Startup Genome
cracking the code of innovation

May 28th, 2011

Startup Genome Report 01

A new framework for understanding why startups succeed

In this report we reveal in-depth research about what makes Silicon Valley startups successful. The report is a 50 page analysis based on data from 650+ web startups. The report was coauthored by Berkeley & Stanford faculty members. Other contributors include Steve Blank, the Sandbox Network, and 10 accelerators from around the globe.

The goal of the report is to lay the foundation for a new framework for assessing startups more effectively by measuring the thresholds and milestones of development that Internet startups move through.

This report is the Startup Genome Project's first step toward cracking the innovation code of Silicon Valley and spreading it to the rest of the world.

Authors

Max Marmer, blackbox
Bjoern Lasse Herrmann, blackbox
Ron Berman, UC Berkeley

With collaboration and support from

Chuck Eesley, Stanford University
Steve Blank, Stanford University
Fadi Bishara, blackbox

contact: StartupGenome@blackbox.vc
web: startupgenome.cc, blackbox.vc

startup benchmark: http://startupgenome.cc/pages/startup-genome-benchmark
report: http://startupgenome.cc/pages/startup-genome-report-1
methodology: http://www.systemmalfunction.com/2011/05/deciphering-genome-of-startups.html

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A. Executive Summary

The goal of the Startup Genome project is to increase the success rate of startups and accelerate pace of innovation around the world by turning entrepreneurship into a science.

With the first Startup Genome report we aim to lay the foundation for a new paradigm of assessing startups and understanding the drivers of entrepreneurial performance.

Many entrepreneurs that we have talked with, especially younger ones, considered describing the repeating patterns of startups an impossible task or even a disgraceful reduction of the artistry of entrepreneurship to numbers and graphs. With this report we do not mean to imply that there is no art to entrepreneurship but rather that entrepreneurship is strongest at the intersection of science and art. By gaining a deeper understanding of the repeating patterns underlying success and failure entrepreneurs can dramatically increase their ability to innovate.

The window of opportunity for this project has only recently been opened. In just the last 2-3 years the number of people extracting and codifying the informal learning of Silicon Valley has hit a point of critical mass. Concurrently the costs of startup creation have fallen dramatically triggering a huge increase in technology entrepreneurship all over the world.

The theories and models that have had the most widespread adoption are effectively applying scientific management principles to startups, with the two most well known theories being Customer Development and the Lean Startup. Yet despite this huge knowledge base emerging about how startups work, startups have been able to absorb little more than the basic patterns of how to build a startup. Most founders don't know what they should be focusing on and consequently dilute their focus or run in the wrong direction. They are regularly bombarded with advice that seems contradictory, which is often paralyzing. And while startups are now gathering way more qualitative and quantitative feedback than they were just a few years ago, their ability to interpret this data and use it to make better business decisions is sorely lacking. The primary cause of these problems is that we lack the necessary structure to assimilate and build upon our accumulated knowledge on the nature of startups.

We believe the solution is the development of a flexible framework that enables the integration of the principles, methodologies and wisdom that have been discovered about how to create a successful startup.

For the last 5 months we've been working closely with Steve Blank, the progenitor of Customer Development and the startup science movement, to build this framework, which currently serves as the foundation of the Startup Genome Project.

In February we publicly announced the project and released a survey to test three key aspects aspects of our framework. We received an overwhelmingly positive response and 650+ startups filled out our survey.

The three key ideas we set out to test were:

1. Startups evolve through discrete stages of development. Each stage can be measured with specific milestones and thresholds.
2. There are different types of startups. Each type evolves through the developmental stages differently.
3. Learning is a fundamental unit of progress for startups. More learning should increase chances of success.

I. Summary of Main Results

The goal of the report is to lay the foundation for a new framework for assessing startups more effectively by measuring the thresholds and milestones of development that Internet startups move through.

Through analyzing the results from our survey we found that Internet startups move through similar thresholds and milestones of development, which we segmented into stages. Startups that skipped these stages performed worse.

We also identified three major types of Internet startups with various sub types. They are segmented based on how they perform customer development and customer acquisition. Each type has varying behavior regarding factors like time, skill and money.

These 2 findings lay the foundation for us to begin organizing and structuring all of a startup's customer related data, which entrepreneurs can use to make better product and business decisions. A first product based on this framework is currently in development. Contact us at startupgenome@blackbox.vc if you would like to know more.

Summary of additional findings:

1. Founders that learn are more successful: Startups that have helpful mentors, track metrics effectively, and learn from startup thought leaders raise 7x more money and have 3.5x better user growth.

2. Startups that pivot once or twice times raise 2.5x more money, have 3.6x better user growth, and are 52% less likely to scale prematurely than startups that pivot more than 2 times or not at all.

3. Many investors invest 2-3x more capital than necessary in startups that haven't reached problem solution fit yet. They also over-invest in solo founders and founding teams without technical cofounders despite indicators that show that these teams have a much lower probability of success.

4. Investors who provide hands-on help have little or no effect on the company's operational performance. But the right mentors significantly influence a company's performance and ability to raise money. (However, this does not mean that investors don't have a significant effect on valuations and M&A)

5. Solo founders take 3.6x longer to reach scale stage compared to a founding team of 2 and they are 2.3x less likely to pivot.

6. Business-heavy founding teams are 6.2x more likely to successfully scale with sales driven startups than with product centric startups.

7. Technical-heavy founding teams are 3.3x more likely to successfully scale with product-centric startups with no network effects than with product-centric startups that have network effects.

8. Balanced teams with one technical founder and one business founder raise 30% more money, have 2.9x more user growth and are 19% less likely to scale prematurely than technical or business-heavy founding teams.

9. Most successful founders are driven by impact rather than experience or money.

10. Founders overestimate the value of IP before product market fit by 255%.

11. Startups need 2-3 times longer to validate their market than most founders expect. This underestimation creates the pressure to scale prematurely.

12. Startups that haven't raised money over-estimate their market size by 100x and often misinterpret their market as new.

13. Premature scaling is the most common reason for startups to perform worse. They tend to lose the battle early on by getting ahead of themselves.

14. B2C vs. B2B is not a meaningful segmentation of Internet startups anymore because the Internet has changed the rules of business. We found 4 different major groups of startups that all have very different behavior regarding customer acquisition, time, product, market and team.

II. The Startup Lifecycle

Our foundational structure of startup assessment is the startup lifecycle. Understanding where a startup is in their lifecycle allows us to assess their progress. The startup lifecycle is made of 6 stages of development, where each stage is made up of levels of substages. This creates a directed tree structure and allows for more granular assessment by being able to pinpoint the main drivers of progress at each stage. We call each of these stages the Marmer Stages. However, in this report only the top level stages are discussed. Our first four top-level stages are based loosely on Steve Blank's 4 Steps to the Epiphany, but one key difference is that the Marmer Stages are product centric rather than company centric.

Our 6 stages are:

1) Discovery
2) Validation
3) Efficiency
4) Scale
5) Profit Maximization (not covered in this report)
6) Renewal (not covered in this report)

Our assessment of the stages does not include traditional ways of assessment like funding, team size, user growth, etc. They are based on milestones and thresholds that vary based on the type of startup. An example for a milestone is building a mvp and an example for a threshold is certain rate of retention.

We attempt to provide evidence for the existence of the Marmer Stages in two ways:

1) That the Marmer Stages correlate with traditional indicators of progress.
2) That startups that don't move through the stages in order show less progress.

Overview of Results:

	Avg. Months Working	Avg. Funding Raised	Avg. Number of Employees	Avg. % User Growth in last month	Top Competitive Advantages	Top Challenges
1. Discovery	7	$227,000	1	6%	IP Technology	Customer Acquisition Over capacity
2. Validation	11	$800,000	4	21%	Partners Insider Info	Customer Acquisition Product Market Fit Problem Solution Fit
3. Efficiency	17	$900,000	4	29%	Traction IP Insider Info	Customer Acquisition Team building Fundraising
4. Scale	25	$3,000,000	17	43%	IP Traction Technology	Customer Acquisition Team Building

	Avg. Number of Pivots	Pivot Variance	Avg. Funding Raised (Scale Stage)	Avg. # of Employees
Inconsistent Startups	1.6	5.0	$1,100,000	3
Consistent Startups	1.2	2.0	$3,400,000	20

III. Types of Internet Startups

We created our types by defining a spectrum of 100% marketing to 100% sales and created 3 points by selecting the two end points and the mid point. In the future, we plan to define a more fluid spectrum with more than 3 points, as we understand the underlying variables better and see where startups cluster. Our fourth type, Type 1N (The Social Transformer), is the same as Type 1 (The Automizer) but the product has network effects.

Type 1 - The Automizer

Common characteristics: self-service customer acquisition, consumer focused, product centric, fast execution, often automize a manual process.

- technology heavy founding teams perform better than other teams
- market size is 2x bigger for Type 1 (The Automizer) compared to Type 2 (The Integrator)
- more likely to tackle existing markets
- need the least capital of all types

Examples:
Google, Dropbox, Eventbrite, Slideshare, Mint, Pandora, Kickstarter, Hunch, Zynga, Playdom, Modcloth, Box.net, Basecamp, Hipmunk, etc.

Type 1N - The Social Transformer

Common characteristics: self service customer acquisition, critical mass, runaway user growth, winner take all markets, complex ux, network effects, typically create new ways for people to interact.

- need 50% longer than Type 1 (The Automizer) and Type 2 (The Integrator) to reach scale stage
- business heavy and balanced teams perform better than technology heavy teams
- market size is 2x bigger for Type 1N (The Social Transformer) compared to Type 2 (The Integrator)
- more likely to tackle new markets
- more likely to have large team growth at the scale stage
- need more capital than Type 1 (The Automizer) and Type 2 (The Integrator)
- more likely to have large user growth

Examples:
Ebay, OkCupid, Skype, Airbnb, Craigslist, Etsy, IMVU, Flickr, LinkedIn, Yelp, Aardvark, Facebook, Twitter, Foursquare, Youtube, Dailybooth, Mechanical Turk, MyYearbook, Prosper, Paypal, Quora, etc.

Type 2 - The Integrator

Common characteristics: lead generation with inside sales reps, high certainty, product centric, early monetization, SME focused, smaller markets, often take innovations from consumer Internet and rebuild it for smaller enterprises.

- business heavy and balanced founding teams perform better than technology heavy teams
- more likely to tackle existing markets with a product that is cheaper
- more likely to maintain small teams even when they scale
- monetize a high percentage of their users

Examples:
PBworks, Uservoice, Kissmetrics, Mixpanel, Dimdim, HubSpot, Marketo, Xignite, Zendesk, GetSatisfaction, Flowtown, etc.

Type 3 - The Challenger

Common characteristics: enterprise sales, high customer dependency, complex & rigid markets, repeatable sales process.

- To reach scale stage they need about 2x more time compared to 1N and 3x more time compared to Type 1 (The Automizer) and Type 2 (The Integrator).
- business heavy founding teams perform better than technology and balanced founding teams
- market size is 6-7 times bigger than all other types
- more likely to either tackle existing markets with a better product or tackle a new market
- are more likely to either pivot a lot or not at all
- more likely to have large team growth at the scaling phase
- need significantly more capital than the other types
- monetize a high percentage of their users

Examples:
Oracle, Salesforce, MySQL, Redhat, Jive, Ariba, Rapleaf, Involver, BazaarVoice, Atlassian, BuddyMedia, Palantir, Netsuite, Passkey, WorkDay, Apptio, Zuora, Cloudera, Splunk, SuccessFactor, Yammer, Postini, etc.

	Avg. Months to Move Through Marmer Stages	Primary Service Providers Hired	Type of Founding Team that is Most Successful	Market size Estimation (Efficiency & Scale Stages)
Type 1 (The Automizer)	21	User Experience, Backend Development	Technical Heavy Team	$11B
Type 1N (The Social Transformer)	32	User Experience, Backend Development	Balanced Team	$13B
Type 2 (The Integrator)	16	Sales, Business Development, PR	Balanced Team	$7B
Type 3 (The Challenger)	64	Sales, Business Development, PR	Business Heavy Team	$65B

	Primary Motivation	Market Type	Avg. Team Size (Scale Stage)	Avg. Funds Raised (Scale Stage)	Avg. User Growth in Last Month	Percentage of User Base is Paid
Type 1 (The Automizer)	Change the World	Existing Market (Better or Cheaper)	20	$600,000	14%	8%
Type 1N (The Social Transformer)	Change the World	New Market	28	$2,300,000	33%	10%
Type 2 (The Integrator)	Build a Great Product	Existing Market (Cheaper)	11	$700,000	11%	20%
Type 3 (The Challenger)	Build a Great Product	Existing Market (Better) or New Market	46	$4,100,000	36%	27%

IV. Entrepreneurial Learning

We examined whether founders learned in the following ways:

a) Learning from best practice

Companies that follow startup thought leaders like Steve Blank, Paul Graham, etc. are 80% more likely to raise money. Almost all companies that raised money had helpful mentors. Companies without helpful mentors almost always failed to raise funding.

b) Ability to listen to customer feedback

Companies that are tracking metrics average a monthly growth rate that is 7x companies that are not tracking metrics and are 60% more likely to raise funding than companies that don't track metrics.

c) Ability to act on feedback

Companies that fail to listen and act on feedback tend to scale without validating the size and interest of the market. These companies tend to either pivot not at all or more than 2 times. They also have a harder time raising money and growing the team.

d) Conclusions

The Marmer Stages: The stage-based developmental model seems to correlate well with traditional measures of startup behavior and success. However, it shows clearly that a snapshot analysis of startups is lacking, since conclusions about specific startups cannot be drawn without a longitudinal gathering of data.

Stage Consistency: The concept of consistency, introduced in this report, seems to be a strong predictor of "problems". Having a simple measure for consistency is yet stronger evidence for the validity of the stages model.

Types of Startups: Although intuition directs us to think startups behave differently by type, our data shows the differences quite clearly, and can provide startups with useful benchmarks. Firms can now more properly align their actions according to their type, and not act on general advice that does not pertain to them.

Learning: We have given initial evidence that the ability to learn affects startups in the long run. Our future work will focus on modeling and measuring what "startup learning" looks like, and how startups can improve and enhance their learning, and as a result, their chances of success.

