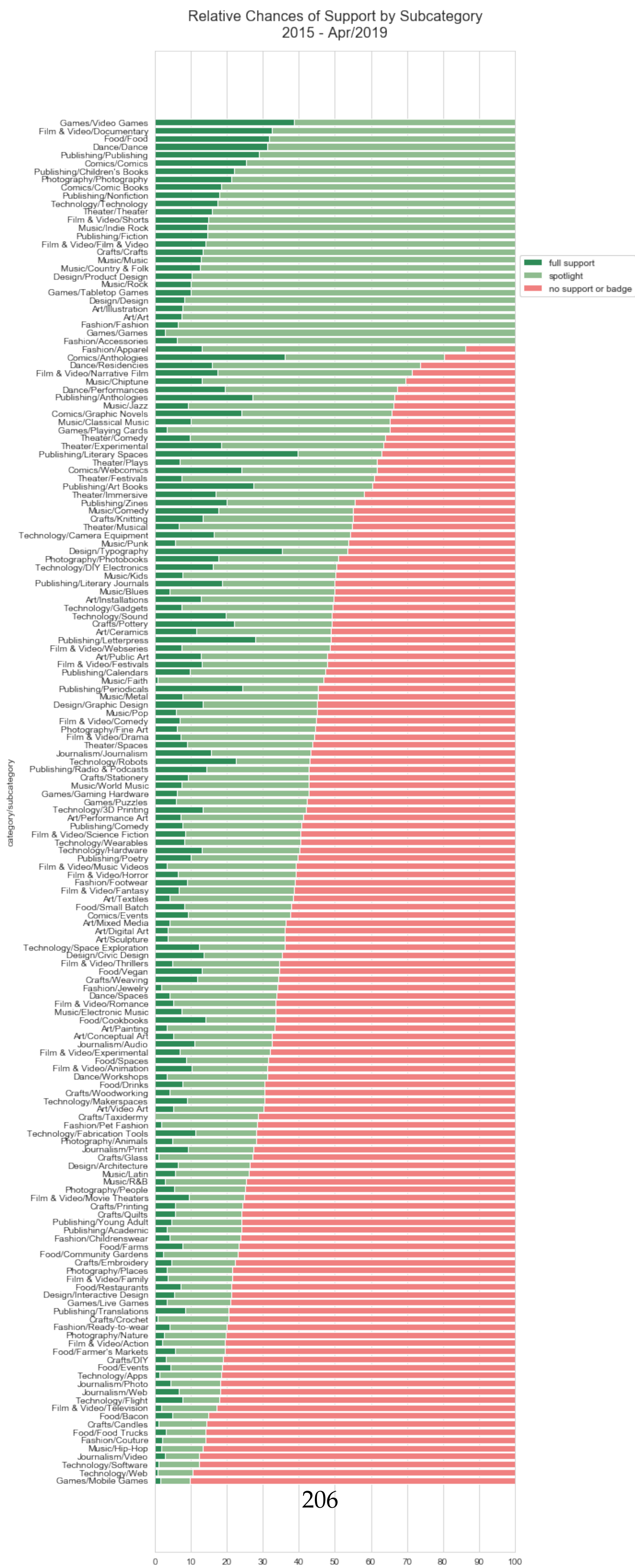
Comics were most likely to be supported, followed by Publishing and Dance. This is true, for full support and for projects that got featured on the landing page.

Creators who aim for project support in Technology, Food and Journalism had the lowest chances to receive full support or to be spotlighted.

As all projects that were fully supported or spotlighted succeeded, the green area coincides with success chances within a category. Simultaneously, the red area stands for the proportion of failed projects since all projects without support or only being rewarded the badge have failed.

