crowdfunding_slide_deck

August 8, 2019

1 10 Years of Crowdfunding on Kickstarter - Exploratory Analysis

1.1 by Marie-Luise Klaus

1.2 Investigation Overview

This exploratory data analysis is dedicated to the 10th anniversary of the crowdfunding platform Kickstarter in April 2019. The main goal is to analyse current trends and determine possible factors that contribute to the success of a campaign.

Throughout the course of this notebook, I will have two main questions in mind. Based on our data:

1) Is it still worthwile financing your project on Kickstarter, now that crowdfunding has become mainstream?
2) What determines the success of a crowdfunding campaign on Kickstarter?

1.3 Dataset Overview

The Kickstarter data set was gathered in July 2019 from an automated web scraping service called Web Robots. They publish monthly data on all ongoing and completed Kickstarter projects and released it to the public in the form of csv files on their website.

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

After assessing and cleaning the data, I was left with information on 10 years of Kickstarter campaigns, from Kickstarter's launch in April 2009 to April 2019. The focus of my analysis was the remaining 165,452 observations. As for the features of this dataset, 24 variables were selected for analysis.

The main feature that I explored was the status of a project. It depicts whether the crowdfunding was a success or failure. Supported was this by investigating how project characteristics were associated with the success of a campaign. In the course of this analysis, I suspect the following factors will be the most influential on a project: the funding goal, successfully pledged dollars, the number of backers, the promotional support provided by Kickstarter, the dates of campaigns and the project category.

```
In [1]: # import all packages and set plots to be embedded inline
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        %matplotlib inline

        # suppress warnings from final output
        import warnings
        warnings.simplefilter("ignore")
        sns.set_style("whitegrid")

In [2]: # read in 4 files and concatinate the data into a single pandas 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)

In [3]: # convert time data to date time format
        master_df[['created_at', 'launched_at', 'state_changed_at', 'deadline', 'last_update_a

        # engineer variable to asses funding duration
        master_df['duration'] = master_df['deadline'] - master_df['launched_at']
        # convert duration time delta to float of days
        master_df['duration_days'] = (master_df['duration'].astype('timedelta64[h]') / 24)

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

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

        # 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()

        # remove features that are irrelevant to this presentation to keep our dataframe neat
        ks_compl = ks_compl.drop(labels=['project_name', 'url', 'blurb', 'image', 'slug', 'crea
                                         'creator_id', 'creator_name', 'country', 'city', 'sta
                                         'loc_type', 'currency', 'state_changed_at', 'launched
                                         'goal_real', 'goal_current_usd','pledged_real', 'pled
                                         'current_fx_rate(usd)', 'hist_exchange_rate(usd)', ],

In [4]: # 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
```

```
In [5]: # 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 [6]: # 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 [7]: # remove outlier projects with extremely high goals, pledges or backers counts
        # to make visualization and interpretation possible

        # identify goal quartiles and 95% quantile of each skewed feature
        goal_min = ks_compl.goal_hist_usd.min()
        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()
        pledged_95 = ks_compl.pledged_hist_usd.quantile(q=0.95)
        backers_95 = ks_compl.backers_count.quantile(q=0.95)

        # bin observations into ordinal goal categories
        bin_edges = [0, goal_25, goal_50, goal_75, goal_95, goal_975, goal_outliers, goal_max]
        bin_names = ['low', 'medium', 'moderately high', 'high', 'very high', 'extreme', 'outl

        # create a column to classify campaigns by goal level
        pd.set_option('mode.chained_assignment', None)
        ks_compl['goal_level'] = pd.cut(ks_compl['goal_hist_usd'], bin_edges, labels=bin_names
        ks_compl_95 = ks_compl.copy()
        print("Projects completed : ", format_num(len(ks_compl_95)))

        # select 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 without outlier for successful and failed projects
        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
```

```
In [8]: # 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"]

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

        # define commonly used colors
        cust_green = '#66cdaa'
        cust_red = '#f08080'
        cust_blue = '#43a2ca'
        status_colors = [cust_blue, cust_green, cust_red]
        fill_red = '#fee0d2'
        fill_green = '#e0f3db'
        backers_color = '#a6611a'
        pledged_color = "#c994c7"
        goal_color =  sns.color_palette("Blues_r")[0]
        feat_color = sns.color_palette("Set1")
        category_colors = ['#a6cee3','#e5c494', '#1f78b4', '#33a02c', '#fb9a99', '#b3b3b3', '#
                           '#ff7f00', '#cab2d6', '#6a3d9a', '#b2df8a', '#984ea3', '#ffd92f', '
```

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

In recent years, crowdfunding became popular as a form of capital investment to fund any kind of ventures. With more competition, campaign creators likely face bigger challenges courting 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. Under these circumstances, it would also make sense for project creators to realize lower fundraising capital goals.

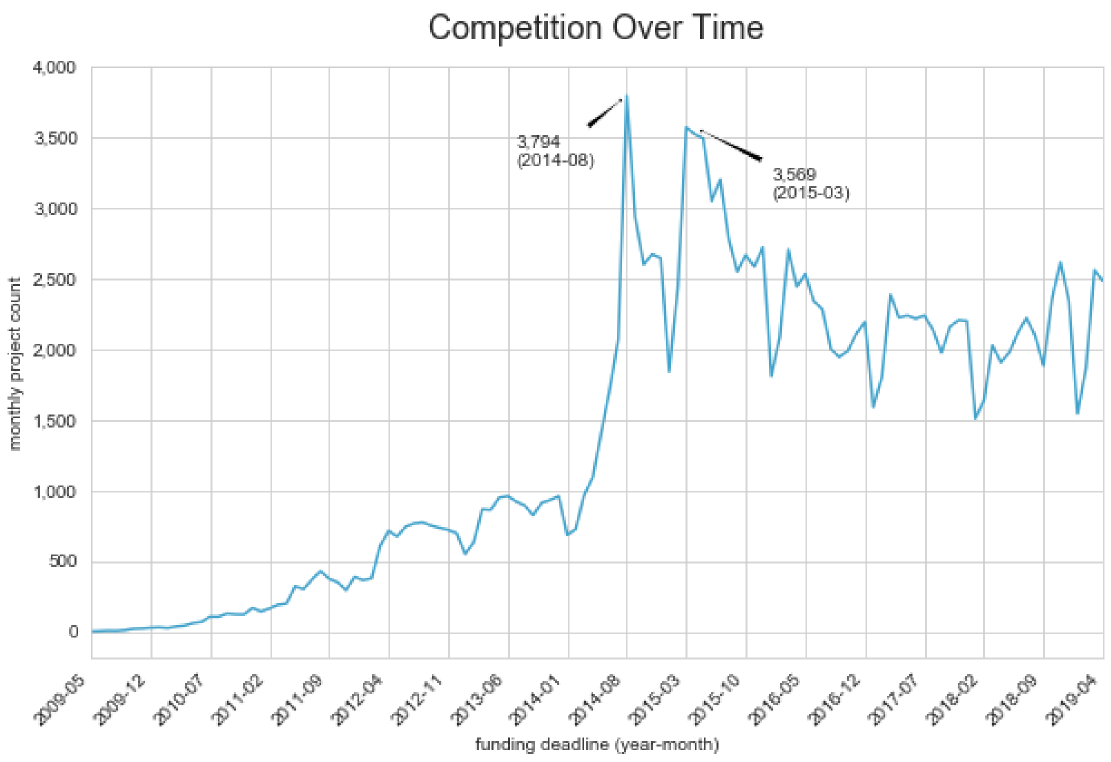
In the following analysis, I'm going to investigate how crowdfunding as an investment opportunity on Kickstarter has evolved over time. My goal is to find an answer if running a campaign today pays off compared to previous years. Did the overall conditions worsen due to the Kickstarter's popularity?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

2.1 Increased competition

After rather moderate growth in the first 5 years after Kickstarter's launch, crowdfunding activities exploded in August 2014 and again in March/April 2015. Crowdfunding activities settled down thereafter. 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 have been increasing notably.

```
In [9]: # create dataframe to summarize project counts per month over the course of 120 months
        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_failed
            # 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 valu
            # 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

        # settings
```

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

# plot monthly counts of projects of completed projects by month over time
ax = df_project_counts['total'].plot(color=status_colors[0])

# 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"))

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

format_yticks(4000,500)
plt.ylabel('monthly project count')

timeline_ticks(df_project_counts)
plt.xlabel('funding deadline (year-month)')

plt.show()
```



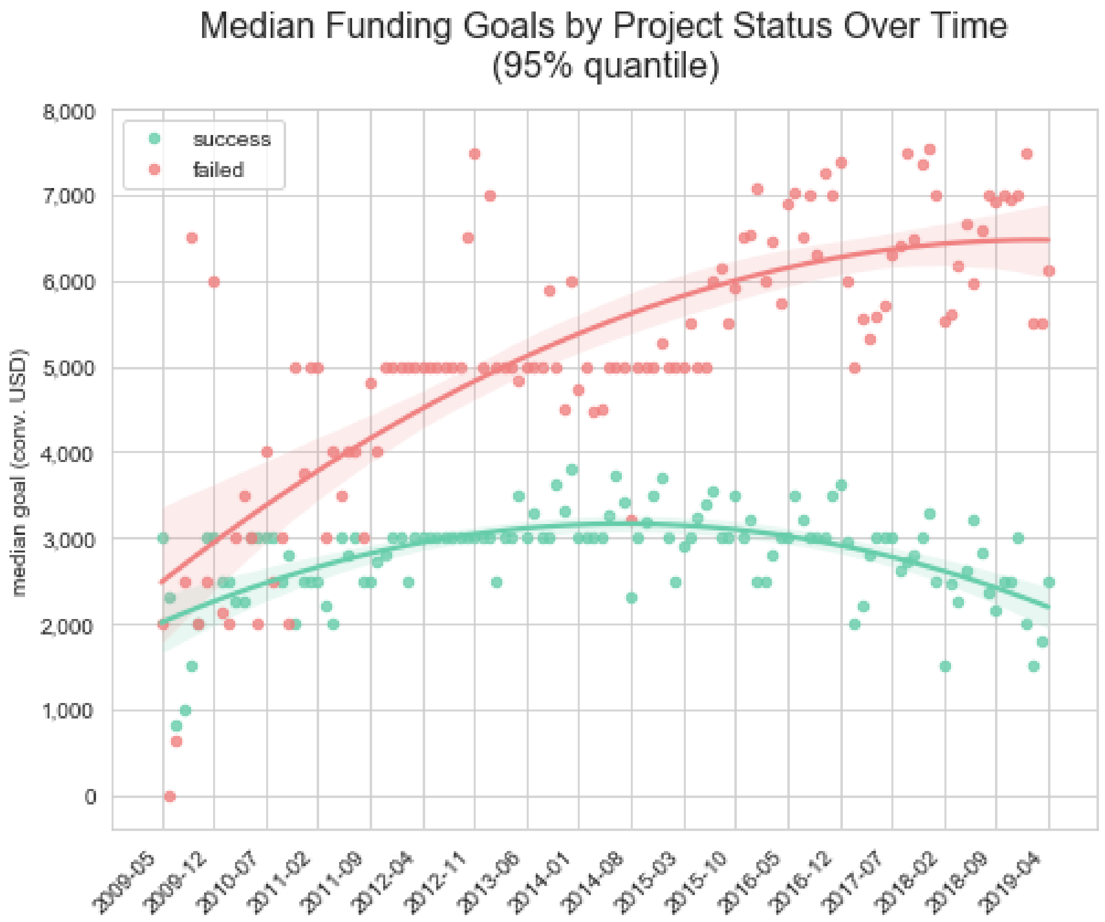
2.2 Decreasing funding goals

I noticed a trend of declining funding goals of successful projects since 2017. While successful projects realized goals of roughly USD 3,100 between 2014 to 2016, creators today usually aimed for goals USD 500 lower.

Compared to failed campaigns, successful goals have been relatively balanced over the entire time. In contrast, the median goals of failed campaigns increased over the years. Only in 2018 they came to an halt. On Kickstarter's anniversary, failed campaigns sought 3 times higher goals.