V. Looking Forward

Working on this report has caused us to think deeply about the new generation of data driven businesses on the horizon and the opportunities and challenges it creates. While the possibility of measuring almost all aspects of business in real-time is an approaching reality that offers enormous potential, the major challenge will be extracting insights from this data deluge in order to make better business decisions.

One of our key focuses in the next few months will be developing a more intricate ontology to map the progress of startups along many more dimensions than just customer development and getting a deeper understanding of the underlying metrics and thresholds that determine stages. This should drastically increase our ability to test hypotheses and organize data.

B. The Startup Genome Report

I. Introduction

Two months ago we set out on a mission to crack the innovation code of Silicon Valley and share it with the rest of the world. Today we are releasing our first Startup Genome Report for highly scalable Internet startups, based on the results of our first survey. We want to thank Sandbox, FastCompany, Inc., ReadWriteWeb, Hackernews, youngupstarts, Yourstory.in and many more who helped us spread the word and gather a total of 650+ survey results. And a special thank you to all our fellow entrepreneurs who shared information about their company for this cause.

The results should be interesting for both Entrepreneurs and Investors. We hope it will help you recognize some of the patterns you've experienced with respect to how startups operate, succeed and fail, and improve your ability to assess your own startup and those of others.

Before digging into the results we want to mention two people who have helped us a lot. Ron Berman, a UC Berkley PhD candidate and former VC analyst, who became part of the Startup Genome team. Thank you Ron for showing us what number crunching really means. And Chuck Eesley, a professor at the Stanford Technology Ventures Program who helped steer the analysis and gave us confidence that our approach and findings have the potential to define a new paradigm in entrepreneurship.

Hypotheses

With the first Startup Genome survey we wanted to test three core ideas in our model for how Internet startups develop.

1. Startups evolve through discrete stages of development. Each stage can be measured with specific milestones and thresholds.
2. There are different types of startups. Each type evolves through the developmental stages differently.
3. Learning is a fundamental unit of progress for startups. More learning should increase chances of success.

Important: This report is only for Internet startups. Although we see patterns that could apply to industries this report only contains data from Internet startups.

II. The Stages To Success

1.1 Milestone Based Assessment Vs. Snapshot Based Assessment

We interviewed a lot of VCs and one major difference that stood out between VCs with outstanding track records and more average VCs was how they assessed startups. Average VCs would draw conclusions by taking a snapshot of just a few data points such as team, traction and market, and their questions would be focused on metrics like amount of money raised, and unfair competitive advantages. While these can be good validators that entrepreneurs are onto something a snapshot of the team and traction can often be misleading. A great set of resumes can't tell you how well the team actually works together. And traction was often measured in absolute numbers of users and revenue, but those metrics are second and third order effects of progress for an early stage startup. In the early stages a startup’s conversion funnel is a much better indicator of future growth than revenue.

Better performing VCs understood that startups are a search process for product market fit and a scalable business model. As a result, they drew conclusions based on more subtle data points such as the team's pace of learning, why they made certain pivots, the body language between the founders and stage specific metrics. This was part of the inspiration for trying to formalize the patterns of milestone based assessment.

One of the foundational ideas of the Startup Genome Project is that startups evolve through stages of development, where each stage of the startup's life cycle has a different set of milestones, challenges and metrics. In the near future, once we are able to identify more precisely what stage a startup is in, we will be able to give entrepreneurs tools and resources that help them figure out whether they are making progress, and how they should allocate their time and energy to increase their chances of success.

1.2 The Startup Lifecycle

Our foundational structure of startup assessment is the startup lifecycle. Understanding where a startup is in their lifecycle allows us to assess their progress. The startup lifecycle is made of 6 stages of development, where each stage is made up of levels of substages. This creates a directed tree structure and allows for more granular assessment by being able to pinpoint the main drivers of progress at each stage. We call each of these stages the Marmer Stages. However, in this report only the top level stages are discussed. Our first four top-level stages are based loosely on Steve Blank's 4 Steps to the Epiphany, but one key difference is that the Marmer Stages are product centric rather than company centric.

Our assessment of each stage is based on thresholds we found from our own experience and those of others. An example of a threshold would be, for a consumer startup without network effects to move from Stage 2 to 3 they must pass the threshold Sean Ellis discovered, that at least 40% of the user base says they'd be very disappointed if the product no longer existed.

The 6 Stages

1) Discovery

Purpose: Startups are focused on validating whether they are solving a meaningful problem and whether anybody would hypothetically be interested in their solution.

Events: Founding team is formed, many customer interviews are conducted, value proposition is found, minimally viable products are created, team joins an accelerator or incubator, Friends and Family financing round, first mentors & advisors come on board.

Time: 5-7 months (average for all types)

2) Validation

Purpose: Startups are looking to get early validation that people are interested in their product through the exchange of money or attention.

Events: refinement of core features, initial user growth, metrics and analytics implementation, seed funding, first key hires, pivots (if necessary), first paying customers, product market fit.

Time: 3-5 months (average for all types)

3) Efficiency

Purpose: Startups refine their business model and improve the efficiency of their customer acquisition process. Startups should be able to efficiently acquire customers in order to avoid scaling with a leaky bucket.

Events: value proposition refined, user experienced overhauled, conversion funnel optimized, viral growth achieved, repeatable sales process and/or scalable customer acquisition channels found.

Time: 5-6 months (average for all types)

4) Scale

Purpose: Startups step on the gas pedal and try to drive growth very aggressively.

Events: Large A Round, massive customer acquisition, back-end scalability improvements, first executive hires, process implementation, establishment of departments.

Time: 7-9 months (average for all types)

5) Profit Maximization (not assessed in this report)

6) Renewal or Decline (not assessed in this report)

What happens at each stage can vary strongly based on the type of startup. The different types of startups will be discussed in more detail in section 3 of this report.

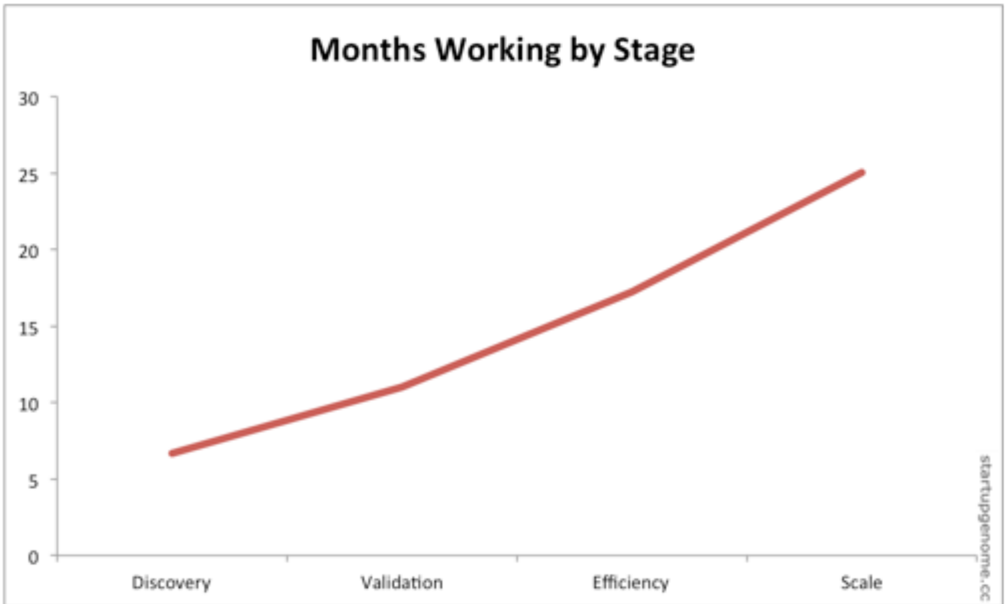
1.3 Marmer Stages vs. Traditional Indicators of Success

We attempt to provide that evidence for the existence of the Marmer Stages in two ways:

1) The Marmer Stages correlate with traditional indicators of progress.

2) Startups that don't move through the stages consistently, show less progress.

Traditional Indicators of Progress Correlated with the Marmer Stages



filter: only consistent startups that raised money / n=82, 90% significance level (SL)

This graph shows ...

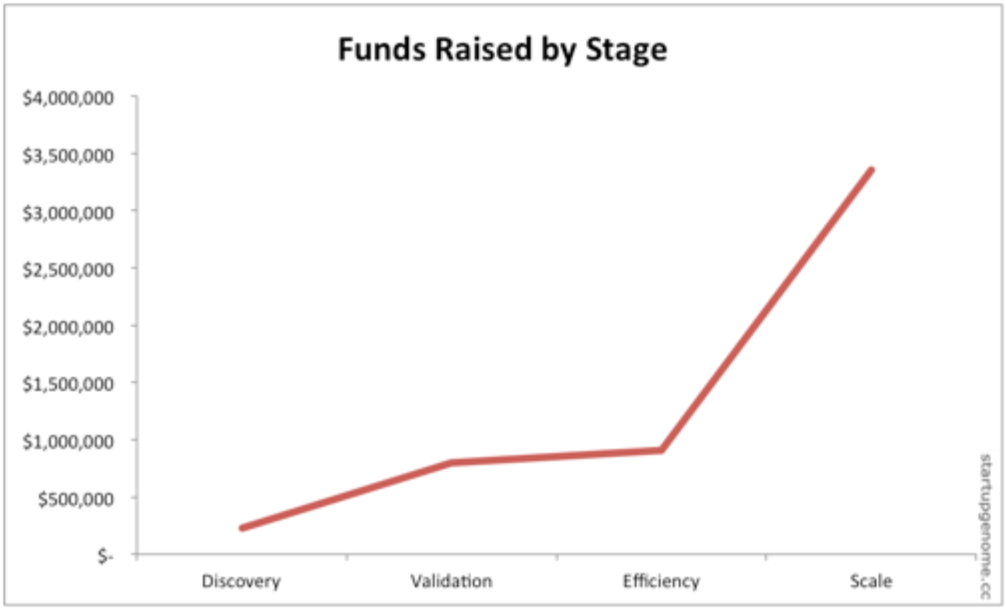
on average how long funded startups in each stage have been working.

This is consistent with the Marmer Developmental Stages because ...

The time startups spend in each stage increases monotonically and is convex. This indicates that each stage is harder to complete and takes more time.

Lessons Learned ...

The time a startup needs to move through the first stages is much longer than many first time founders expect. Many are deceived by the belief that they should be able to complete stage 1 (Discovery) within just one month. Because it normally takes much longer this creates pressure to jump stages, resulting in inconsistency.
This graph is also helpful for an investor to be aware of when an investment makes sense.



filter: only startups that raised money / n=100, 95% SL

This graph shows ...

How much money startups raise on average per stage. In stage 1 startups raised 150k on average. In stage 2 when the product is built and startups have gotten some initial validation of their product but haven't achieved product market fit yet they raised 600k on average. In stage 3 the average is 900k - at stage 4 the average is at 3M. Those averages vary by type of startup.

This is consistent with the Marmer Developmental Stages because ...

1) There are no negative slopes
2) The values in stages 2-4 fall within our recommended range.

Lessons Learned ...

Our recommended round size at each stage:

Stage 1: 10-50k
Stage 2: 100k-1.5M depending on type
Stage 3: 0 (recommended to wait until stage 4 until raising)
Stage 4: 1.5 - 7M depending on type

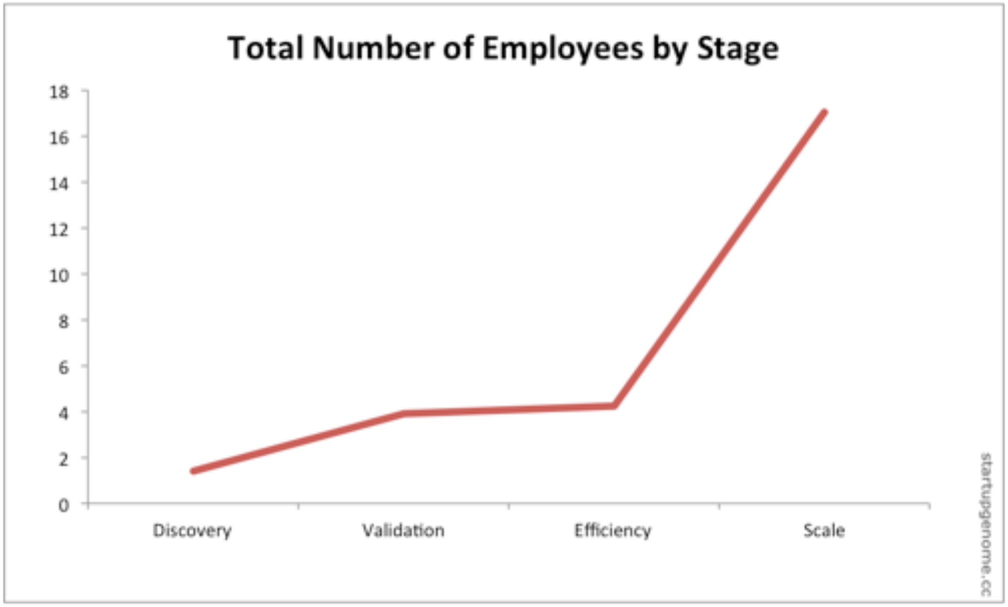
There is not much difference in the capital raised between stage 2 and 3, which is to be expected in our model because in Stage 3 a startup should be focused on efficiency and there's no need for excess capital beyond what was raised in stage 2.

Startups do their big raise at stage 4, which we call the Scale stage. This stage occurs once a startup has proved they have a product people want, can cost effectively acquire customers and can use the money in order to accelerate their ability to scale.

We think the value for stage 1 was higher than we'd recommend because many investors are over investing in stage 1. We believe investing just 10-50k in stage 1 rather than doing a larger seed of 100k reduces risk for investors and has no negative impact on startups. The basic idea is that investors should not place a large bet on most types of startups until they see them find problem solution fit and produce something that at least solves a piece of the problem. This can help prevent investors from betting on teams that look great on paper but ultimately have no chemistry and fail to execute. The constraint of having less than 50k probably even positively influences first time entrepreneurs, helping them to not get too far ahead of themselves.

Lessons Learned ...