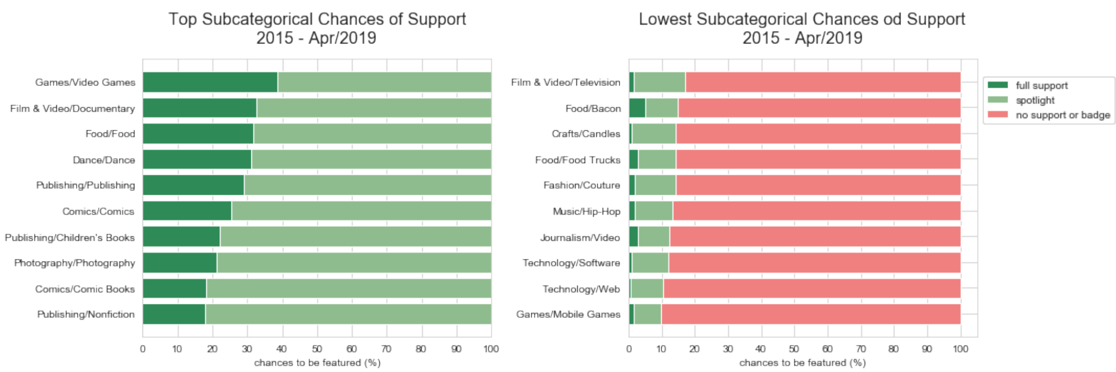
Let's dig into subcategories next by evaluating *comb cat*.

```
In [166]: # settings
          plt.figure(figsize = [7, 30])

          # calculate chances
          comb_cat_r = calc_support_chance("comb_cat")

          # stacked bar plots for subcategorical success rates by category
          plot_support_by_cat(comb_cat_r, 'comb_cat')

          # labels and ticks
          plt.title("Relative Chances of Support by Subcategory\n2015 - Apr/2019", fontsize=16
          plt.ylabel("category/subcategory")
          plt.xlabel("chances to be featured (%)")

          plt.show()
```


Relative Chances of Support by Subcategory
2015 - Apr/2019
full support
spotlight
no support or badge
category/subcategory
Games/Video Games
Film & Video/Documentary
Food/Food
Dance/Dance
Publishing/Publishing
Comics/Comics
Publishing/Children's Books
Photography/Photography
Comics/Comic Books
Publishing/Nonfiction
Technology/Technology
Theater/Theater
Film & Video/Shorts
Music/Indie Rock
Publishing/Fiction
Film & Video/Film & Video
Crafts/Crafts
Music/Music
Music/Country & Folk
Design/Product Design
Music/Rock
Games/Tabletop Games
Design/Design
Art/Illustration
Art/Art
Fashion/Fashion
Games/Games
Fashion/Accessories
Fashion/Apparel
Comics/Anthologies
Dance/Residencies
Film & Video/Narrative Film
Music/Chiptune
Dance/Performances
Publishing/Anthologies
Music/Jazz
Comics/Graphic Novels
Music/Classical Music
Games/Playing Cards
Theater/Comedy
Theater/Experimental
Publishing/Literary Spaces
Theater/Plays
Comics/Webcomics
Theater/Festivals
Publishing/Art Books
Theater/Immersive
Publishing/Zines
Music/Comedy
Crafts/Knitting
Theater/Musical
Technology/Camera Equipment
Music/Punk
Design/Typography
Photography/Photobooks
Technology/DIY Electronics
Music/Kids
Publishing/Literary Journals
Music/Blues
Art/Installations
Technology/Gadgets
Technology/Sound
Crafts/Pottery
Art/Ceramics
Publishing/Letterpress
Film & Video/Webseries
Art/Public Art
Film & Video/Festivals
Publishing/Calendars
Music/Faith
Publishing/Periodicals
Music/Metal
Design/Graphic Design
Music/Pop
Film & Video/Comedy
Photography/Fine Art
Film & Video/Drama
Theater/Spaces
Journalism/Journalism
Technology/Robots
Publishing/Radio & Podcasts
Crafts/Stationery
Music/World Music
Games/Gaming Hardware
Games/Puzzles
Technology/3D Printing
Art/Performance Art
Publishing/Comedy
Film & Video/Science Fiction
Technology/Wearables
Technology/Hardware
Publishing/Poetry
Film & Video/Music Videos
Film & Video/Horror
Fashion/Footwear
Film & Video/Fantasy
Art/Textiles
Food/Small Batch
Comics/Events
Art/Mixed Media
Art/Digital Art
Art/Sculpture
Technology/Space Exploration
Design/Civic Design
Film & Video/Thrillers
Food/Vegan
Crafts/Weaving
Fashion/Jewelry
Dance/Spaces
Film & Video/Romance
Music/Electronic Music
Food/Cookbooks
Art/Painting
Art/Conceptual Art
Journalism/Audio
Film & Video/Experimental
Food/Spaces
Film & Video/Animation
Dance/Workshops
Food/Drinks
Crafts/Woodworking
Technology/Makerspaces
Art/Video Art
Crafts/Taxidermy
Fashion/Pet Fashion
Technology/Fabrication Tools
Photography/Animals
Journalism/Print
Crafts/Glass
Design/Architecture
Music/Latin
Music/R&B
Photography/People
Film & Video/Movie Theaters
Crafts/Printing
Crafts/Quilts
Publishing/Young Adult
Publishing/Academic
Fashion/Childrenswear
Food/Farms
Food/Community Gardens
Crafts/Embroidery
Photography/Places
Film & Video/Family
Food/Restaurants
Design/Interactive Design
Games/Live Games
Publishing/Translations
Crafts/Crochet
Fashion/Ready-to-wear
Photography/Nature
Film & Video/Action
Food/Farmer's Markets
Crafts/DIY
Food/Events
Technology/Apps
Journalism/Photo
Journalism/Web
Technology/Flight
Film & Video/Television
Food/Bacon
Crafts/Candles
Food/Food Trucks
Fashion/Couture
Music/Hip-Hop
Journalism/Video
Technology/Software
Technology/Web
Games/Mobile Games
0
10
20
30
40
50
60
70
80
90
100
chances to be featured (%)