```
In [10]: def group_data_monthly(feature, median=True):
             if median:
                 # total
                 grouped = ks_compl_95.groupby([ks_compl_95.deadline.dt.year,
                                                ks_compl_95.deadline.dt.month]).median()[featu
                 # success
                 grouped_s = ks_success_95.groupby([ks_success_95.deadline.dt.year,
                                                    ks_success_95.deadline.dt.month]).median()
                 # failed
                 grouped_f= ks_fail_95.groupby([ks_fail_95.deadline.dt.year,
                                               ks_fail_95.deadline.dt.month]).median()[feature
             else:
                 # total
                 grouped = ks_compl_95.groupby([ks_compl_95.deadline.dt.year,
                                                ks_compl_95.deadline.dt.month]).mean()[feature
                 # success
                 grouped_s = ks_success_95.groupby([ks_success_95.deadline.dt.year,
                                                    ks_success_95.deadline.dt.month]).mean()[fe
                 # failed
                 grouped_f= ks_fail_95.groupby([ks_fail_95.deadline.dt.year,
                                                ks_fail_95.deadline.dt.month]).mean()[feature]
             # insert 0 occurence for 2009-6
             grouped_f = np.insert(grouped_f,1,0)

             # create dataframe
             df = pd.DataFrame(data={'total':grouped,
                                     'success':grouped_s,
                                     'failed': grouped_f,
                                     'date': dates})
             return df
```

```
In [11]: # settings
         plt.figure(figsize=[8,6])

         # calculate monthly median goals of completed projects of 95 quantile data frame
         df_goals = group_data_monthly('goal_hist_usd')

         # overwrite date because seabrorn can't plot dates
         df_goals['date'] = np.arange(0, len(df_goals), 1)

         # scatterplots of monthly means and fit a polynomial regression of 2nd degree
         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("median goal (conv. USD)")
         plt.title("Median Funding Goals by Project Status Over Time\n(95% quantile)", fontsiz
         plt.legend()
         plt.show()
```



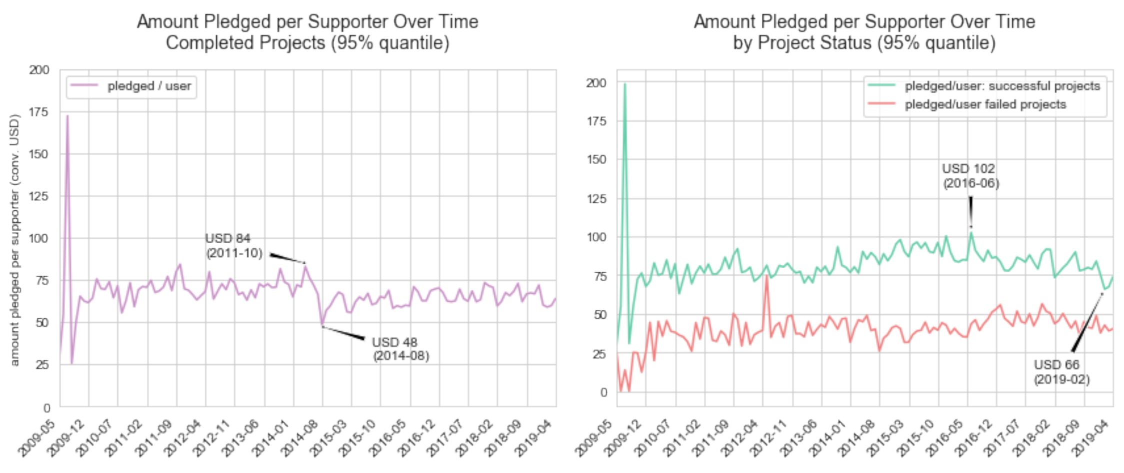
2.3 Supporters pledge smaller amounts

Lately, the money each supporter spent on rewards has been declining. Creators had to attract more of supporters to collect the same amount of funding. In 2018, successful projects on average collected USD 7 less per backer than in the record year of 2016. This may be a negative development for some creators, but it may also be a strategic chance for business starters to increase their reach, funding or customer numbers.

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

         # add the average amount pledged per supporter to each campaign of the 95% quantile d
         for df in [ks_compl_95, ks_success_95, ks_fail_95]:
             df['pledged_rate'] = (df['pledged_hist_usd'] / df['backers_count']).fillna(0)

         # calculate monthly median pledged rate of completed projects of 95 quantile data fra
         df_pledged_rate = group_data_monthly('pledged_rate', False)
```

```
# # 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"))
```

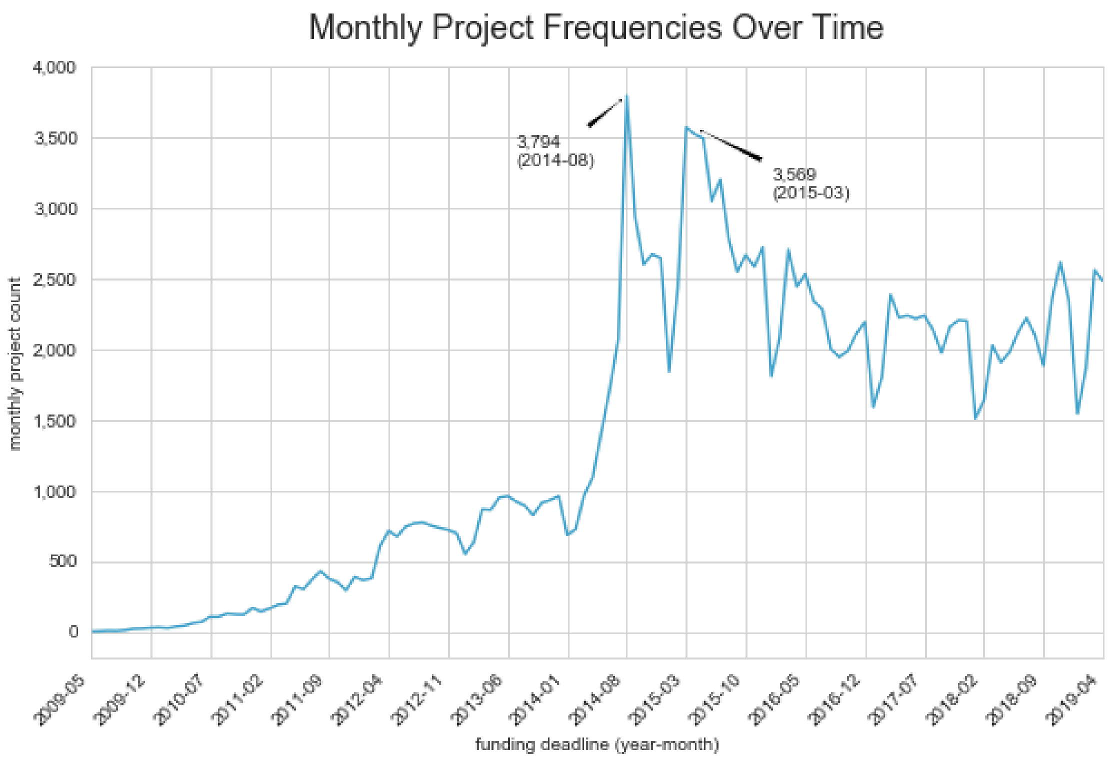
```
         # low in 08/2014
         ymin_2 = ks_success_95.groupby([ks_success_95.deadline.dt.year,
                                       ks_success_95.deadline.dt.month])['pledged_rate']\
                                       .mean().sort_values().values[5]
         xmin_2 = str(df_pledged_rate[df_pledged_rate.success == 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()
```



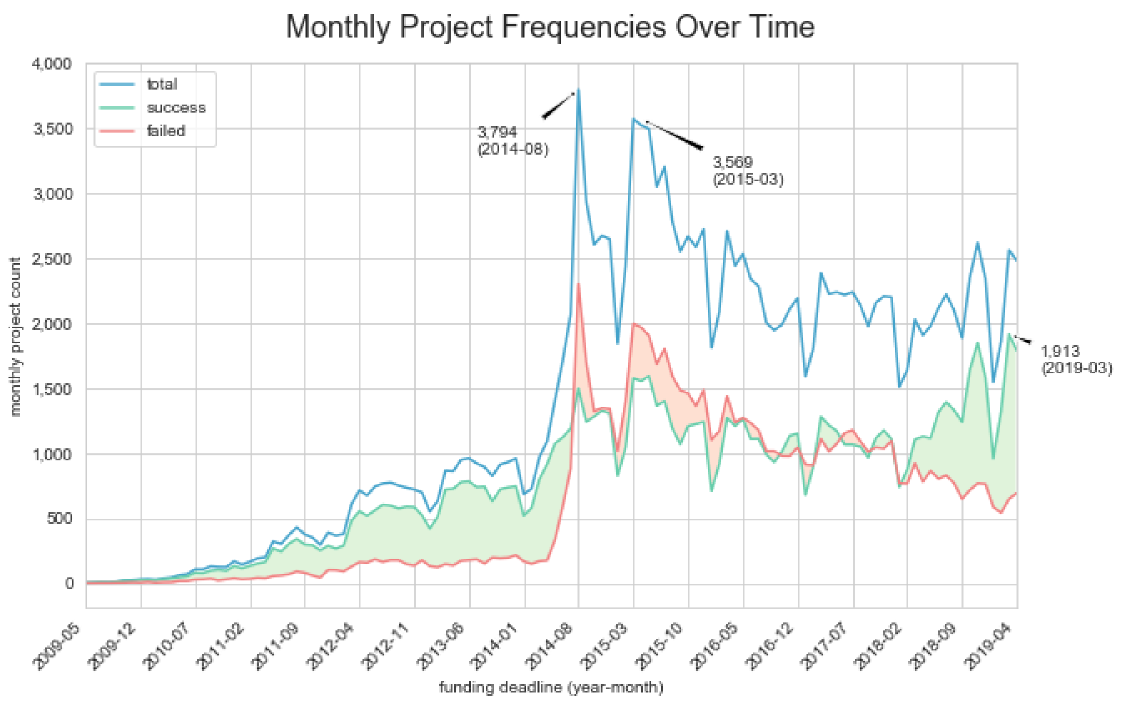
2.4 In 2018, 63.5% of campaigns were successful!