Raise a lot of money after product/market fit and a cost efficient customer acquisition process is achieved.



filter: only startups that raised money / n=129, 95% SL

This graph shows ...

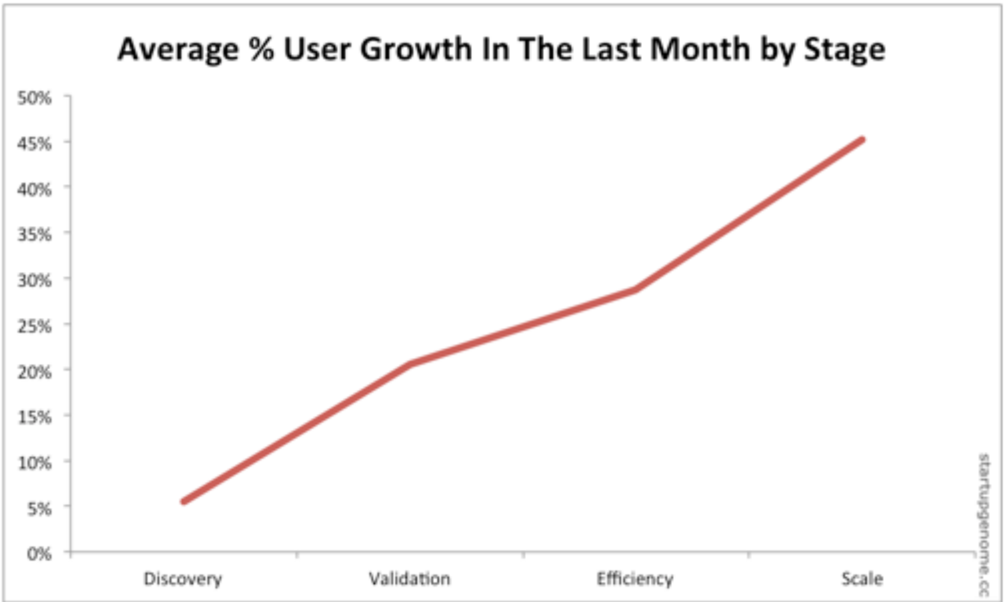
the size of the team excluding the founding team and part time employees by stage. The number stays relatively constant through the first 3 stages until they start scaling in stage 4.

This is consistent with the Marmer Developmental Stages because ...

1) There are no negative slopes
2) The team size stays relatively constant through the Discovery, Validation, Efficiency stages, and only grows at the scale stage.

Lessons Learned ...

Don't worry about hires that won't be a part of the core team until the Scale stage



filter: Only Consistent Startups working full time / n=199

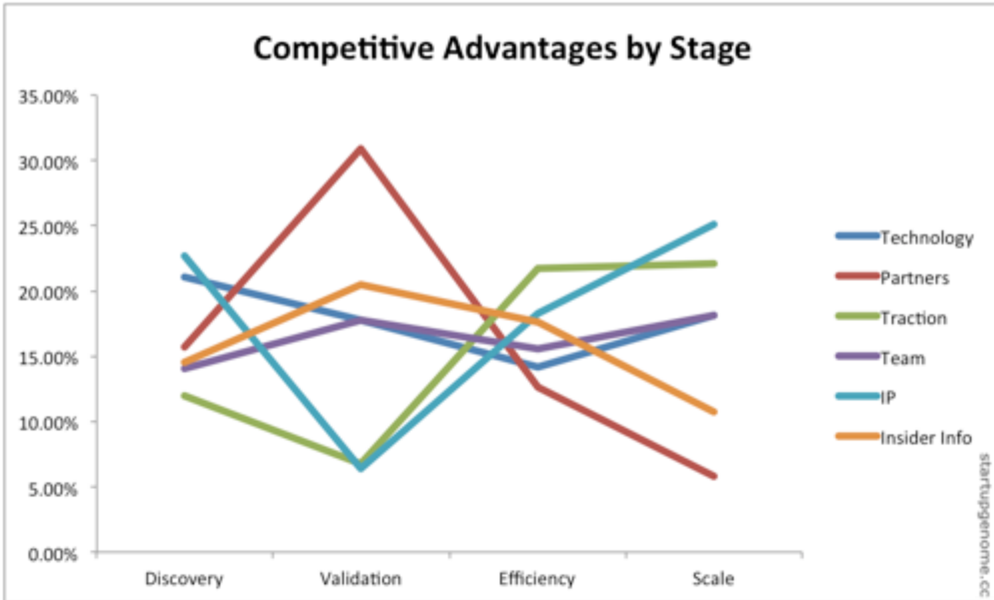
This graph shows ...

the average percentage user growth in the last month by stage.

This is consistent with the Marmer Developmental Stages because ...

In the discovery stage there is little focus on growth. In the validation stage as the product improves growth should increase. In the efficiency stage growth flattens but it paves the way for fast growth in the scale stage.

It might be expected that the growth would be higher in stage 1 because if a startup has 2K users and they grew from 1k users in the last month they will show 100% growth. However the average user growth is much lower because although startups typically have a big initial spike when they launch their mvp in Stage 1, their growth quickly flattens out. And most Stage 1 startups that filled out the survey have been around long enough to enter the plateau.



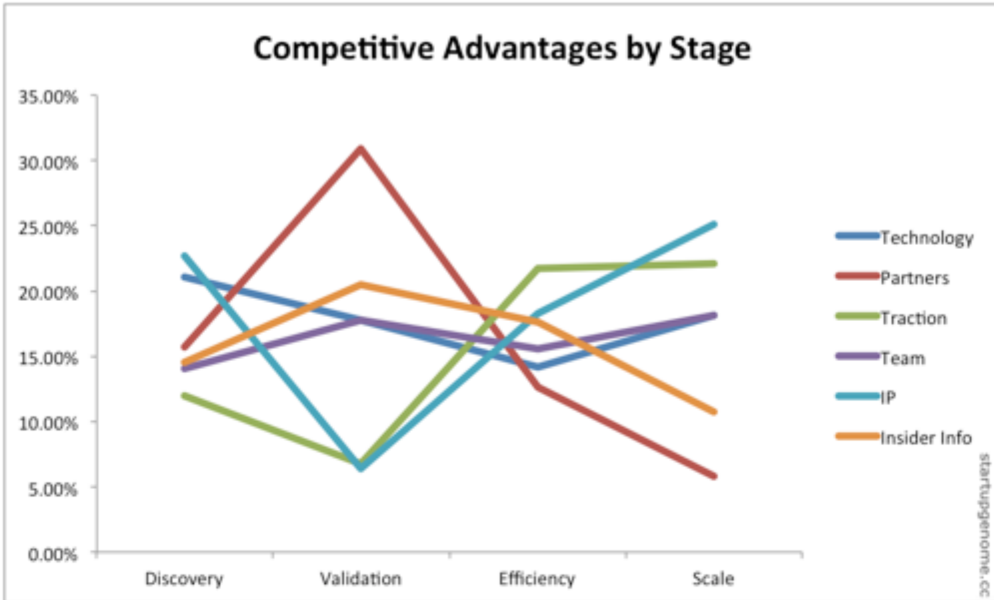
filter: only consistent startups that raised money

This graph shows ...

the breakdown of what founders believed to be their competitive advantage by stage.

	Discovery	Validation	Efficiency	Scale
Top Competitive Advantages	IP Technology	Partners Insider Info	Traction IP Insider Info	IP Traction Technology

- The importance of technology changes slightly over time. Especially in the beginning it is perceived as more important than other competitive advantages.
- Partners as a competitive advantage experience a spike in stage 2
- Traction dips in stage 2 and spikes in stage 3.
- Team stays fairly consistent throughout all stages.
- The importance of IP fluctuates significantly through the stages
- Insider info is important in the first 2 stages and then takes a nosedive. For example, when Marc Benioff left Oracle to start Salesforce he was an SVP at Oracle and was armed with a lot of insight about where the enterprise software world was headed.



filter: only consistent startups that raised money

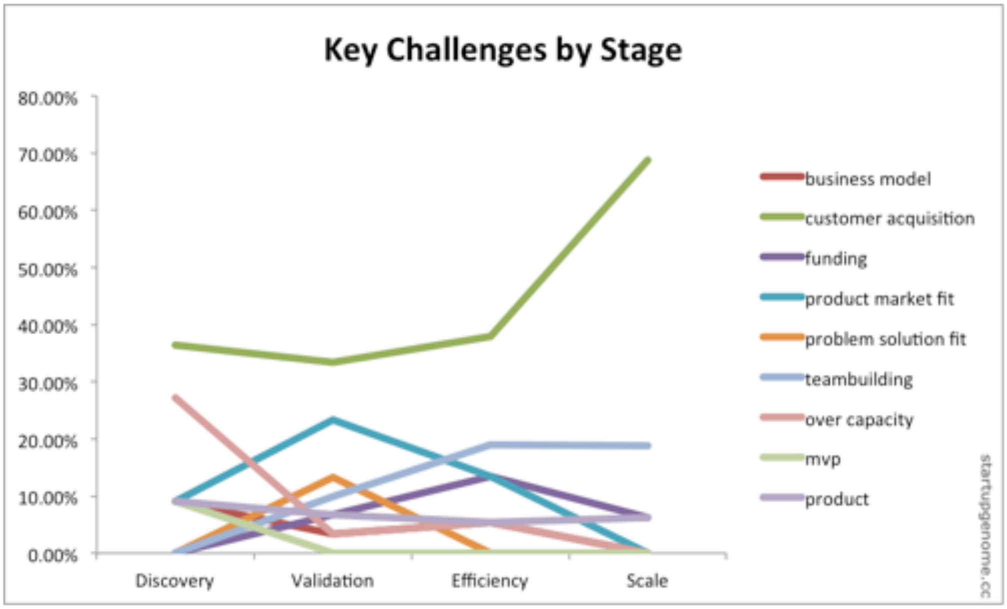
This is consistent with the Marmer Developmental Stages because ...

Technology — This is always a key piece of an Internet startup.

Partners - In the validation stage partners can be used to validate concepts with little traction. For example, the deal Microsoft struck with IBM to develop the DOS operating system, allowed them to take on a complex project with high certainty of success.

Traction — It is the least important competitive advantage in Discovery, though it's surprising the percentage is even that high as the startup probably has no traction in Discovery when they haven't even built their mvp, unless they were spun out of an existing organization or blog. In
Validation traction drops to expected levels when founders realize few people actually use or want their product. Traction increases after product market fit once startups enter the Efficiency and Scale stages.

Intellectual Property (IP) is surprisingly high in Discovery and takes a big nose dive in Validation. This is probably because many startups were born from the commercialization of IP but begin doubting the importance of their IP when most people don't want to user their product. In stage 3 and 4 IP becomes more important because the startup is clearer about the IP that users actually value.



filter: only consistent startups that raised money

This graph shows ...

The key challenges startups report in each stage

	Discovery	Validation	Efficiency	Scale
Top Challenges	Customer Acquisition Over capacity	Customer Acquisition Product Market Fit Problem Solution Fit	Customer Acquisition Team building Fundraising	Customer Acquisition Team Building

This is consistent with the Marmer Developmental Stages because ...

Product market fit spikes as a key challenge in the validation stage. But it was surprising some startups in stage 3 still considered product market fit a challenge. Looking into these responses it seems the cause is that they were overly optimistic about the threshold we asked them to estimate.

Throughout the 4 stages customer acquisition is overwhelmingly the biggest challenge. Our assumption is that most startups fail due to a lack of customers, so in some sense this is to be suspected. However in stages 1-3 startups shouldn't be directly focused on customer acquisition. Challenges like Problem Solution Fit, Product Market Fit, and Feature Development are more actionable challenges that treat the root cause of the lack of customers. Based on our experience working with startups many fail to acquire customers at the speed they would like because they either build too many features or they overcompensate for a non functional product by creating lots of buzz. The focus on customer acquisition suggests the latter to be true for some startups. The result will be a slow death. An additional cause for customer acquisition being such a frequently reported challenge may be that many investors are asking to see startups' traction rather than the metrics that make sense at each stage.

The challenge of team building and raising funding increases in stages 1-3 but levels off in stage 4. We think this is probably because companies that make it through the milestones of stages 1-3 don't have trouble raising funding. And team building is significantly easier when higher salaries can be offered and startups can pay for recruiting resources. It is notable that the challenge of fundraising peaks in the efficiency stage when startups probably shouldn't be looking to raise money. Upon further investigation it appears most of these startups have product/market fit in markets too small for investor interest, or are in overly crowded markets with a team that does not significantly standout.

This graph surprised us because ...

Barely anybody considered product to be their main challenge.

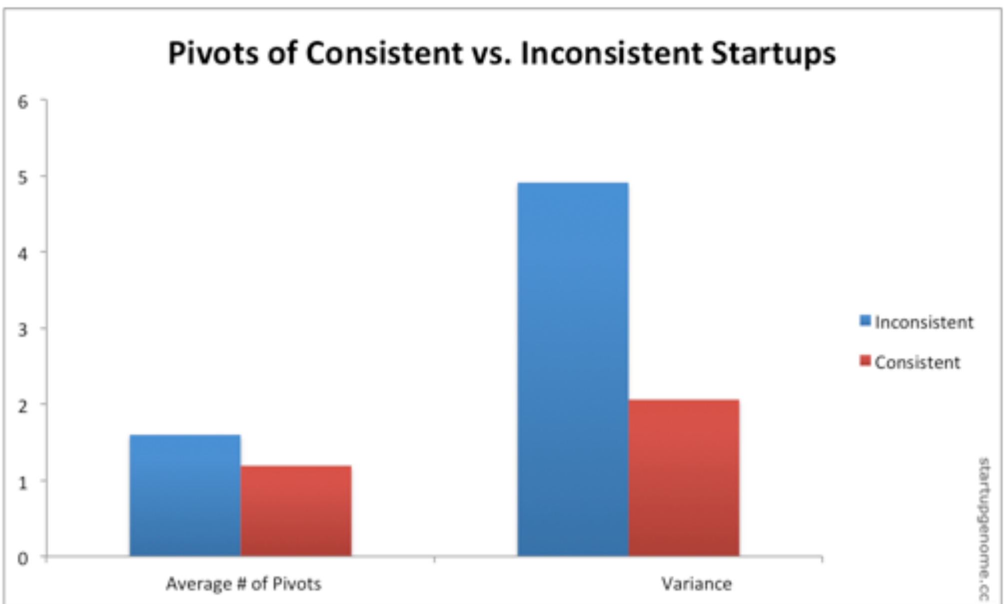
In Validation many startups felt like they hadn't found problem/solution fit, yet finding problem solution fit is a key part of the Discovery stage. According to our assessment they had a working product but hadn't yet figured out whether anyone wanted it. As a result most of these startups will need to pivot back to Discovery when they fail to get Validation in stage 2.