As the above plot is difficult to read because of the high number of subcategories, I am going to plot a best of.

```
In [167]: # save 10 most successful combined categories
          subcats_s = comb_cat_r[-10:]

          # save 10 most likely to fail categories
          subcats_f = comb_cat_r[:10]

          # settings
          plt.figure(figsize=[15,5])

          # left plot: top subcategories
          plt.subplot(1,2,1)
          plot_support_by_cat(subcats_s, 'comb_cat')
          # remove legend
          ax = plt.gca()
          ax.get_legend().remove()
          plt.title("Top Subcategorical Chances of Support\n2015 - Apr/2019", fontsize=16, pad=
          plt.xlabel("chances to be featured (%)")

          # rightplot: bottom subcategories
          plt.subplot(1,2,2)
          plot_support_by_cat(subcats_f, 'comb_cat')
          plt.title("Lowest Subcategorical Chances od Support\n2015 - Apr/2019", fontsize=16, p
          plt.xlabel("chances to be featured (%)")

          plt.tight_layout()

          plt.show()
```



The above plot confirms that certain project types are more likely to be chosen for full support or to be spotlighted. Video Games are at the top, followed by Documentaries and Food. The lowest chances of support had Software projects, Web Tech projects and Mobile Games.

It is quite odd that Video Games are at the top, while Mobile Games were at the bottom. There is quite a number of projects without subcategories among the top categories. This may be an indication for creators increasing their chances by publishing without subcategory or by generally choosing more universal category names to attract Kickstarter's attention.

7.5.1 Summary Featured

According to our data, the support offered by Kickstarter is extremely relevant to win a campaign. Strictly supported projects were successful. 45% of the projects were spotlighted on Kickstarter's channels and 12% of completed projects got full support. Fully unsupported projects or projects only receiving the "Projects We Love" badge failed without exception.

Projects receiving the 'Projects We Love' badge in addition to being spotlighted, typically collected 2 to 2.5 times higher funding. Interestingly, the "Projects We Love" badge didn't influence how much each individual backer pledged, but the total number of supporters. While spotlighted projects attracted a median of {{int(ks_compl_95[ks_compl_95.featured == 'spotlight'].backers_count.median())}} supporters, fully supported campaigns convinced a medium of {{int(ks_compl_95[ks_compl_95.featured == 'full support'].backers_count.median())}} supporters. Thus, backers counts more than doubled when campaigns were picked by staff.

As a result of the strong effect of Kickstarter's support, it is important to understand what kind of projects Kickstarter was most likely to promote.