With the hype of Kickstarter in late 2014, we found an abnormally high percentage of failed projects. 61% flopped. During the years of recession the likelihood of failing minimally exceeded the success rates. 51% of projects failed. By the beginning of 2018, Kickstarter turned success and failure rates upside down. On average, 63.5% of completed campaigns had the chance to succeed. Actually, the record for successful campaigns was set only recently, in March 2019. Chances of winning were 74%!

```
In [13]: # create dataframe to summarize project counts per month over the course of 120 month
         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_failed
    # 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

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

# plot monthly counts of projects of completed projects by month over time
ax = df_project_counts['total'].plot(color=status_colors[0])

# 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"))

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

format_yticks(4000,500)
plt.ylabel('monthly project count')

timeline_ticks(df_project_counts)
plt.xlabel('funding deadline (year-month)')

plt.show()
```



```
In [14]: # settings
         plt.figure(figsize=[10,6])

         # 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 Frequencies Over Time", fontsize=18, pad=15)

format_yticks(4000,500)
plt.ylabel('monthly project count')

timeline_ticks(df_project_counts)
plt.xlabel('funding deadline (year-month)')

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



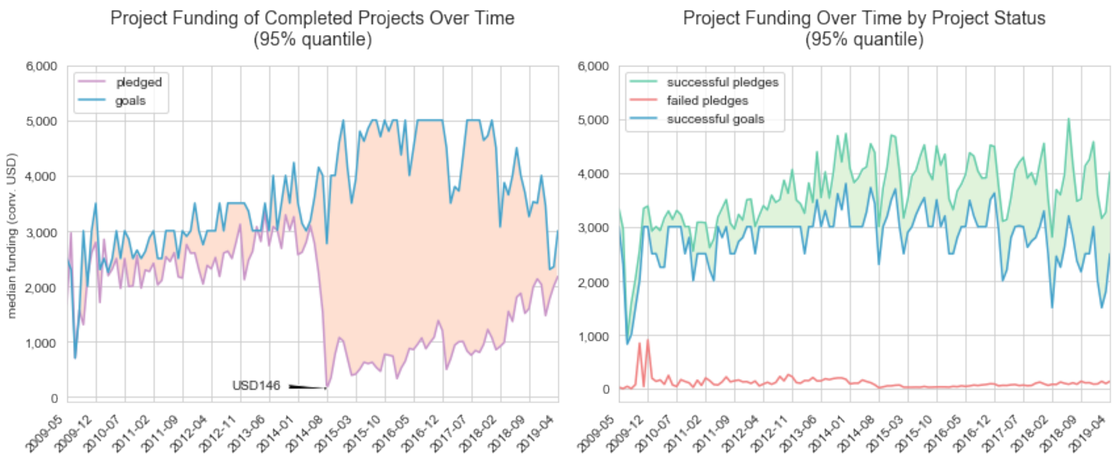
2.5 The total financial backing has been stable

Regardless of today's successful goals being lower, the total financial backing per project remained relatively constant since 2014. Recently, the total collected funding per project even increased slightly. While creators raised median investments of USD 5,038 between 2014-2017, they realized USD 5,371 in 2018.

However, the plot on the right reveals an extreme discrepancy between goals and pledges. When Kickstarter suddenly boomed in August 2014, the total funding capacity of all completed projects dropped from plus USD 3k down to USD 146. Obviously, the total funding capacity couldn't keep up the pace with the growth of project numbers. This gap has been slowly closing. Today, the total funding capacity has almost caught up with the sum of project goals. If this trend continues, in theory, it wouldn't take long to allow settlement of the capital goals of every fundraising.

The most astonishing about the goal-pledges overhead is that successful campaigns were hardly affected by the lack of funding. We can only speculate that the increased crowdfunding activities caused by the hype were generally not suitable for crowdfunding or irrelevant for supporters, so that lost investment dollars were contained.

```
In [15]: # settings
         plt.figure(figsize=[12,5])

         # calculate monthly median pledges of completed projects of 95 quantile data frame
         df_pledged_median = group_data_monthly('pledged_hist_usd')

         # # 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), df_pledged_median.total, df_goals.total ,
                         where=df_goals.total >= df_pledged_median.total,
                         facecolor=fill_red, interpolate=True)

         # annotate minima
         ymin  = min(df_pledged_median.total)
         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(df_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 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.success
                         facecolor=fill_green, interpolate=True)

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

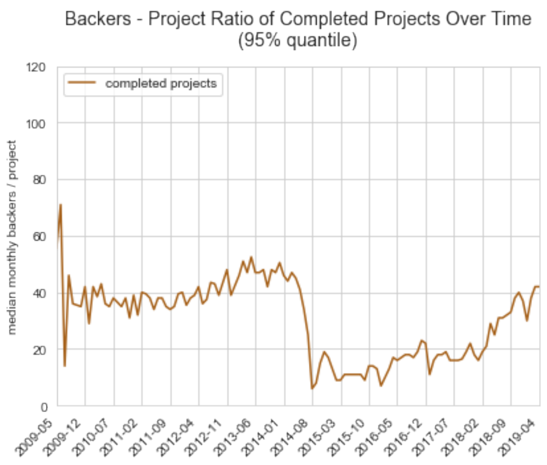


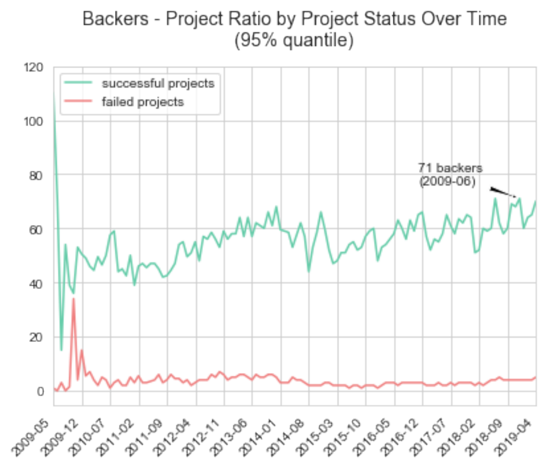
2.6 Growing supporter numbers compensated for increased competition among creators.

We would expect the recent increase in competing projects, lower funding goals and the tendency to pledge greedier to negatively impact campaigns. However, recently, the number of people who supported a project has been increasing at a faster rate than the number of active campaigns.

While a lack of supporters caused severe failure rates during the hype years, the backer/project ratio has been increasing since 2015. Therefore, success rates and the overall funding capacity has been stabilizing. In October 2018, there was even a record median of 72 backers supporting each project.

```
In [16]: # settings
         plt.figure(figsize=[12,5])

         # calculate monthly median pledged rate of completed projects of 95 quantile data fra
         df_backers_r = group_data_monthly('backers_count')

         # 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[0])[: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)", fonts
         plt.tight_layout()
         plt.legend(loc=2)
         plt.show()
```





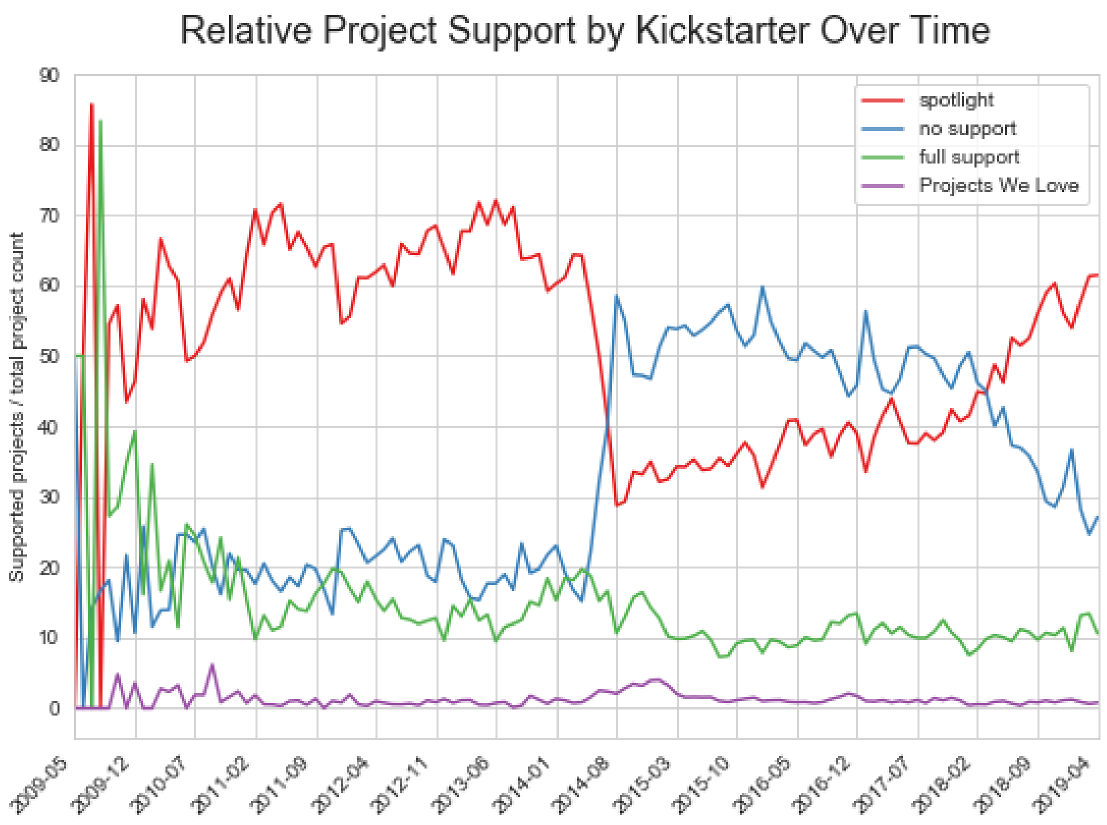
2.7 Better chances to be promoted by Kickstarter

Since early 2018 and regardless of growing campaign numbers, Kickstarter has been promoting a higher percentage of projects on their landing page (and possibly social channels). Today, more than 60% of all fundings are spotlighted on Kickstarter's channels. The proportion of unsupported projects has decreased from 55% in the hype years to only 27% today.