When founders said one of their key challenges was having too little time or having to wear too many hats we summarized this as "over capacity". **It's interesting that being at over capacity was only a significant problem for startups in Discovery.** We think this is probably a combination of founders finding clarity in how they should set their priorities once they get some initial validation, and founders who have this problem simply failing to reach Validation.

1.4 Consistency As An Indicator Of Success

The following graphs look at the differences between startups that move consistently through the developmental stages and startups that do not. Startups that don't move consistently through the stages are called inconsistent. For example, we could recognize a startup as inconsistent if they are performing activities associated with stage 3 or 4 but didn't yet achieve the milestones considered completion indicators for stages 1 and 2. One of the most common reasons to be flagged for inconsistency is premature scaling, which means attempting to scale before validating whether anyone wants the product. When a startup is marked inconsistent, we consider their actual stage to be the last stage where they achieved milestones that indicate stage completion.

If the stage based model is accurate, startups that don't move through the stages should perform worse.



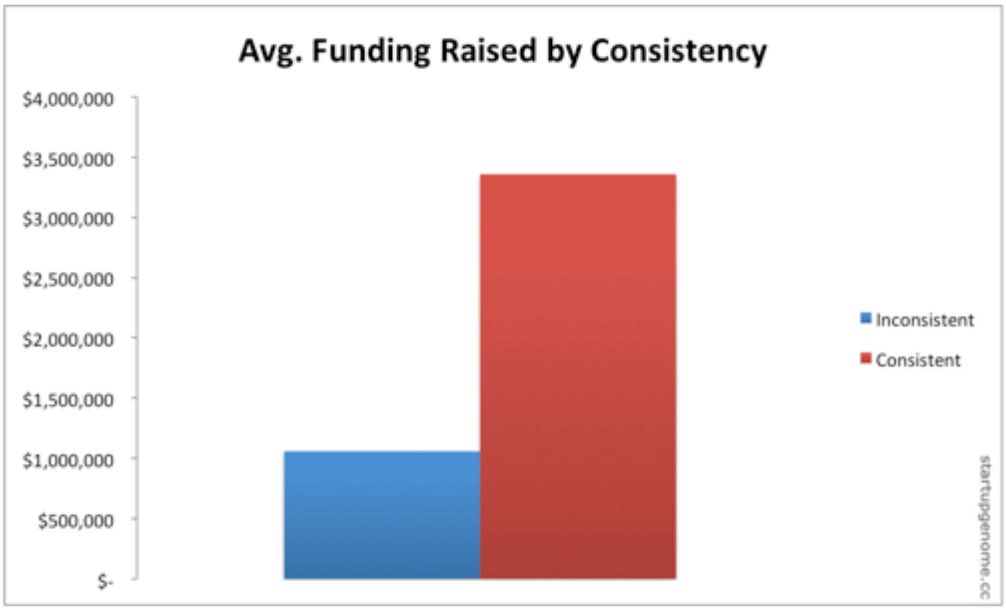
A pivot is a major change in the business. For example a new market or a new value proposition.
n=455, 90% SL for difference in averages

This graph shows ...

Inconsistent startups have very different behavior regarding pivots. While the average number of pivots is very similar for consistent and inconsistent startups their difference in variance is very large. This means that inconsistent startups are either pivoting very often or not at all.

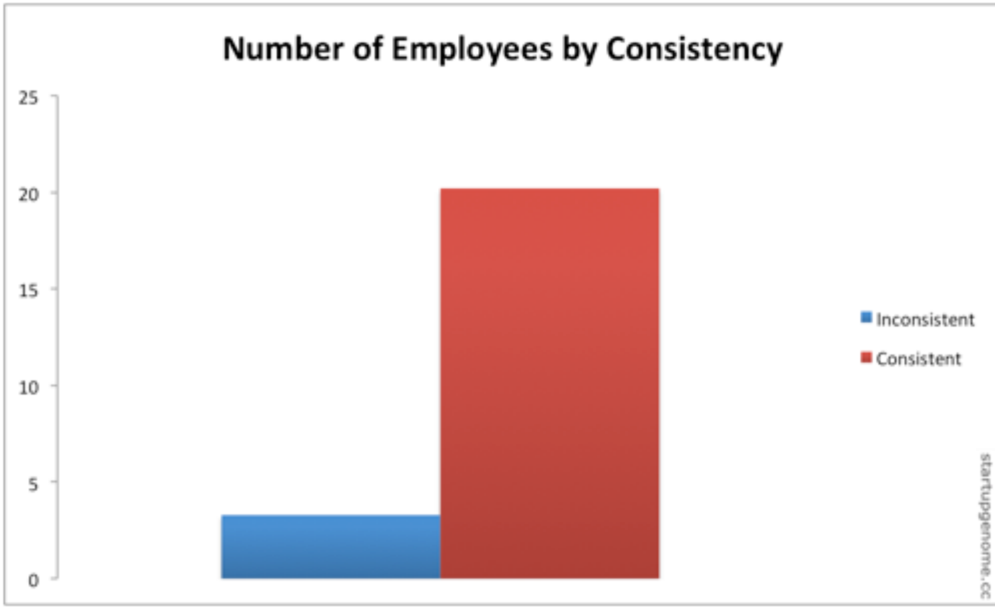
This is consistent with the Marmer Developmental Stages because ...

Startups that move through the stages consistently should find their way.
It's very unlikely a startup gets everything the right the first time and won't need to pivot, but they also should be able to find traction after making a few adjustments, if they are doing what each stage entails.



filter: only startups that raised money that are in the scale stage / n=31, 90% SL

We see that consistent companies raise more money than inconsistent companies. This means that VCs are also able to intuitively discern how startups are moving forward, and reward the startups that are moving through the stages considerably more.



filter: only startups that raised money that are in the scale stage / n=31, 90% SL

Consistent companies grow their emploees 5 times faster in the same amount.

1.5 Improving our Stage Assessment

Our stage assessment at a high level worked reasonably well but we found many ways to improve its accuracy.

Our data is based on averaging the data points in each stage. Within each stage there is large variation but we believe this is because startups can pass through the stages with varying levels of healthiness or competence. Startups can limp into the next stage just barely passing over the threshold or they can pass a stage with flying colors. We will be working on defining the variables that correspond to lower and upper bounds of stage progression.

1.6 Conclusion

We don’t think our analysis definitively proves startups must move through these stages but we have found plenty of indicators, intuitive and numerical, that stages exist. Improving the stage based model presents a big opportunity to gain a deeper understanding of what drives entrepreneurial success, and give entrepreneurs the knowledge and resources to better allocate their energy, prepare for challenges, and drive progress.

III. Startup “Personality” Types

One of the common confusions many entrepreneurs encounter as they start their company is receiving highly contradictory feedback on many decisions they face. One of the main causes of contradiction is that the person giving feedback bases their advice on their personal startup experience and doesn’t take into account whether the entrepreneur has a different type of startup.

We don’t fault the advice giver because sorting out all the different types of startups is no easy task. Until now we’ve seen little work done to formalize what the different types of Internet startups are and what factors they should be differentiated on.

Currently our typing system is focused primarily on the customer development dimension, which deals with how founders search for and validate a scalable customer acquisition strategy. This version of the typing system takes very little about the product and the existence of technology risk into account. Future versions will rely on a more comprehensive ontology that maps startups progress along many more dimensions.

Based on our survey results we created three different Startup Personality Types with a few subtypes.

1.1 Types of Internet Startups

Type 1 - The Automizer

Common characteristics: self-service customer acquisition, consumer focused, product centric, fast execution, often automize a manual process.

Examples: Google, Dropbox, Eventbrite, Slideshare, Mint, Groupon, Pandora, Kickstarter,Zynga, Playdom, Modcloth, Chegg, Powerset, Box.net, Basecamp, Hipmunk, OpenTable etc.

Type 1N - The Social Transformer

Common characteristics: self service customer acquisition, critical mass, runaway user growth, winner take all markets, complex ux, network effects, typically create new ways for people to interact.

Examples: Ebay, OkCupid, Skype, Airbnb, Craigslist, Etsy, IMVU, Flickr, LinkedIn, Yelp, Aardvark, Facebook, Twitter, Foursquare, Youtube, Dailybooth, Mechanical Turk, MyYearbook, Prosper, Paypal, Quora, Hunch, etc.

Type 2 - The Integrator

Common characteristics: lead generation with inside sales reps, high certainty, product centric, early monetization, SME focused, smaller markets, often take innovations from consumer Internet and rebuild it for smaller enterprises.

Examples: PBworks, Uservoice, Kissmetrics, Mixpanel, Dimdim, HubSpot, Marketo Xignite, Zendesk, GetSatisfaction, Flowtown, etc.

Type 3 - The Challenger

Common characteristics: enterprise sales, high customer dependency, complex & rigid markets, repeatable sales process.

Examples: Oracle, Salesforce, MySQL, Redhat, Jive, Ariba, Rapleaf, Involver, BazaarVoice, Atlassian, BuddyMedia, Palantir, Netsuite, Passkey, WorkDay, Apptio, Zuora, Cloudera, Splunk, SuccessFactor, Yammer, Postini, etc.

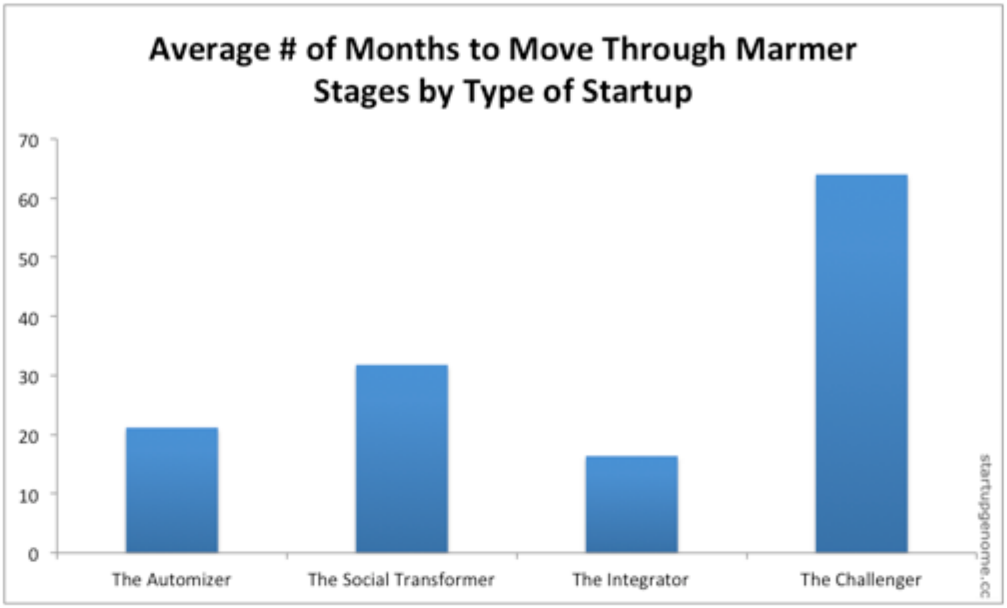
These types are accurate when a startup's users are the same as their payers, but many startups monetize their users indirectly. In those cases we call the customer acquisition strategy used for the payer a "wing". There are many Type 1 (The Automizer) startups with Type 2 (The Integrator) and Type 3 (The Challenger) wings. Startups with wings should read both their core "personality type" based on their user and their wing "personality type" based on their payer.

You can also read more about each type of startup in our extended Startup Personality Types:

http://startupgenome.cc/pages/startup-personality-type-1
http://startupgenome.cc/pages/startup-personality-type-1n-self-service-with
http://startupgenome.cc/pages/startup-personality-type-2-transactional-sale
http://startupgenome.cc/pages/startup-personality-type-3-enterprise-sales

The following graphs attempt to prove that startups exist by showing how the behavior varies amongst the types.

1.2 Types of Startups vs. Traditional Indicators Of Success



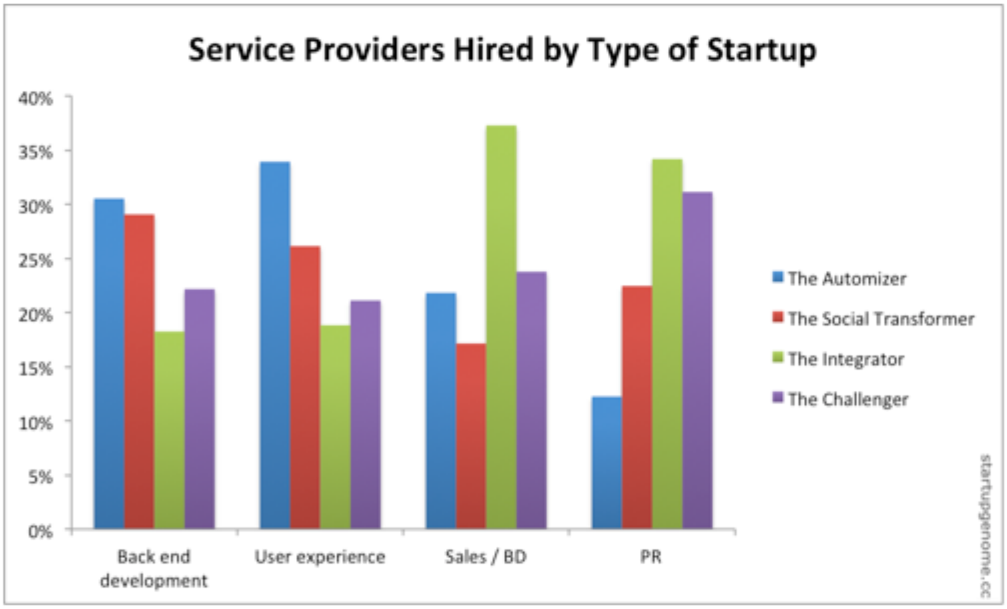
filter: Only startups working full time

This graph shows ...

how long different types of startups take to move through Marmer stages 1 through 4.