In terms of the funding goal, Kickstarter generally preferred to support lower goals. Fully supported projects had a median goal of USD {{format_num(ks_compl_95[ks_compl_95.featured == 'full support'].goal_hist_usd.median())}}, whereas spotlighted projects only aimed for a median goal of USD {{format_num(ks_compl_95[ks_compl_95.featured == 'spotlight'].goal_hist_usd.median())}}. While Kickstarter preferred lower goals, they also encourage projects of high, but reasonable funding by awarding the "Projects We Love" badge. The highest fully supported goal in the past 10 years was USD 2mi. Spotlighted campaigns were below the maximum goal of USD 347k.

The type of a project additionally impacted Kickstarter's promotion activities. Comics were the most likely to be supported, followed by Publishing and Dance campaigns. Creators who aimed for project support in Tech, Food and Journalism had the lowest chances to be fully featured or to be spotlighted.

More specifically, we found among the best chances to be supported:
1) Video Games,
2) Documentary films,
3) Food without subcategory

The lowest chances to be featured had the following subcategories:
1) Software projects,
2) Web projects and
3) Mobile Games.

Admittedly, it feels odd to find video games at the top, while mobile games were at the bottom. Additionally, I identified projects without chosen subcategories among the top chances for support. This suggests creators to increase their chances by publishing without subcategory or by choosing universal categories to attract Kickstarter's attention.

7.6 6.4 Summary: What determines the success of a crowdfunding campaign on Kickstarter?

To find out what kind of crowdfunding campaigns were most successful on Kickstarter, we visually analyzed the following features in our data set:

1) the required and realized funding,

2) whether Kickstarter actively supported a campaign,

3) the time of year,

4) the project category and

5) the campaign duration.

To determine whether a campaign was considered successful or not, we looked into two main factors: first, the general chance to successfully end a campaign, and second, the amount of funding that was ultimately collected. When creators decide on a goal, they generally have to consider whether to maximize their chances to successfully finish a campaign or to generate the maximum funding possible. Both targets oppose each other diametrically. Because of Kickstarter's all-or-nothing-approach, increasing the goal typically decreases the chances for succeed. Anyhow, creators risk insufficient funding by aiming for low goals.

The lower the goal, the better. If creators want to keep at least a 50% chance, it appears to be advisable to stay below a benchmark of USD 10k. On average goals below USD 5k had a greater than 60% chance of succeeding. Very risk-averse creators may even choose to stick to goals below USD 1,5k.

Successful projects realized an average surplus of 17% above goal. The surplus that creators realize depends on the chosen goal that is chosen. Roughly, the surplus rate above goal describes a u-form. For goals under USD 3k, the surplus rate descended exponentially. The lower the chosen goal the higher was the surplus rate. Low goal projects typically realized a surplus of 34%, whereas goals between USD 1,5k to 13k made a median surplus of 11-12%.

Creators seeking funding above USD 18k, were able to count on increasing surplus rates. In particular, goals from 45k up to 113k realized a median surplus of 26%. However, the surplus rates become less reliable as the volatility of pledges increases.

It is highly unlikely to successfully collect funding beyond USD 100k. Creators seeking high funding may consider alternative investment possibilities to Kickstarter. 3 quarters of successful goals were below USD 9,6k anyways. The success chances of projects between USD 65k to 113k were only 20%. For even higher goals, success chances draw closer to zero.

The higher a goal the higher the average pledge per backer The higher a goal the higher was the average amount each supporter invested. For successful low goal projects (below USD 1,5k) the median pledged per backer was USD 37. Moderately high goals generated a median of USD 83. Successful very high goal projects generated the highest median funding per backer: USD 151.

Creators may consider this behavior when defining the rewards for pledges.

Kickstarter's promotion support is extremely relevant for success. In the last 10 years, only the projects that were supported by Kickstarter succeeded. Since 2018, on average, 54% of the projects were spotlighted on Kickstarter's landing page (and optionally on Kickstarter's social media channels). 11% of completed projects were fully supported. Meaning, they got picked by staff and were awarded the "Projects We Love" badge.

All crowdfundings that were not announced on Kickstarter's landing page failed. This includes a few campaigns that got the "Projects We Love" badge, but were not spotlighted in any way.