Additionally, more projects than ever are picked by staff to be awarded the "Projects We Love" badge as the proportion of fully supported projects has kept constant at a rate of 10%.

```
In [17]: # 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 of every feature
         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
```

```
# 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

# Visualize how Kickstarter supported projects over time in 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, 90+10, 10))
plt.ylabel("Supported projects / total project count");

plt.title("Relative Project Support by Kickstarter Over Time", fontsize=18, pad=15);
plt.legend()
plt.show()
```



2.8 Crowdfunding on Kickstarter has matured

In spite of: - higher competition,
- lower funding goals,
- lower individual pledges per supporter.

2.8.1 Chances are better than ever!

1) Increasing chances for success

2) Kickstarter's financial funding capacity is at a high

3) The financial backing per project has been stable over time

4) Increasing number of backers per project

5) Increasing chances to be promoted by Kickstarter

3 2) What determines the success of a crowdfunding campaign on Kickstarter?

To determine whether a campaign was considered successful or not, I looked into two main factors: first, the general chance of successfully ending 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 or to generate the maximum possible funding. Both targets oppose each other diametrically. Because of Kickstarter's all-or-nothing-approach, raising the goal typically decreases the chances for success, yet creators risk insufficient funding by aiming for low goals.

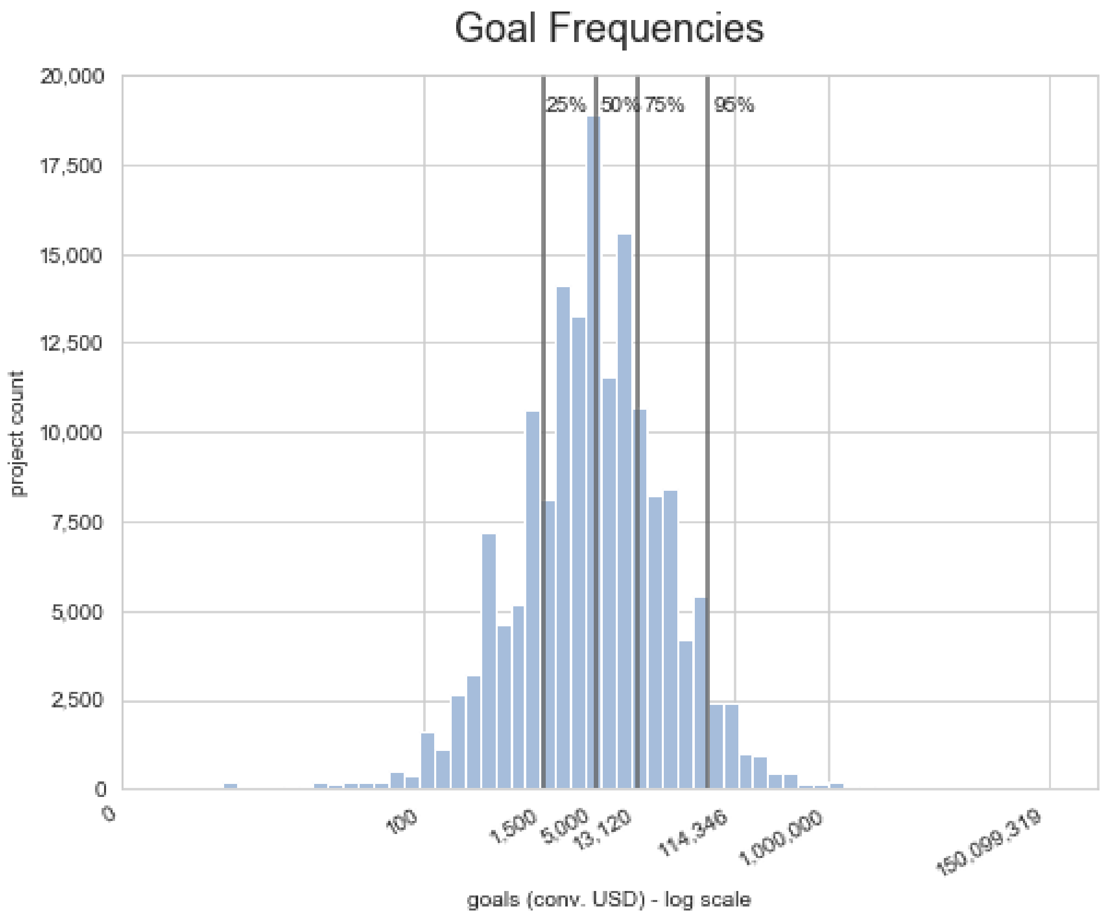
3.1 Goals

Let's understand the distribution of goals first. There is an extremely wide scope of funding goals. They ranged from zero to USD 150mi. However, 95% of projects choose goals below USD 114k. Goals in the scope of several million can be considered as outliers.

Due to the extremely skewed nature of funding goals, I log-transformed goals to make visualization possible. Generally, 3 quarters of goals were set below USD 13k. The median goal of all completed projects was only USD 5k.

```
In [18]: # settings
         plt.figure(figsize=[8,6])
         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="#a6bddb");

ax = plt.gca()
# annotate quantiles
for q, text in zip([goal_25, goal_50, goal_75, goal_95], ["25%", "50%", "75%", "95%"]
    # calculate log quantile
    log_q = np.log10(q)
    ax.axvline(x=log_q, color='#636363', ymax=1, linestyle="-")
    ax.annotate(text, xy=(log_q*1.01, 19000),fontsize=10)

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

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

x_ticks = [0.1, 100, goal_25, goal_50,  round(goal_75, 2), round(goal_975,2), 1000000
x_tick_labels = [format_num(x_tick) for x_tick in x_ticks]
plt.xticks(np.log10(x_ticks), x_tick_labels, rotation=30, ha='right')
plt.xlabel('goals (conv. USD) - log scale')

plt.show()
```



3.2 The lower the goal the better

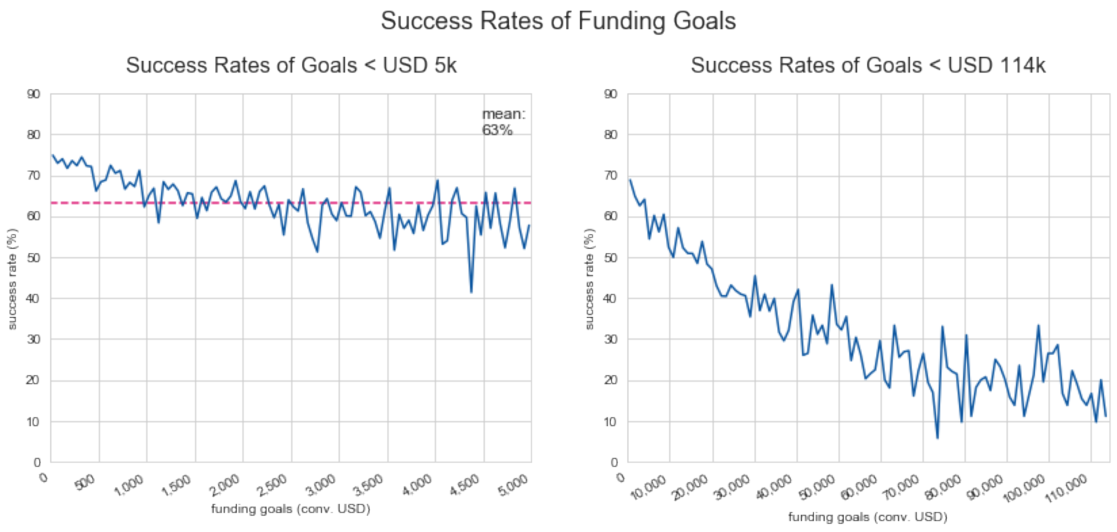
If creators want to keep at least a 50% chance, it appears to be advisable to stay below a benchmark of USD 10k. On average goals below USD 5k had a greater than 60% chance of succeeding. Very risk-averse creators may even choose to stick to goals below USD 1,5k.

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.

```
In [19]: # 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()) / 100
             bins = np.arange(df['goal_hist_usd'].min(),df['goal_hist_usd'].max()+bin_size, bin
             # 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 cent
             bins_c = bins[:-1] + bin_size/2
```

```
    # Use cut function to bin values into discrete intervals to segment and sort data
    # 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'], bins
    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['tota
    # 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=(goals_bi

# settings
plt.figure(figsize=[14,5])
goal_50 = ks_compl['goal_hist_usd'].median()
goal_975 = ks_compl['goal_hist_usd'].quantile(q=0.975)

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 5k", fontsize=16, pad=15)

locs = np.arange(0, goal_50+500, 500)
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 extreme 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 114k", fontsize=16, pad=15)
```

```
        locs = np.arange(0, 130000+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("success rate (%)")

        plt.suptitle("Success Rates of Funding Goals ", fontsize=18, y=1.05)
        plt.show()
```