This graph supports the existence of types because ...

Challenger startups take significantly longer than other types of startups. Social Transformer startups take longer because it takes them a while to establish their network effect but we expect their growth to be much faster in stage 5 (profit maximization). Automizer and Integrator startups take about the same time, though we think many Automizers were mistyped as Integrators if they served SME's with a self-service customer acquisition strategy.



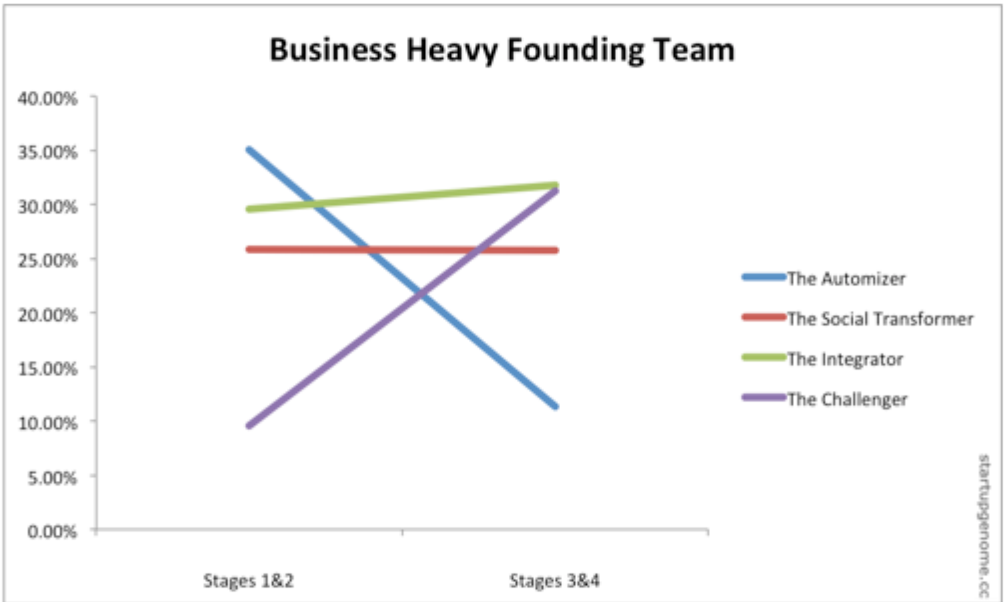
filter: only consistent startups working full time that raised funding

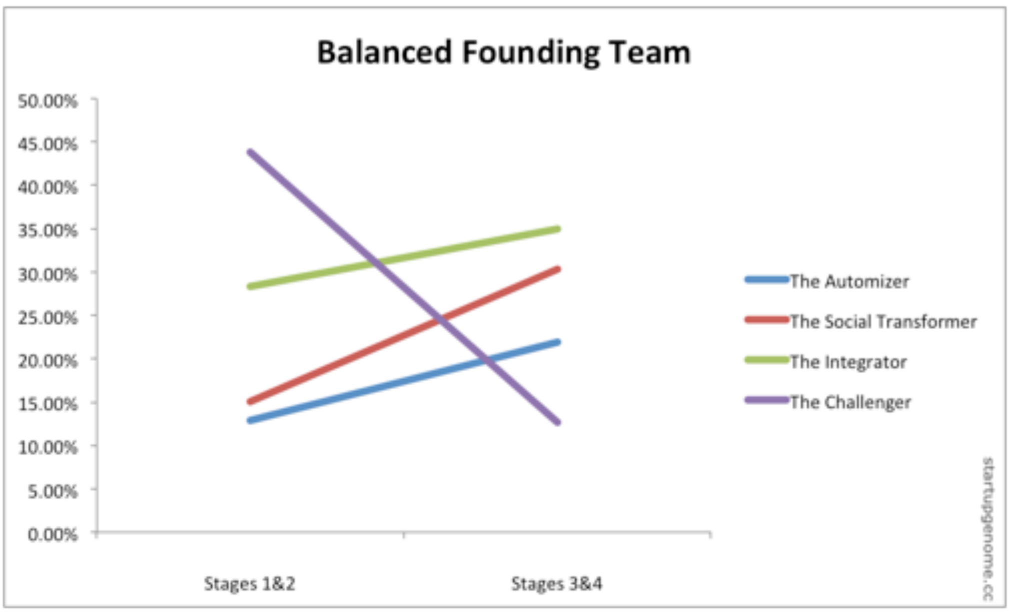
This graph shows ...

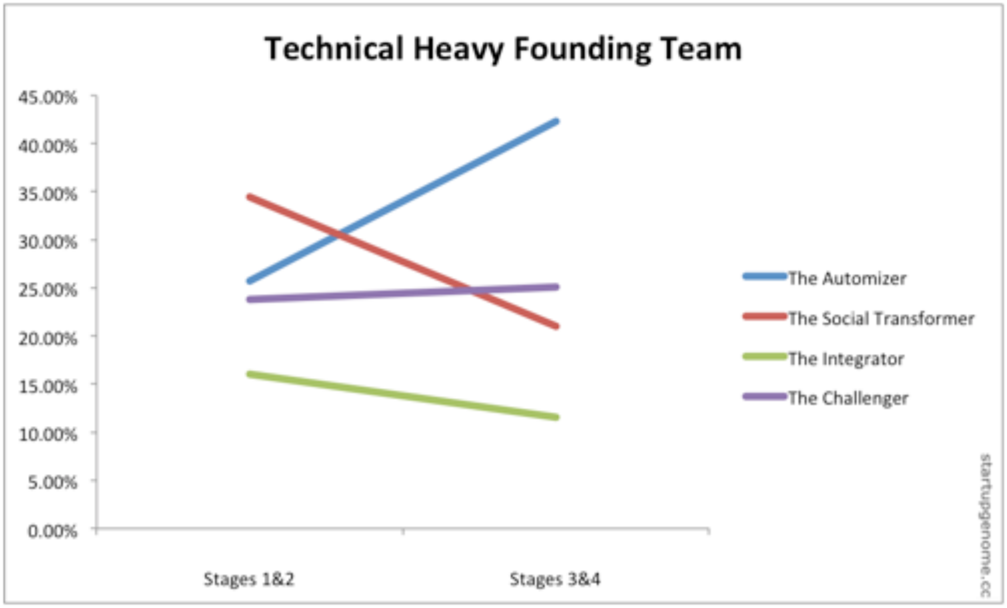
how different types of startups hire different types of service providers.

This graph supports the existence of types because ...

Type 1 (The Automizer) & 1N startups look for outside help much more with user experience and back end development. These types of startups typically have much larger user bases. Type 2 (The Integrator) and 3 are more focused on sales and PR because they are much more business oriented.


Business Heavy Founding Team
40.00%
35.00%
30.00%
25.00%
20.00%
15.00%
10.00%
5.00%
0.00%
Stages 1&2
Stages 3&4
The Automizer
The Social Transformer
The Integrator
The Challenger
startupgenome.cc


Balanced Founding Team
50.00%
45.00%
40.00%
35.00%
30.00%
25.00%
20.00%
15.00%
10.00%
5.00%
0.00%
Stages 1&2
Stages 3&4
The Automizer
The Social Transformer
The Integrator
The Challenger
startupgenome.cc



filter: only consistent startups

These graphs show ...

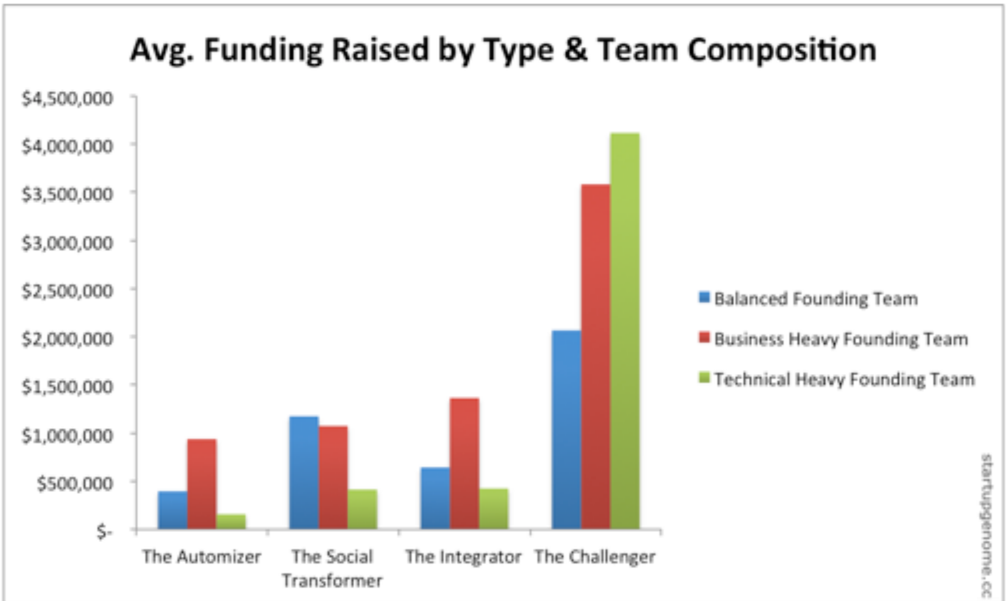
the increase or decrease of certain types of startups as they move through the developmental stages depending on the composition of the founding team. So for example, 35% of business heavy teams in Stage 1 & 2 were doing Type 1 (The Automizer) Startups. But by Stage 3 & 4 only 12% of the business heavy teams were doing Type 1 (The Automizer) startups. This decrease indicates that business heavy teams do not do as well with Type 1 (The Automizer) startups.

The key takeaways from these graphs are ...

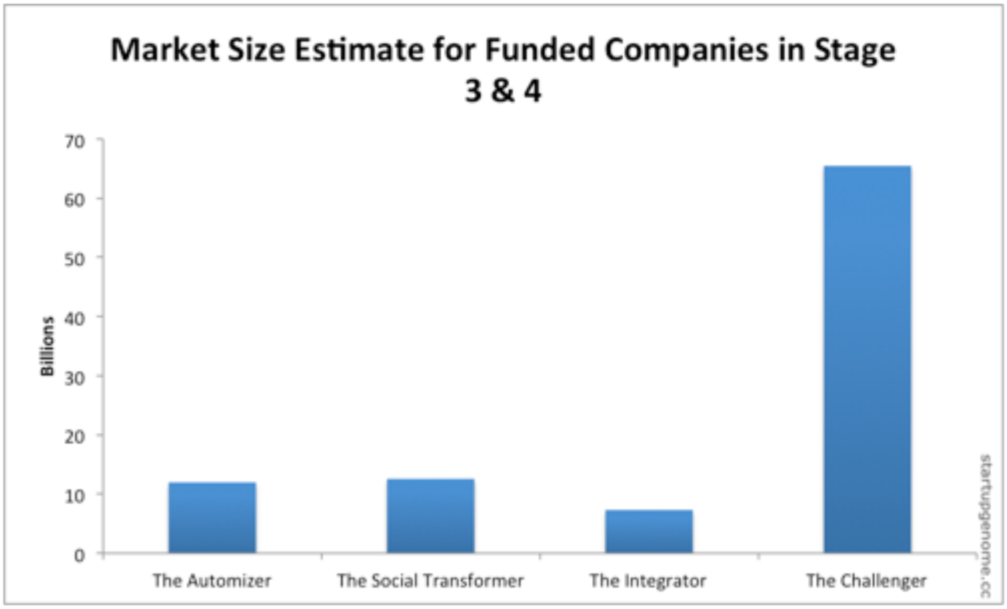
1. Business heavy teams are great at Type 3 (The Challenger) startups and not so great at Type 1 (The Automizer) startups
2. Balanced teams did not do well with Type 3 (The Challenger) startups
3. Technical teams did very well with Type 1 (The Automizer) startups and did not do very well with Type 1N (The Social Transformer) startups.

This graph supports the existence of types because ...

The composition of the founding team makes them more likely to succeed with some types of startups compared to others.



Interestingly though, according the conclusions of the preceding graphs capital is not allocated correctly in many cases. Our data shows that technical heavy founding teams are the least likely to succeed with Type 3 (The Challenger) “Challenger” startups yet that team composition raised the most money. Business Heavy Founding Teams are also the least likely to succeed with Type 1 (The Automizer) “Automizer” startups, yet they also raised the most money.



filter: only consistent startups working full time that raised funding

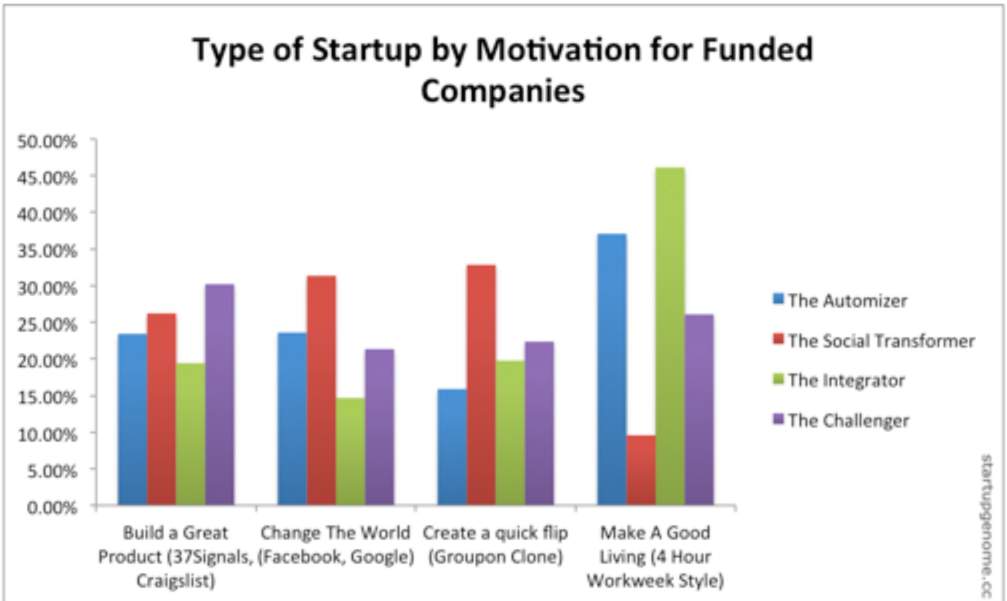
This graph shows ...

how different types of startups estimate their market size in millions.
Type 3 (The Challenger) startups believe they are tackling much bigger markets.
Type 2 (The Integrator) startups estimate their market size to be very small. The market size of 1 and 1N are about the same.