Being fully featured by Kickstarter additionally drove the total collected funding. Projects which received the 'Projects We Love' badge in addition to being spotlighted on the landing page, had more than a double the number of supporters, which resulted in 2 to 2.5 times higher funding compared to campaigns that were only spotlighted.

Generally, Kickstarter tends to support projects with lower goals. Spotlighted projects on average sought a goal of USD 3,4k. Creators who intend to collect higher funding should aim for the badge in addition to being featured on the website. Fully supported projects realized a median goal of USD 7,1k.

Comics, Publishing and Dance projects were most likely to be supported by Kickstarter. The category of a campaign impacted the chances to be promoted by Kickstarter. Comics were the most likely to be supported, followed by Publishing and Dance campaigns. Creators who aimed for project support in Technology, Food and Journalism had the lowest chances to be feature

More specifically, we found among the best chances to be supported in the following project types:
1) Video Games, 2) Documentary films,
3) Food without subcategory.

The lowest chances to be featured had the following subcategories: 1) Software projects, 2) Web projects and 3) Mobile Games.

Kickstarter is a platform to fund creative projects with comparatively low financial requirements. Creative projects and categories attributed to lower commercial potential seem to be most common and are highly successful. Written work and comics dominate the top categories. Fiction & nonfiction publishing projects, children's books and comic books usually ended in success. Tabletop games clearly win the race of projects with the highest success rates.

Tech and food projects are most likely to fail but realize the highest total funding.* Even though they are among the most popular categories, gadgets, hard- and software and web projects had low chances of success. In addition to technology ventures, I found 3 food subcategories among the ventures with the lowest chances: small batch, drinks and restaurants. We can attribute their high capital requirements to their poor success chances. It's important to say that higher failure rates do not necessarily imply that Kickstarter is generally a bad place for these types of projects. On the positive side, once successful, tech campaigns generated the highest median pledges of plus USD 22k.

Universal category names are more likely to succeed. The top chances of project categories show a tendency to not have subcategories selected. Publishing, comics, film & video, art and music performed generally well if they were communicated universally, instead of niche topics.

Video Games instead of Mobile Games. While every single “video game” campaign succeeded, projects of the subcategory “mobile games” disappointed with a failure rate of 93%.

Design instead of Art. Product design and illustrations worked in 100% of all cases, yet paintings were likely to fail. Generally, campaigns labeled as *Design* worked better than labeled as *Art*.

Country & Folk Music flourished, Hip-Hop flopped. The taste in music seems to matter. While crowdfunding worked well for Country & Folk music, Hip-Hop campaigns failed at a rate of 78%.

A heaven for Short films and Documentaries. Film & Video projects appear on both sides of success chances. Short films and documentaries were a guarantee for success, while animations and web series were more likely to fail.

The Funding Duration is 30 days. Period. Although creators are free to choose their funding duration, it seems to be universally accepted to run a campaign within a period of roughly 30 days. It would seem natural to assume that a longer time frame would allow projects to increase their chances of success and collect a higher funding. However, I found that longer durations are not rewarded with success. In fact, campaign periods ranging between 15 to 32 days were generally linked with the best chances.

The capital requirements may affect the chances of success though. The average funding durations appear to be prolonged when the goals was set higher. Successful goals under USD 1,5k had a mean funding duration of 28 days. Successful very high goal projects (USD 13k - 65k) were able to extend the funding duration by one week (35 days) without loosing chances of success.

The second most popular period of 60 days turned out to be not advisable since it’s associated with the lowest chances.

The time of year matters.* The time of the year on average affected the general success chances, investor counts and collected funding. Considering all factors, I found the best chances are in December. Generally, October to December and April to July were the most promising months to run a campaign. January to March performed suboptimally. November was the safest bet for every creator whose primary goal was to end a campaign successfully. Those creators should avoid running a campaign in January since success rates were roughly 10% lower. Creators who seek high funding had the best chances in December or June and should avoid January to March.

The most valuable categories. I identified the most valuable project categories by depicting pledges against success rates. Accordingly, the most valuable campaigns were:

1) Design, in particular Product Design

2) Games, in particular Video Games and Tabletop Games

3) Film & Video Documentaries

In contrast, the following projects had low funding potential:

1) Mobile games,
2) Hip-Hop music and
3) generally journalistic projects.