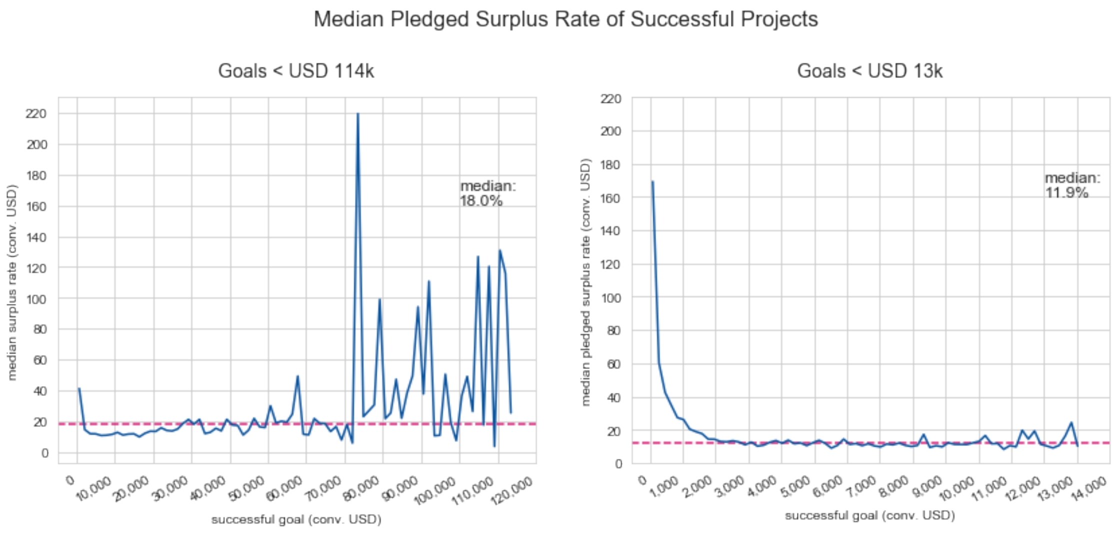
3.3 Successful projects realize an average surplus of 18%

The plots illustrate that the surplus creators realize depends on the goal chosen. Roughly, the surplus rate above goal describes a u-form. For goals below USD 3k the surplus rate descended exponentially. The lower the goal that was chosen the higher was the surplus rate. Low goal projects typically realized a surplus of 40%, 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 114k realized a median surplus of 26%. However, the surplus rates become less reliable as the volatility of pledges increases.

```
In [20]: # settings
        plt.figure(figsize=[14,5])

        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_si
    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

# calculate relative differences between goal and pledged 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['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']

# left plot: binned median pledges and respective binned goals
plt.subplot(1,2,1)
# for successfull campaigns with goals below 95%-quantile
ks_goal_975_s = ks_compl_success[ks_compl_success.goal_hist_usd < goal_975]
df_binned = binned_pledges(ks_goal_975_s, 80)
plt.errorbar(x = df_binned['goal_bin'], y = df_binned['surplus_r'], color=goal_color 
# annotate median
plt.axhline(df_binned.surplus_r.median(), color='#dd1c77', linestyle='--')
plt.annotate("median:\n" + str(round(df_binned.surplus_r.median(),1)) + "%", xy=(1000

# ticks and labels
plt.title("Goals < USD 114k", fontsize=14, pad=15)
locs = np.arange(0, 113000+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)")
format_yticks(220, 20)
plt.ylabel("median surplus rate (conv. USD)")

# right plot: binned median pledges vs. respective binned goals: moderately high goal
plt.subplot(1,2,2)
goal_75 = ks_compl['goal_hist_usd'].quantile(q=0.75)
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=goal_color 
plt.axhline(df_binned.surplus_r.median(), color='#dd1c77', linestyle='--')
plt.annotate("median:\n" + str(round(df_binned.surplus_r.median(),1)) + "%", xy=(1200

# ticks and labels
plt.title("Goals < USD 13k", 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(220, 20)
```

```
        plt.ylabel("median pledged surplus rate (conv. USD)")

        plt.suptitle("Median Pledged Surplus Rate of Successful Projects", fontsize=16, y=1.0
        plt.show()
```



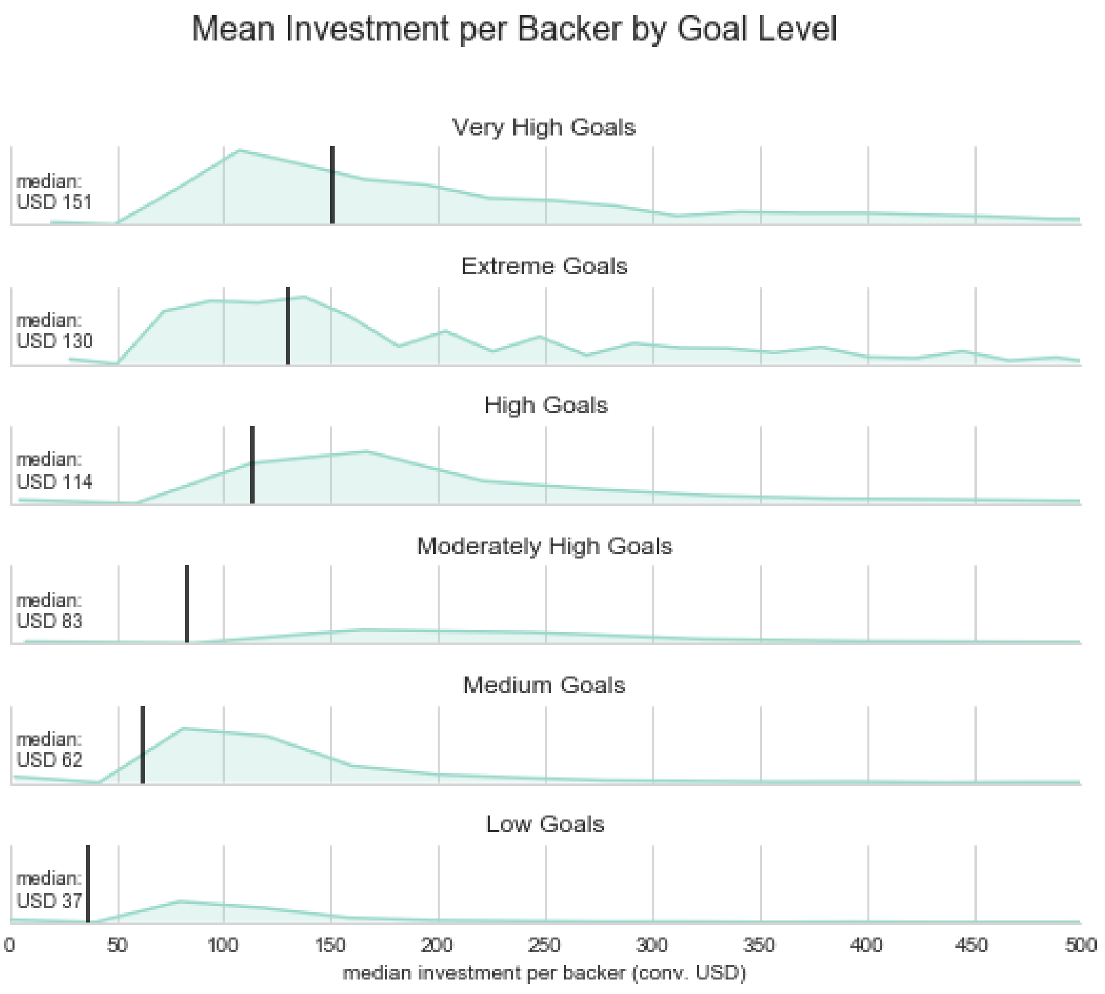
3.4 The higher a goal the higher the average pledge per backer

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 generate a median of USD 83. Successful very high goal projects generate the highest median funding per backer: USD 151.

Creators may consider this behavior when defining the rewards for pledges.

```
In [21]: # calculate the pledged investment per backer
        ks_compl['pledged_backer_r'] = ks_compl['pledged_hist_usd'] / ks_compl['backers_count
        ks_compl_95['pledged_backer_r'] = ks_compl_95['pledged_hist_usd'] / ks_compl_95['back
        ks_compl_success = ks_compl[ks_compl.status == "successful"]

        # 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()
```



3.5 Kickstarter's promotional 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). 10% of completed projects were fully supported. Meaning, they got picked by staff and were awarded the "Projects We Love" badge.

Every crowdfundings that was 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 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.

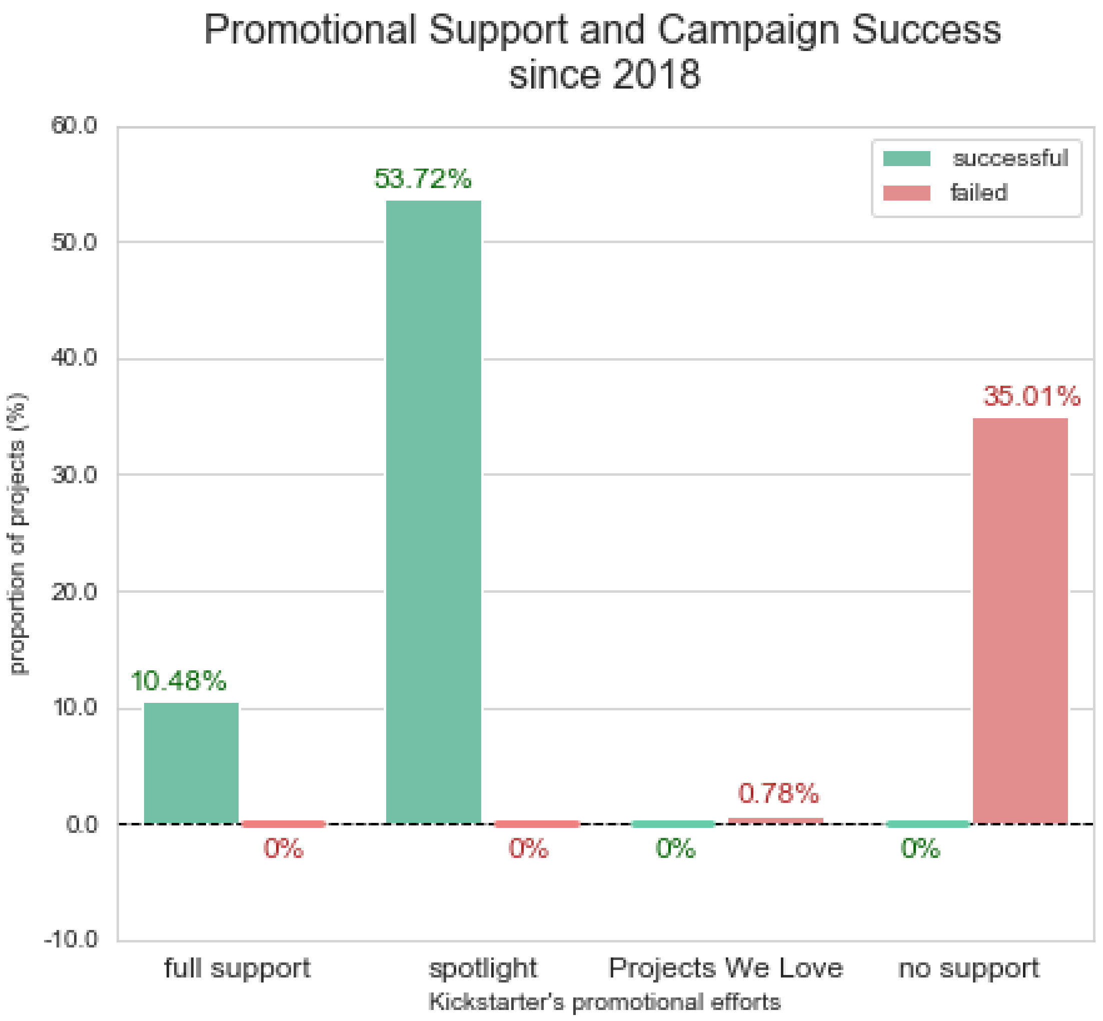
Generally, Kickstarter's preference was to support projects with lower goals. Spotlighted projects on average sought a goal of USD 3.3k. Creators who intend to collect higher funding should aim for the badge in addition to being featured on the website. Fully supported projects realized a median goal of USD 7.1k.

```
In [22]: ks_compl_95_latest = ks_compl_95[ks_compl_95.deadline.dt.year > 2017]
         ks_compl_95_latest_full = ks_compl_95_latest[ks_compl_95_latest.featured == 'full sup
         print(ks_compl_95_latest_full.pledged_hist_usd.median())
         ks_compl_95_latest_spot = ks_compl_95_latest[ks_compl_95_latest.featured == 'spotligh
         print(ks_compl_95_latest_spot.pledged_hist_usd.median())
```