This graph supports the existence of types because ...

It makes sense that Type 3 (The Challenger) Startups, which typically sell enterprise software, have very large markets, although it's much harder for them to gain market share compared to the other types of startups.

We consider Type 2 (The Integrator) startups to be the domain of most napkin entrepreneurs, (http://steveblank.com/2011/03/29/napkin-entrepreneurs/) so we'd expect their market size to be smaller.



filter: only consistent startups working full time that raised funding

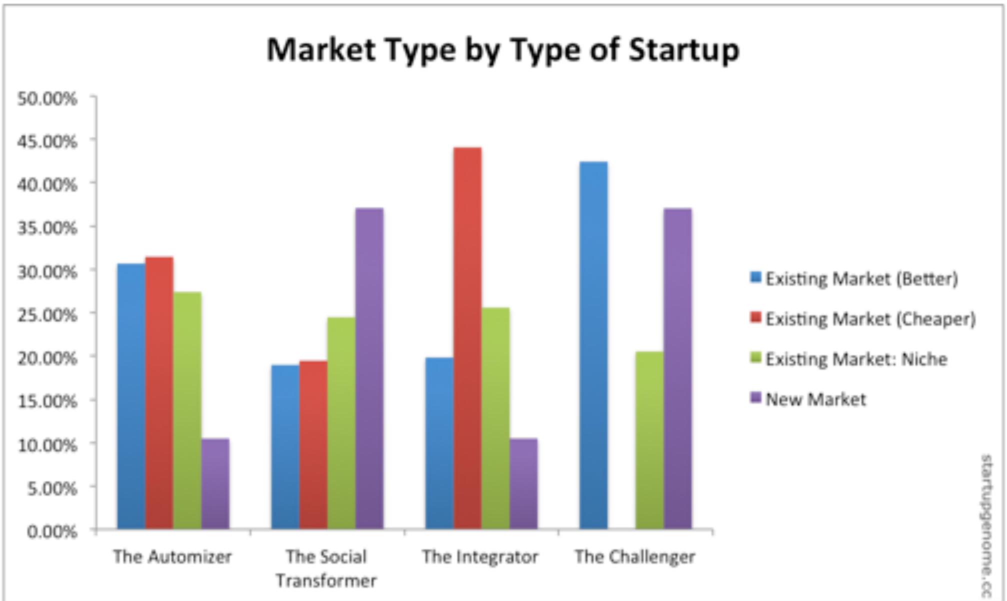
This graph shows ...

what type of startup a founder is likely to start based on their motivation.

Founders that want to build a great product are most likely to do a Type 3 (The Challenger) “Challenger” startup. Perhaps it’s because those products have the largest allowable feature creep. Founders that want to change the world are most drawn to Social Transformer startups. Founders that want to create a quick flip are also most drawn to social transformer startups, probably because crossing their critical mass threshold is something larger companies are very willing to pay quickly for. Founders that want to make a good living are most likely to do a Type 2 (The Integrator) startup with low overhead.

This graph supports the existence of types because ...

Founders with different motivations prefer to do different types of startups.



filter: only consistent startups working full time that raised funding

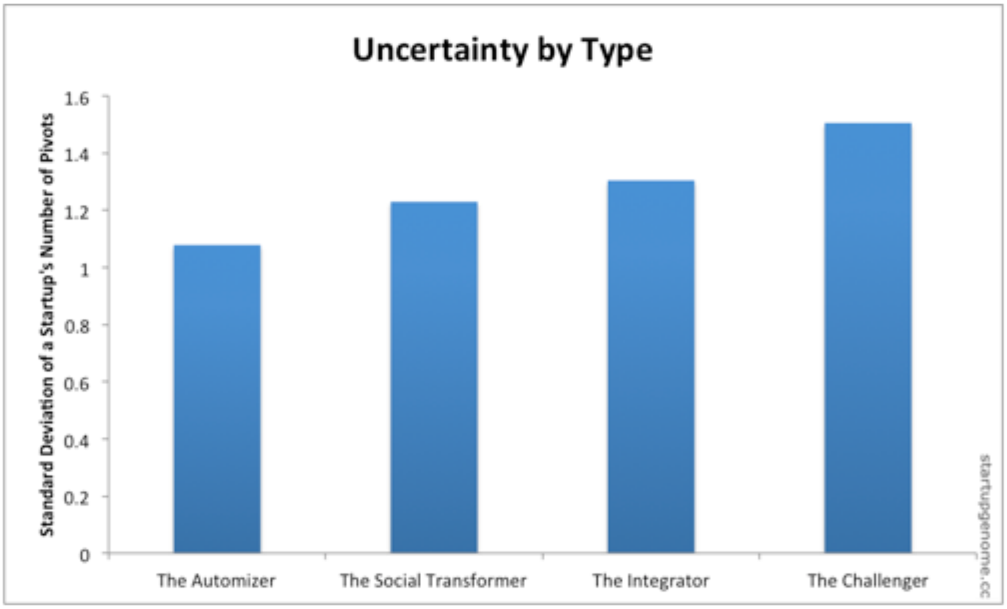
This graph shows ...

what types of markets different types of startups enter.

Automizer startups tackle all flavors of existing markets but generally avoid new markets, as many of them are trying to optimize previously manual workflows. Most Social Transformer startups are creating new markets and Integrator startups are primarily entering existing markets by creating a cheaper alternative. Challenger startups are focused on improving on existing software or establishing a new paradigm.

This graph supports the existence of types because ...

Different types of startups choose differentiate their product very differently.



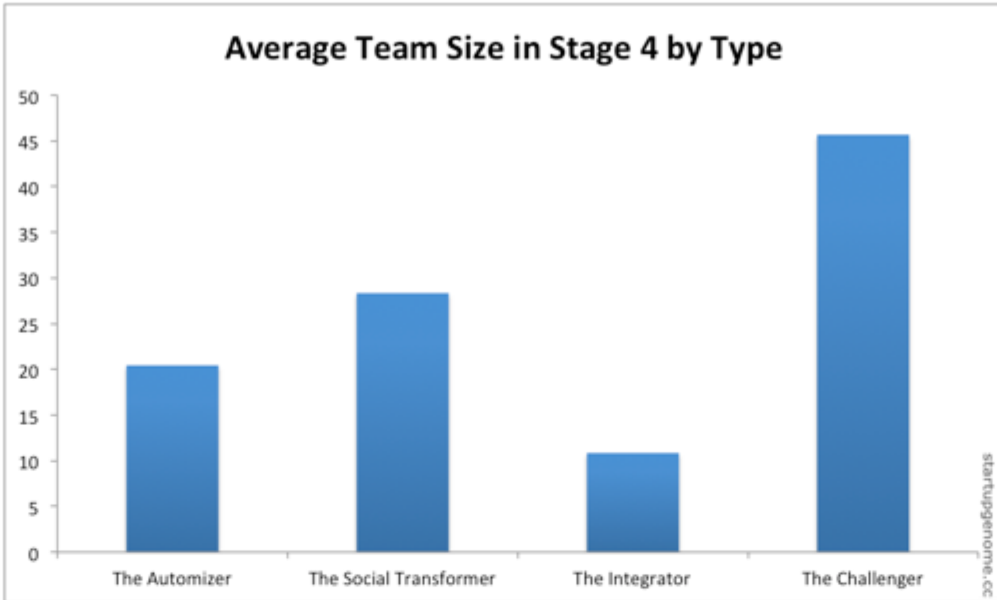
filter: only consistent startups working full time that raised funding

This graph shows ...

The standard deviation of the number of pivots between different types of startups. This means all Type 1 (The Automizer) startups pivot about the same number of times. Where as Type 3 (The Challenger)'s either pivot a lot or little.

This graph supports the existence of types because ...

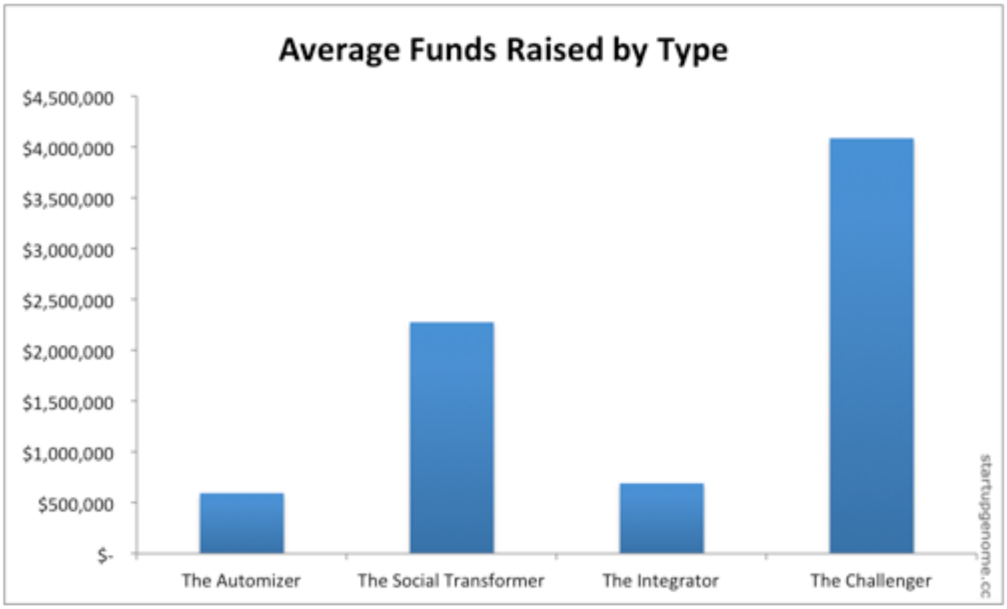
Type 3 (The Challenger) startups would be expected to have greater variance in their number of pivots due to high dependency on small number of clients.



filter: only consistent startups working full time that raised funding

This graph shows ...

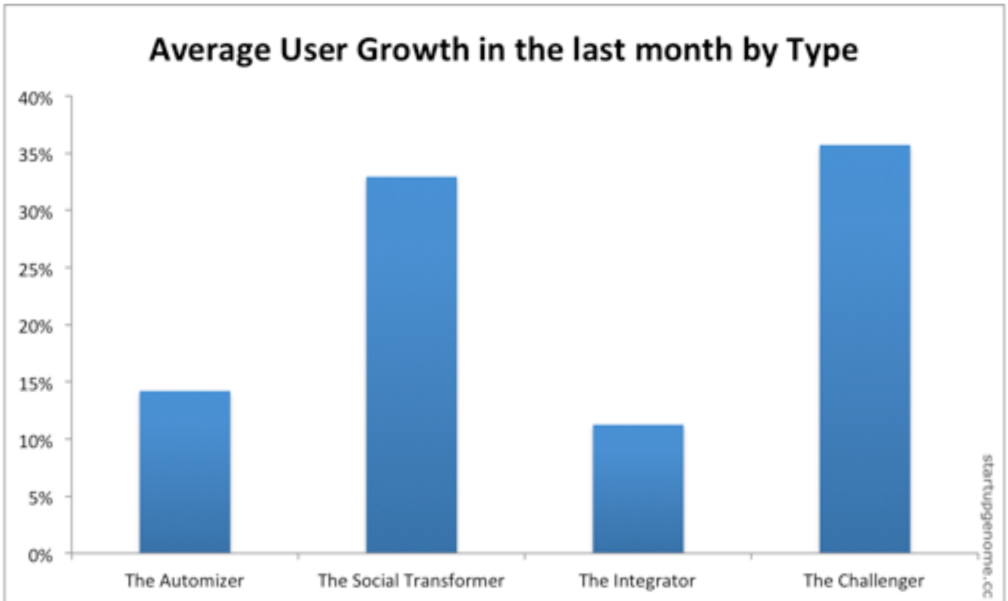
The team size of Type 3 (The Challenger) startups and Type 1N (The Social Transformer) startups both tend to have much larger teams.



filter: only startups working full time that raised funding that are in the scale stage

This graph shows...

Type 3 (The Challenger) startups need to raise significantly more money than other types of startups. Type 1N (The Social Transformer) raise a lot more than Type 1 (The Automizer).



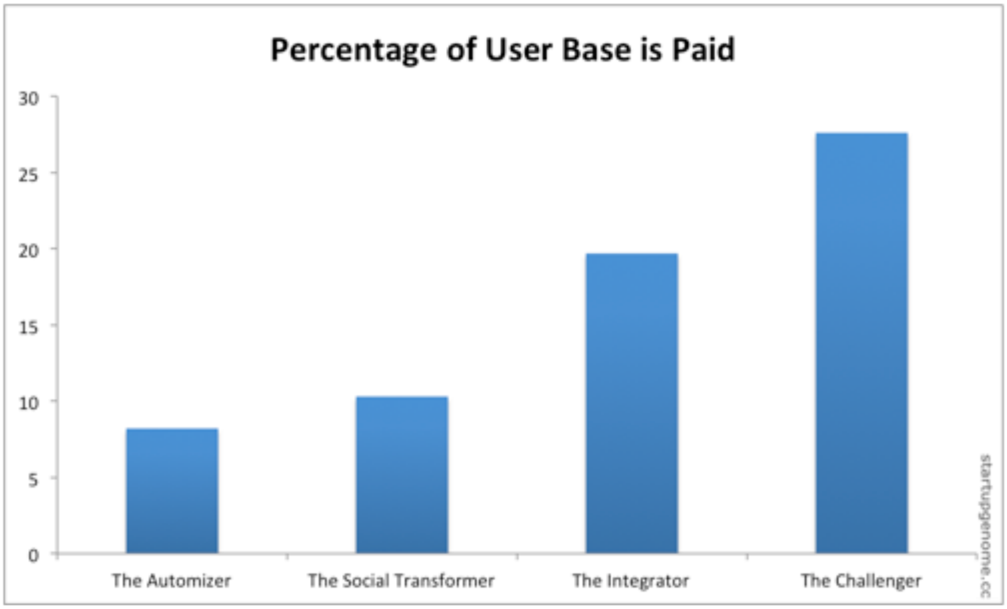
filter: only startups working full time that raised funding

This graph shows ...

Both Type 1N (The Social Transformer) and Type 3 (The Challenger) have had significantly more user growth in the last month than the other 2 types.

This graph supports the existence of types because ...

1Ns need to grow and Type 3 (The Challenger) have a small user base so the percentage increase is also high for them.



filter: only startups working full time that raised funding]

This graph shows ...

Type 2 (The Integrator) and Type 3 (The Challenger) startups have a much higher percentage of their user base paying.

This graph supports the existence of types because ...

Type 2 (The Integrator) and 3 startups are generally more B2B focused and thus have a higher percentage of paying clients.

1.3 Areas of Improvement

While our type assessment worked well enough to show clear differences amongst the types, we think there were a number of problems in our assessment that made the differences softer than they are. Also, it was necessary to aggregate subtypes together, such as, “Type1”, “Type 1 (The Automizer) with a 2 Wing”, and “Type 1 (The Automizer) with a 3 Wing”, all as “Type 1 (The Automizer)” because we didn’t have enough data to analyze them independently. Averaging the wings minimized some contrast.

1.4 Network Effects vs. Virality vs. User Data

Suboptimal assessment also occurred because many startups misunderstood network effects—self-reporting they had network effects when they didn’t. To clarify network effects are when the value to a user increases when other users join. If the product has network effects it should have little to no value if there is only one person using it, and the value should continue to increase exponentially at least until there are thousands of users, if not indefinitely.

There were 2 primary ways people misunderstood network effects:

1) People confused network effects for being able to improve their product because they had more user data or feedback.

Pandora and Google are good examples of this. They can improve their algorithms when more people use the product but the core value proposition of the product is not altered when more people use the product. All Internet products have the opportunity to gain more feedback the more users they have but some companies are able to better use user feedback to improve the product

2) People confused the difference between network effects and virality

Zynga and Groupon both have slight network effects but are driven primarily by virality not network effects. Virality is when users acquire other users, usually through some referral mechanism built into the product.
Many social games you can play by yourself but Zynga created many viral in-game incentives that reward you for inviting your friends. There are some social games where a few hundred to a few thousand people are necessary for the game to be interesting, but that is both a weak network effect and very rare. Most social games are played with 1-10 people. Groupon is similar in that in regard, as most deals require less than a few hundred people to buy for the discount (i.e. the value proposition) to be realized. The discount threshold is also

reset on every deal, which is another behavior antithetical to network effects. But Groupon's greatest channel of user acquisition is Facebook, which shows the strength of their virality.

1.5 Differentiating Types

Another place we had suboptimal assessment was the differentiation between Type 2 (The Integrator) and Type 3 (The Challenger). When the Startup Genome survey was released in February we differentiated startups based on their type of user and payer, which was essentially B2C vs. B2B. One problem with that approach is that it doesn't take into account that with the evolution of software as a service and cloud computing, many B2B startups can behave like B2C startups if their product is simple and cheap enough, given that employees have the autonomy to make purchase decisions without needing approval from decision makers or the IT department. We now have a more nuanced assessment based on customer acquisition strategy and their breakdown of sales and marketing.

We defined a spectrum of 100% marketing to 100% sales and created the 3 points by selecting the two end points and the mid point. In the future, we plan to define a more fluid spectrum with more than 3 points, as we understand the underlying variables better and see where startups cluster.

Our fourth type, Type 1N (The Social Transformer), is 100% marketing with network effects. Initially we gave this type of startup it's own type at the same level as the other three types, but as we looked a little deeper into network effects we decided to classify it as an effect that is coming from the product.

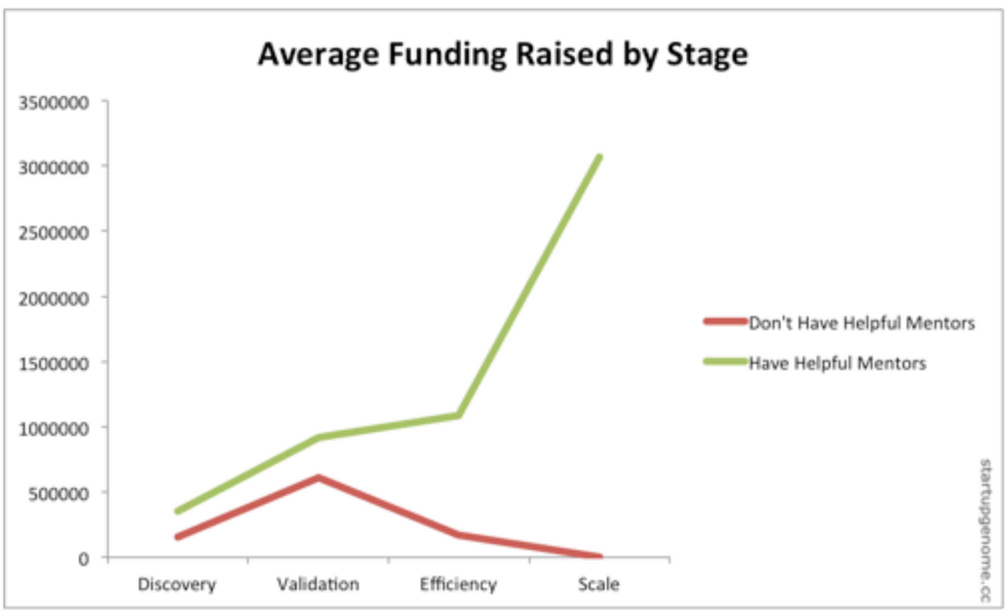
There are many effects or attributes that come from the product and affect the customer acquisition strategy but network effects are probably the strongest.

IV. Learning As The Key To Successful Startups

Paul Graham describes determination, flexibility, imagination, naughtiness and friendship as the core selection criteria for YCombinator (http://www.paulgraham.com/founders.html). It is rare for people to start a company without imagination for what they want to accomplish and the determination to make it happen, but whether founders prove to have the necessary flexibility, friendship and naughtiness only becomes apparent during the process of running a company. Milestone based assessment allows for the measurement of the actual output of the team, not just their starting raw material.

One of our key assumptions is that the flexibility of the founding team is one of the key determinants of success. Our proxies to measure flexibility were:

1.1 Willingness To Listen



filter: only startups working full time that raised funding / n=160

This graphs shows ...

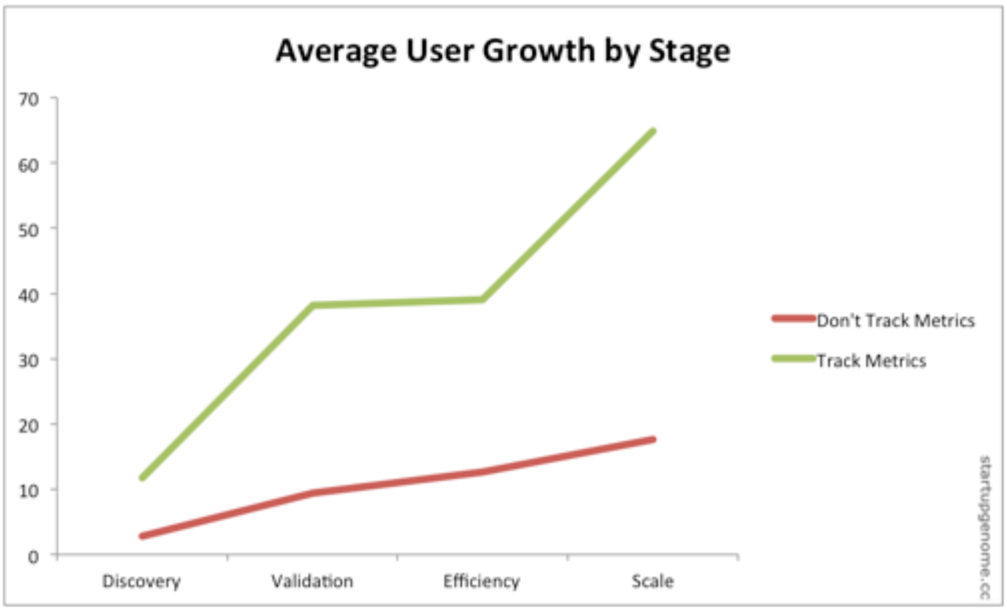
the amount of funding startups have raised based on whether they have helpful mentors or not.

This shows learning is important because ...

Startups with no helpful mentors raise very little money. There are no stage 4 startups that raised money with no helpful mentors.

Lessons Learned ...

Startups that find helpful mentors seem to be more significantly more successful.

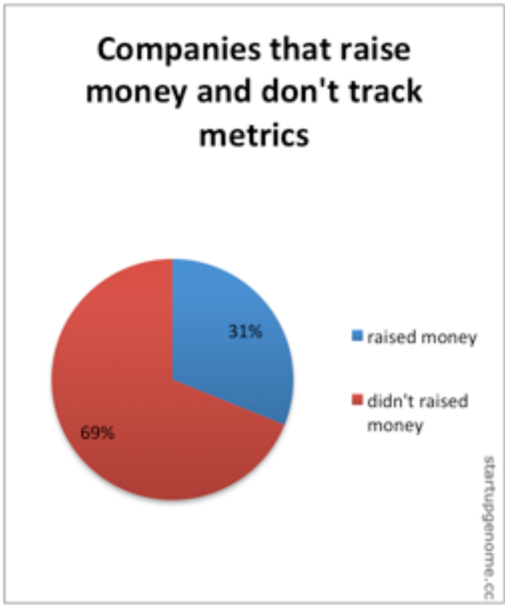


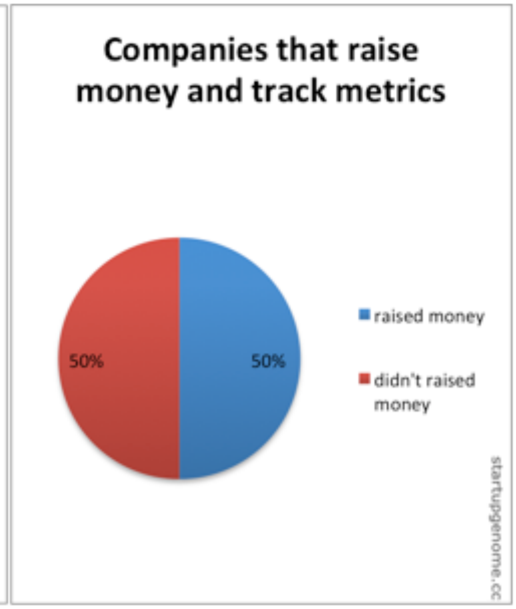
filter: only startups working full time that raised funding / n = 275

This graph shows ...

startups that measure metrics have better user growth.

We attribute this to measuring increasing the speed of learning, and being able to figure out what's working and what's not instead of making decisions on gut feel.



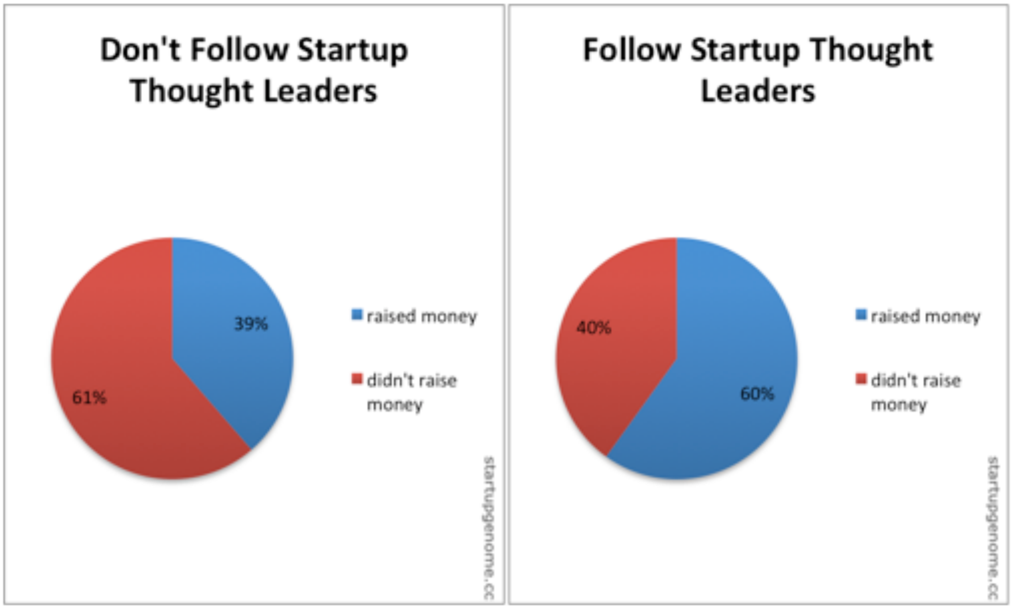


filter: only startups working full time / n=77

This graph shows ...

Startups that don't measure metrics raise money 31% of the time. Startups that measure metrics raise money 50% of the time. This means that startups are 61% more likely to raise money if they measure metrics.