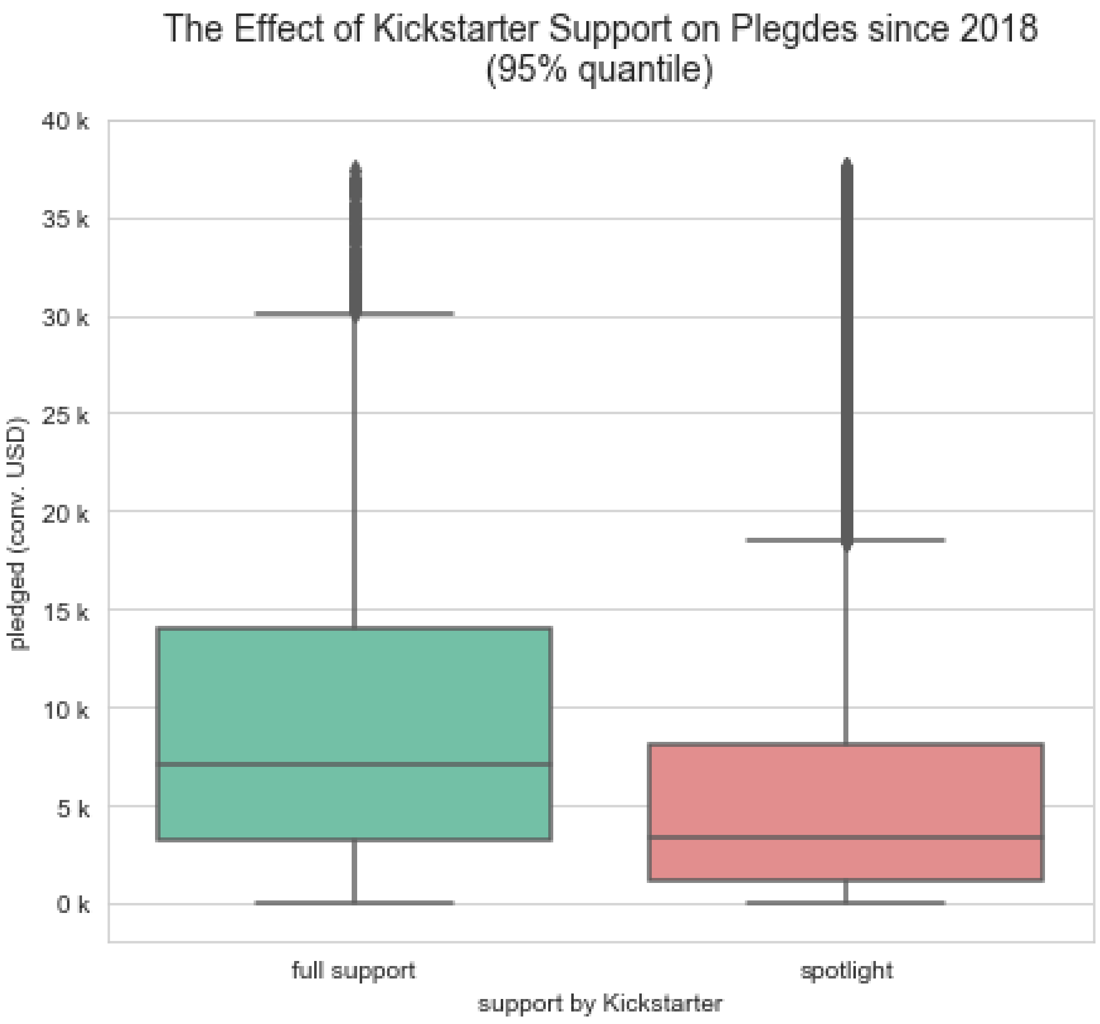
```
7112.0
3350.4364900375317
```

```
In [23]: # only consider projects since 2018 due to latest changes in promotional behavior
         ks_compl_latest = ks_compl[ks_compl.deadline.dt.year > 2017]

         # settings
         plt.figure(figsize = [7, 6])

         # order
         status_order = ks_compl_latest.status.value_counts().index
         feat_order = ['full support', 'spotlight', 'Projects We Love', 'no support']

         # get proportion of most common group - successful projects
         # and calculate relative values
         n_points = ks_compl_latest.shape[0]
         max_feat = ks_compl_latest['featured'].value_counts().max()
         max_feat_prop = max_feat / n_points
         max_status = ks_compl_latest['status'].value_counts().max()
         max_status_prop = max_status / n_points
```

```
# clustered bar chart featured categories vs. project status
sns.countplot(data = ks_compl_latest, x = 'featured', hue = 'status',
             order = feat_order, hue_order = status_order, color=sns.set_palette(statu

# add zero line
ax = plt.gca()
ax.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_latest.featured.value_counts()[feat] / n_points) * 100
    plt.text(i+0.05, ks_compl_latest.featured.value_counts()[feat]+300, str(round(rat
    fontsize=12, color=annot_color[j])
    ax.axhline(linewidth=3, color=bar_color[::-1][j], y=0.1, xmin=xmin, xmax=xmin+0.0
    plt.text(j-k, -1000, "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.legend(loc=1)
plt.title("Promotional Support and Campaign Success\nsince 2018", fontsize=16, pad=15
plt.xlabel("Kickstarter's promotional efforts")
plt.xticks(fontsize=12)

# generate proportion tick marks
ylocs = np.arange(-0.1, 0.6+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.show()
```



```
In [24]: # settings
         plt.figure(figsize = [7, 6])

         # boxplot of latest 95 quantile data to reduce strong skew caused by outliers
         ax = sns.boxplot(data = ks_compl_95_latest, x = 'featured',
                          y = 'pledged_hist_usd', order=feat_order[:2])

         # 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")
         plt.ylabel("pledged (conv. USD)")
         plt.title("The Effect of Kickstarter Support on Plegdes since 2018\n(95% quantile)",
         plt.show()
```



3.6 The time of year matters

The time of year affected the general success chances, investor counts and collected funding. Considering these factors, I found the best chances are in December. Generally, October to December and April to July are 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.

```
In [25]: # 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"]
```

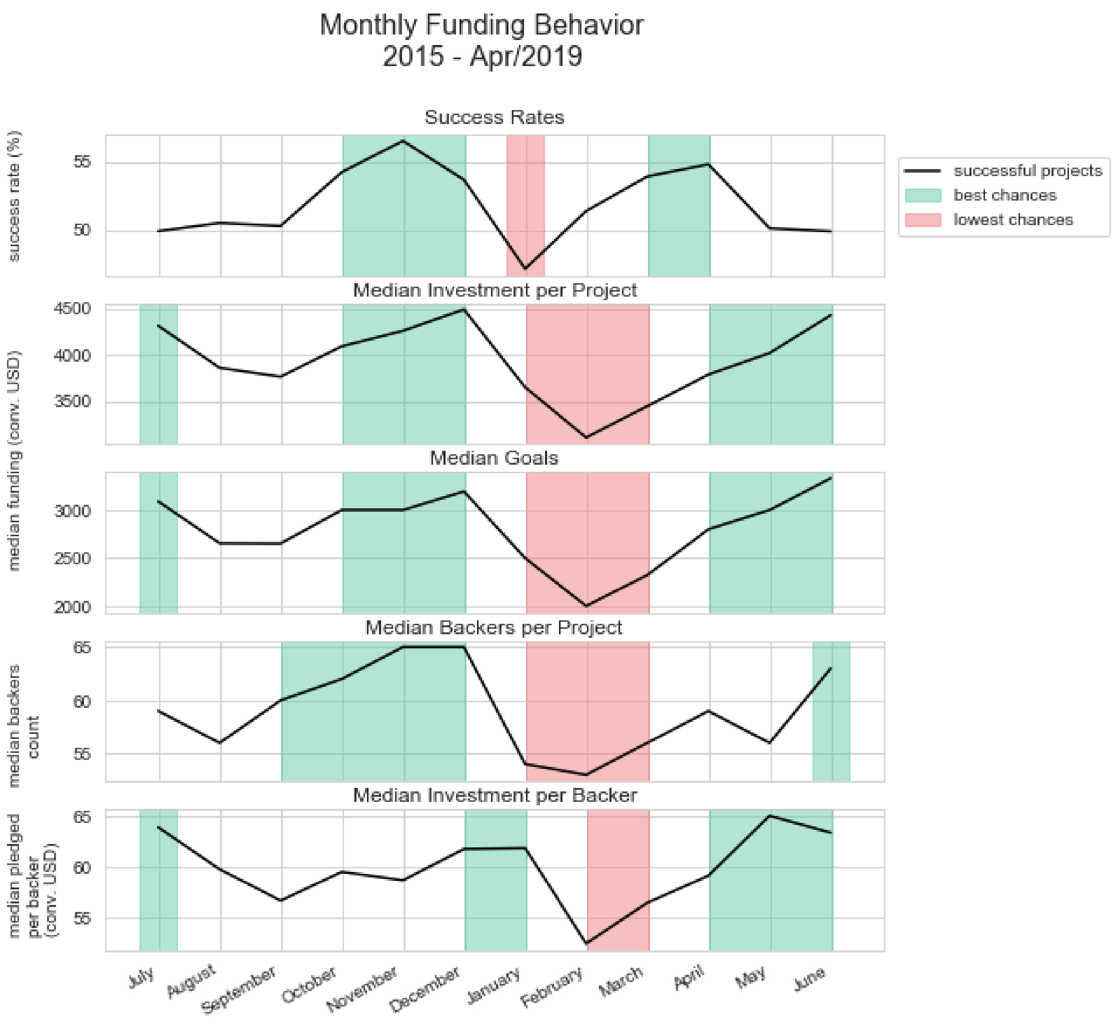
```
        # Due to strong skew, I use median instead of average to calculate the number of
        feat_total = df[feature].groupby([df.deadline.dt.month]).median()
        feat_success = df_s[feature].groupby([df_s.deadline.dt.month]).median()
        feat_fail = df_f[feature].groupby([df_f.deadline.dt.month]).median()

        # 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)
```

```
In [26]: # only consider data after 2015 to today - April 2019, because values were most stabl
         ks_15_19  = ks_compl[ks_compl.deadline.dt.year > 2014 ]
         ks_95_15_19  = ks_compl_95[ks_compl_95.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 by month
         df_success_15  = ks_15_19[ks_15_19.status == "successful"]
         counts =  df_success_15.deadline.groupby([df_success_15.deadline.dt.month]).count()
         # divide Jan-Apr by 5 and other months by 4
         success_proj_counts = [count / 5 for count in counts[:4]] + [count / 4 for count in co

         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 cou

         # create combined dataframe
         ks_months = pd.DataFrame({'avg_total': proj_counts,
                                  'avg_success': success_proj_counts,
                                  'avg_failed': failed_proj_counts})

         # As the interesting behavior is happening in January, I want to shift January to the
         # Rearange ordering so that July is at the frst place
         ks_months_sorted = ks_months[6:].append(ks_months[:6]).reset_index(drop=True)

         # 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
```

```
In [27]: # plot median success rates, goals, pledges, backers counts and pledge-backer ratio
         # grouped by months on one axis
```

```
fig, ax = plt.subplots(5, 1, sharex=True)

# ticks and labels
xlocs = np.arange(0,12)
plt.xticks(xlocs, months, rotation=30, ha='right');

# plot success rates
ax[0].plot(xlocs, ks_months_sorted['success_r'], color='black')


# plot features
for i, feature in enumerate(['pledged_hist_usd', 'goal_hist_usd', 'backers_count', 'pl
    ks_months_95_sorted = group_data(ks_95_15_19, feature)
    ax[i+1].plot(xlocs, ks_months_95_sorted['successful'], color='black', label="succe
    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="lowest chances")  # succes
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\nper backer\n(conv. USD)", va='center', rotation=

fig.suptitle('Monthly Funding Behavior\n2015 - Apr/2019', y=1.04, 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.xticks(xlocs, months, rotation=30, ha='right');
plt.legend(["successful projects", "best chances", "lowest chances"], loc=1,
           bbox_to_anchor=(1.3, 5.7)).legendHandles[2].set_color(cust_red)

plt.show()
```



3.7 The funding duration is 30 days

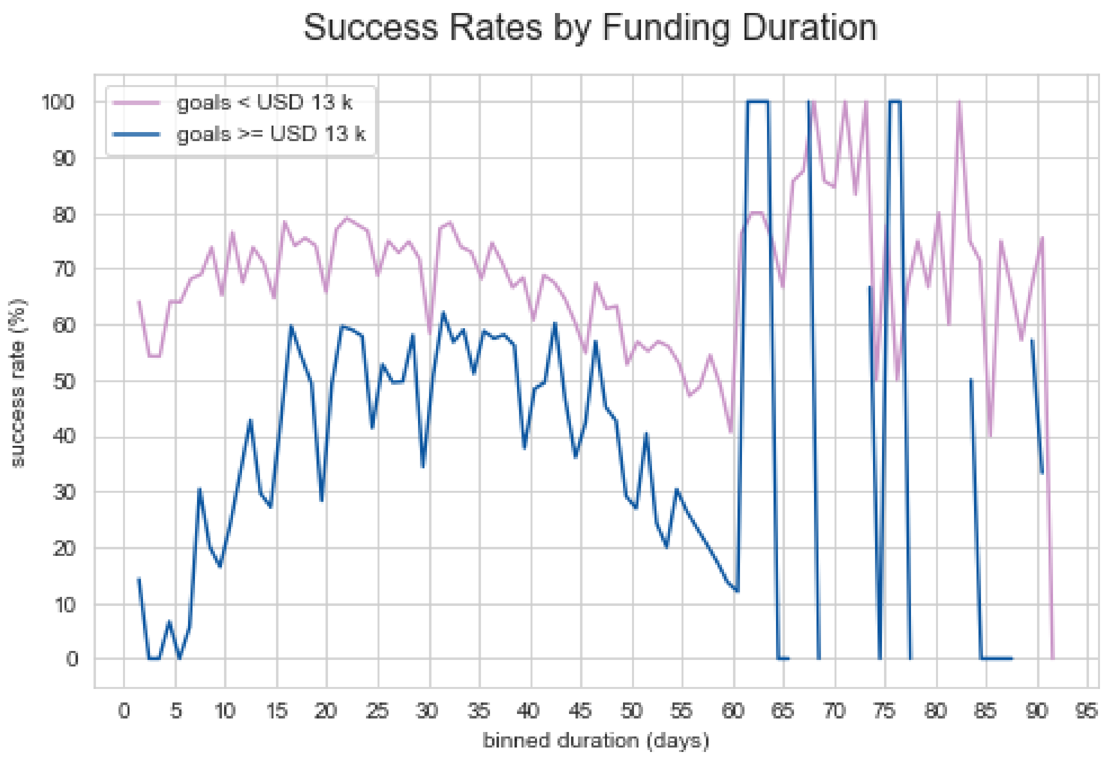
Although creators are free to choose their funding duration, it seems to be universally accepted to run a campaign within a period of roughly 30 days. It would seem natural to assume that a longer time frame would allow projects to increase their chances of success and collect higher funding. However, I found that longer durations are not rewarded with success. In fact, campaign periods ranging from 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 goals were 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 losing 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.

```
In [28]: # 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_si
    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_co
                 / 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, 95+5, 5))
plt.xlabel("binned duration (days)")
plt.yticks(np.arange(0, 100+1, 10))
plt.ylabel("success rate (%)")
plt.legend(['goals < USD 13 k', 'goals >= USD 13 k'])
plt.show()
```



3.8 The most valuable categories

I identified the most valuable project categories by depicting pledges against success rates and filtering by categories with the highest popularity. Accordingly, the most valuable categories were:

1) Design, in particular Product Design,

2) Games, in particular Video & Tabletop Game,

3) Fashion, in particular Apparel,

4) Video & Films, in particular Documentary & Narrative Films.

Universal category names are more likely to succeed.
The top chances in popular project categories show a tendency to not have subcategories. Publishing, comics, film & video, art and music performed generally well if they were communicated universally, instead of niche topics.

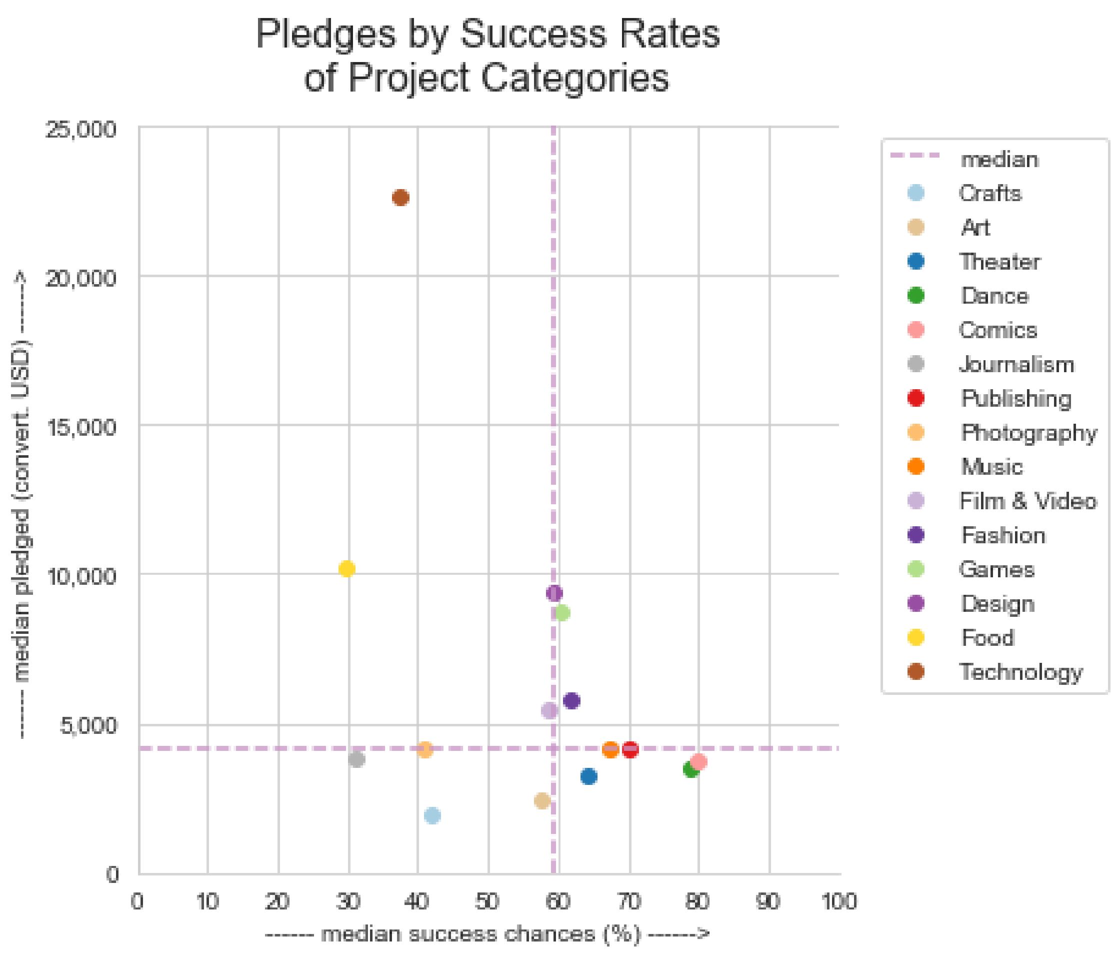
Tech and food projects are most likely to fail but realize the highest total funding.
Even though they are among the most popular categories, gadgets, hard- and software and web projects had low chances for success. In addition to technology ventures, I found 3 food subcategories among the ventures with the lowest chances: small batch, drinks and restaurants. We can attribute their high capital requirements to their poor chances for success. 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.

```
In [29]: # utility to 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_succe
                                 inplace=True)
             # calculate median pledged
             med_cat_pledged = ks_compl.groupby(['status', category]).median()['pledged_hist_us
             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', asce
             return  ks_cat_median

In [30]: # 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 [31]: # utility function to plot multivariate plot of 2 numerical and 1 quantitative variab
         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='--')
```

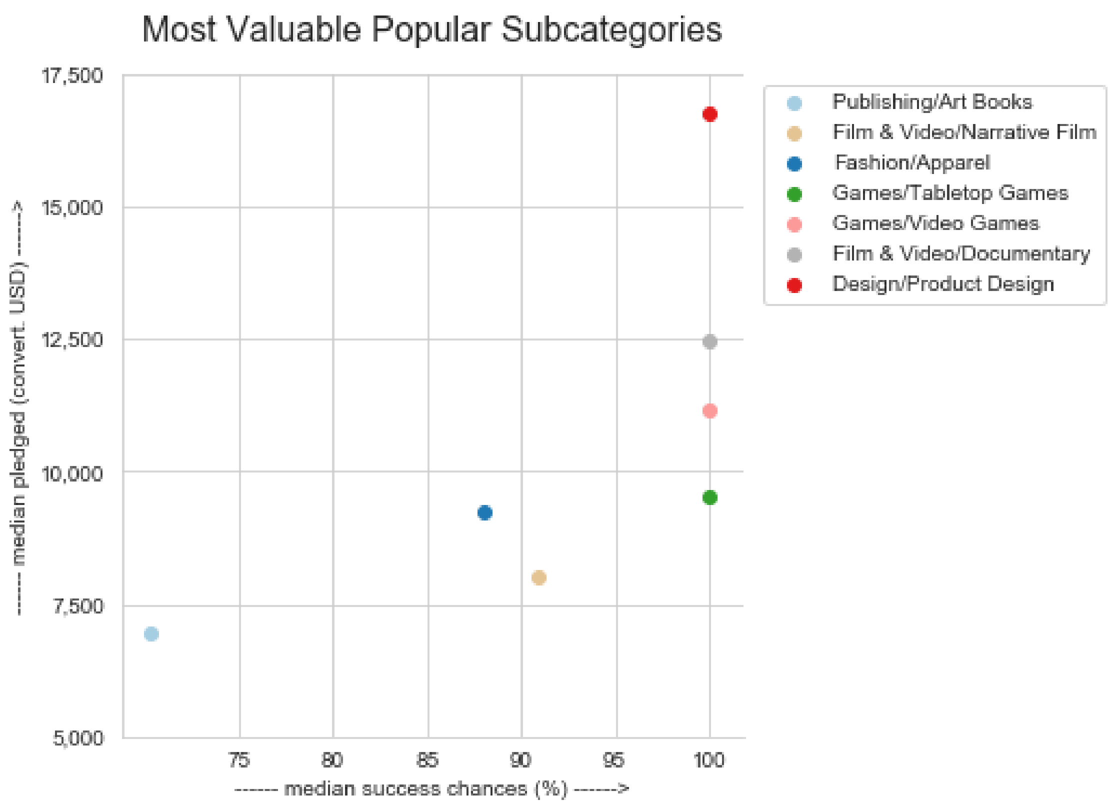
```
    # labels and ticks
    plt.title("Pledges by Success Rates\n" + headline, fontsize=16, pad=15)
    xlocs = np.arange(0, 100+10, 10)
    plt.xticks(xlocs)
    plt.xlabel("------ median success chances (%) ------>")
    format_yticks(df['med_pledged_success'].max(),5000)
    plt.ylabel("------ median pledged (convert. USD) ------>")

    leg = ax[0].legend(loc=1, bbox_to_anchor=(1.4, 1))
    leg.set_title('')
    plt.show()
    return g
```

```
In [32]: # return a dataframe of median goals and pledges grouped by status and category
         ks_cat_median = calc_med_goals_by('category')

         # add success rates to data frame for each category and goal
         df_cat_success = calc_cat_success('category')
         ks_cat_median = ks_cat_median.merge(df_cat_success, on='category')

         # plot pledged investment and success chance in a faceted scatterplot for each catego
         plot_facet_scatter_by(ks_cat_median, 'category', "of Project Categories");
```



```
In [33]: # return a dataframe of median goals and pledges grouped by status and subcategory
         ks_comb_cat_median = calc_med_goals_by('comb_cat')
         # add success rates to data frame for each subcategory and goal
         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')

         # filter by most popular subcategories
         pop_subcats = ks_compl.comb_cat.value_counts().index[:50]
         ks_comb_cat_median = ks_comb_cat_median[ks_comb_cat_median.comb_cat.isin(pop_subcats)

         # filter by best conditions: pledges above 5500 and +70% chance of success
         df_best_types = ks_comb_cat_median[ks_comb_cat_median['med_pledged_success'] >= 6000]
         df_best_types = df_best_types[df_best_types.successful > 70]

         # scatterplot to identify best subcategories by median pledges and success rates
         g = sns.FacetGrid(data = df_best_types, hue = 'comb_cat', height = 5, palette=categor
         g.map(plt.scatter, 'successful', 'med_pledged_success')
```

```
# labels and ticks
plt.title("Most Valuable Popular Subcategories", fontsize=16, pad=15)
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()
```



3.9 Low performing project types

The following popular categories performed below average in terms of their likelyhood to succeed. Additionally, they generally had a low capital funding potential.

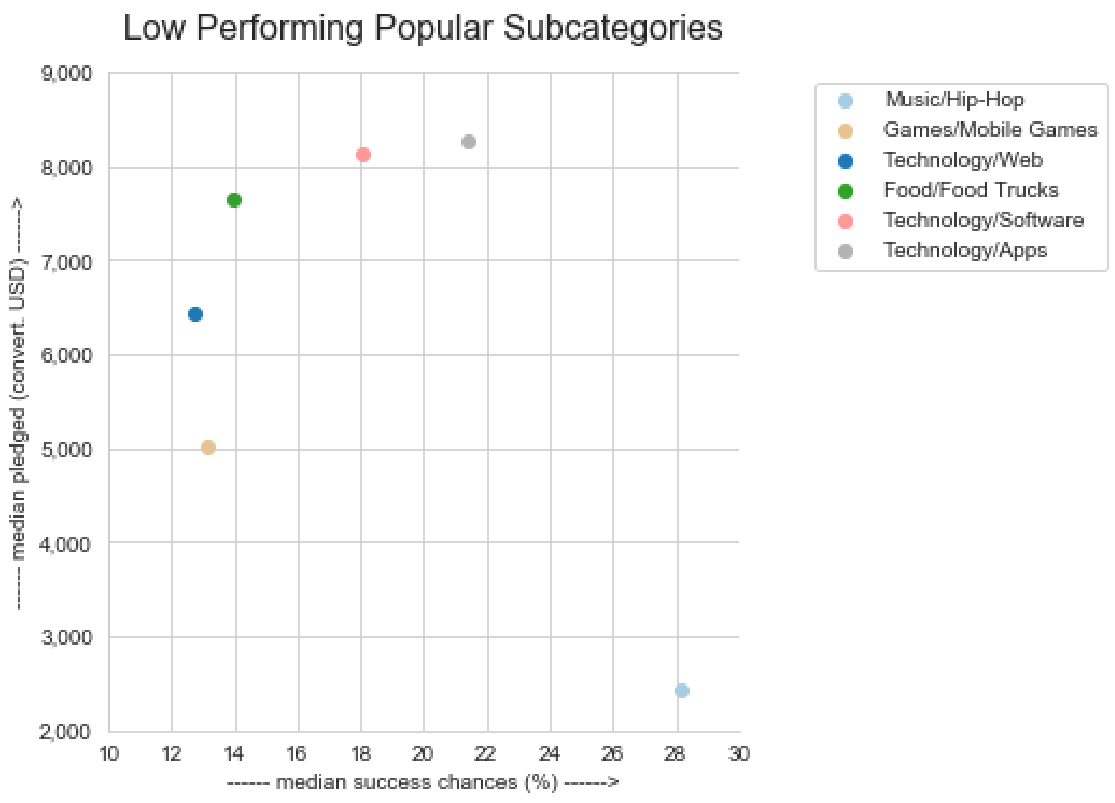
1) Web Tech, Software and Apps

2) Mobile Games

3) Food Trucks

4) Hip-Hop Music

```
In [34]: # filter for low performance: pledges below 10000 and less than 20% chance for succes
         df_worst_types = ks_comb_cat_median[ks_comb_cat_median['med_pledged_success'] < 10000]
         df_worst_types = df_worst_types[df_worst_types['successful'] < 30]

         # scatterplot to identify best subcategories by median pledges and success rates
         g = sns.FacetGrid(data = df_worst_types, hue = 'comb_cat', height = 5, palette=catego
         g.map(plt.scatter, 'successful', 'med_pledged_success')

         # labels and ticks
         plt.title("Low Performing Popular Subcategories", fontsize=16, pad=15)
         format_xticks(30, 2, 10)
         plt.xlabel("------ median success chances (%) ------>")
         format_yticks(df_worst_types['med_pledged_success'].max(), 1000, 2000)
         plt.ylabel("------ median pledged (convert. USD) ------>")

         plt.legend(loc=1, bbox_to_anchor=(1.6, 1))
         plt.show()
```



4 6 Rules For Success on Kickstarter

1) Choose the lowest goal possible below USD 10k

2) Choose a funding period lower than 32 days

3) Launch in October-November or April-June

4) Aim at being promoted by Kickstarter

5) Launch one of the following project types:

   - **Design:** Product Design,
   - **Games:** Video & Tabletop Games,
   - **Fashion:** Apparel,
   - **Video & Films:** Documentary & Narrative Films.

6) Avoid crowdfunding of:
   - Web Tech, Software and Apps
   - Mobile Games
   - Food Trucks
   - Hip-Hop Music

Once you're ready to finish your presentation, check your output by using nbconvert to export the notebook and set up a server for the slides. From the terminal or command line, use the following expression: > `jupyter nbconvert <file_name>.ipynb --to slides --post serve --template output_toggle`

This should open a tab in your web browser where you can scroll through your presentation. Sub-slides can be accessed by pressing 'down' when viewing its parent slide. Make sure you remove all of the quote-formatted guide notes like this one before you finish your presentation!

```
In [ ]:
```