1.2 Drive To Learn



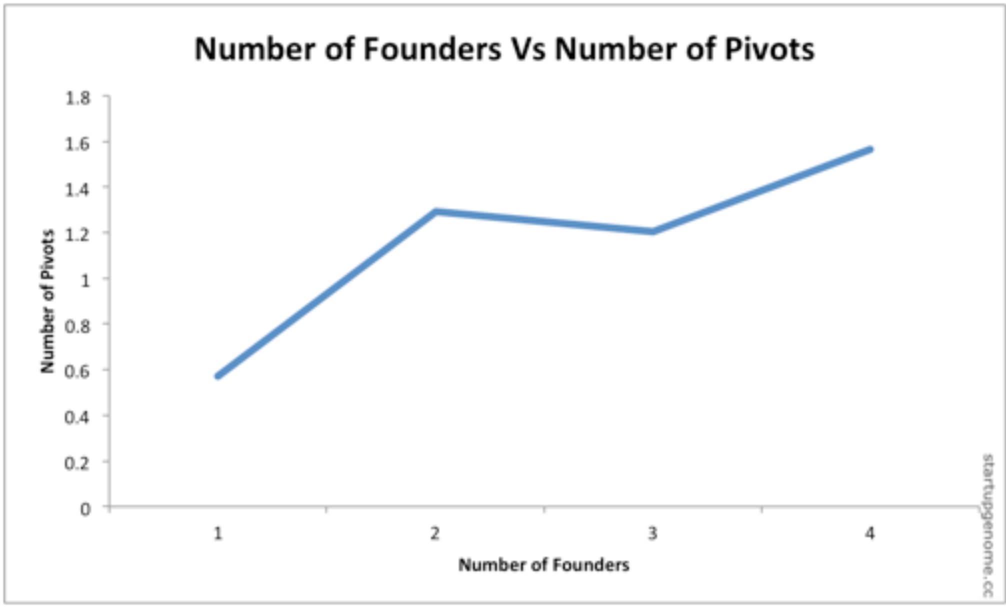
filter: only startups working full time that raised funding

This graph shows ...

Startups that don’t follow startup thought leaders raise money 38% of the time. Startups that follow startups thought leaders raise money 60% of the time. This means startups are 80% more likely to raise money if they follow startup thought leaders like Steve Blank, Eric Ries, Dave McClure, and Paul Graham.

We used following the latest thought leaders as a proxy for willingness to learn. We considered a startup to be following a thought leader if they considered their advice helpful.

1.3 Ability To Act On Feedback

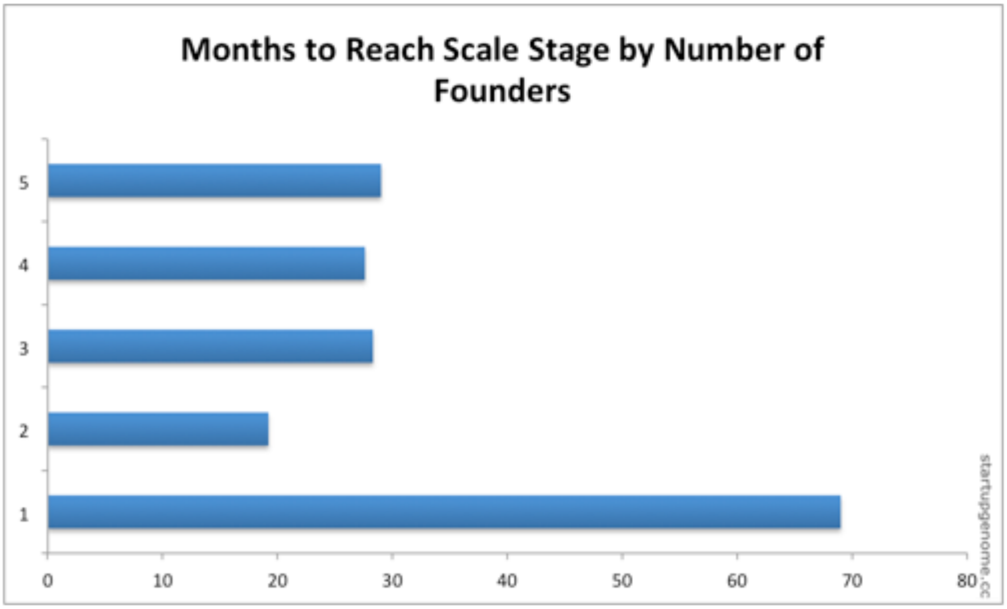


filter: Only startups working full time that raised funding / n=358

this graph shows ...

solo founders hardly pivot at all whereas teams with 4 founders pivot a lot.

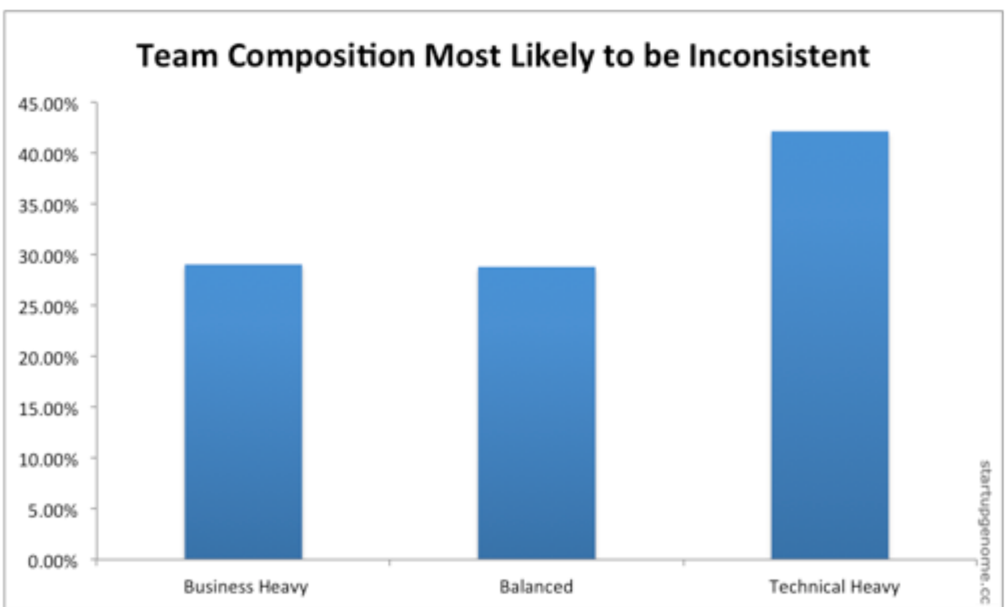
It appears 2-3 founders create a healthy tension between sticking with the current plan and reexamining direction.



filter: only startups working full time that raised funding

This graph shows ...

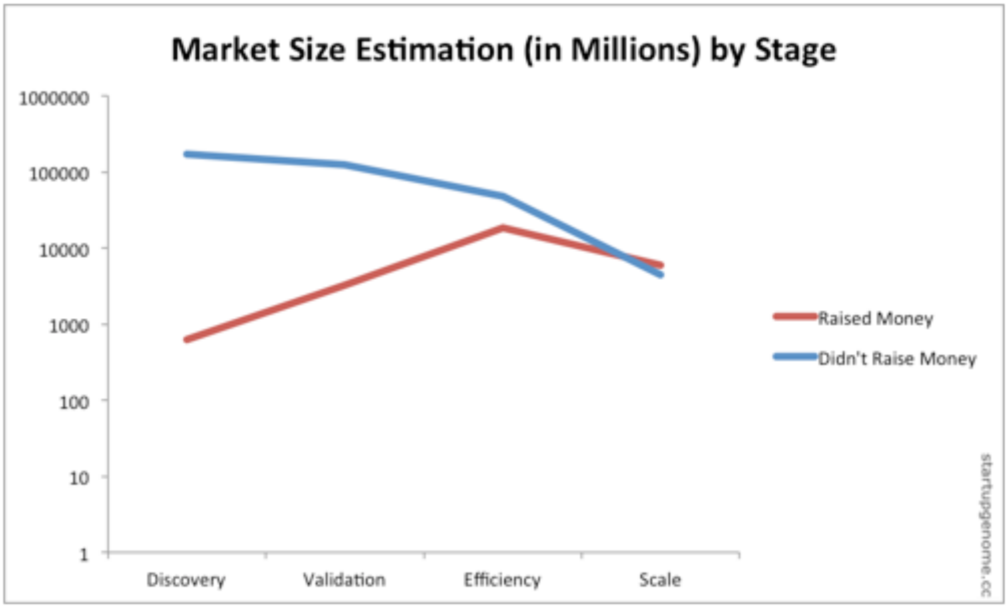
Solo Founders take a very long time to get to stage 4. Teams with 2 Founders are the fastest. 3 and 4 founders are about equal.



This graph shows...

It's about evenly spread but the founder most likely to be inconsistent is the maker. This may be because they are the least likely to get out of the building and get qualitative feedback from customers.

V. Miscellaneous Observations



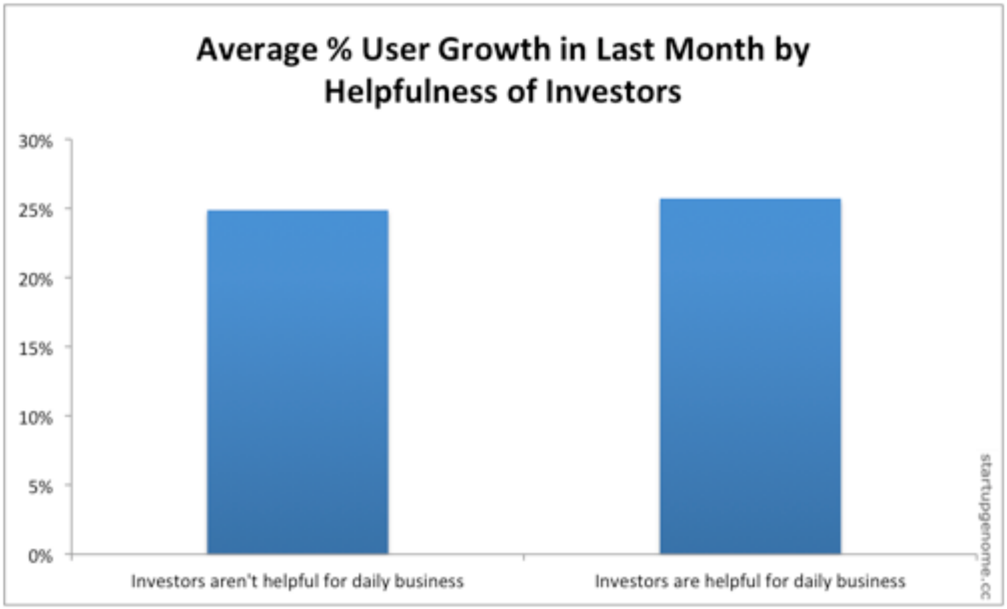
filter: only startups working full time that raised funding

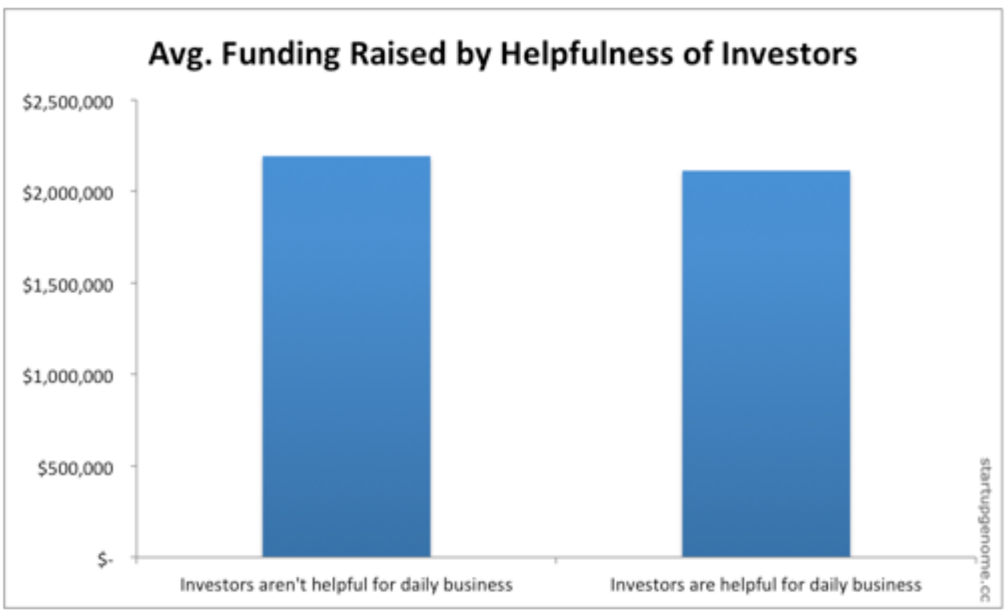
This graph shows...

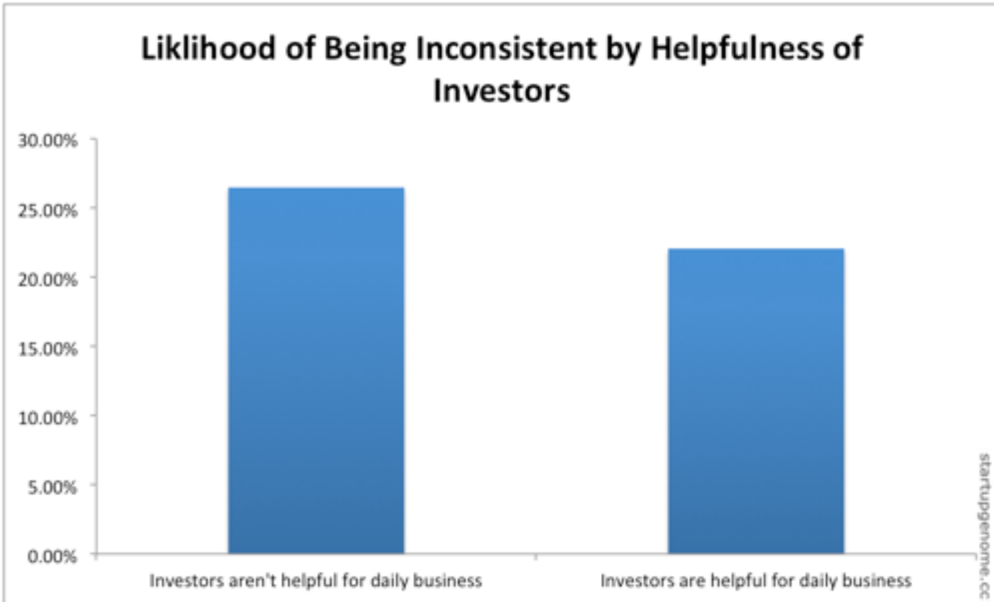
What size entrepreneurs estimate their market to be based on what stage they are in and whether they raised funding. (Note that the Y-axis is a logarithmic scale). In stages 1-3 startups that didn't raise money estimate their market size to be dramatically larger than startups that did raise money. Their estimates converge at stage 4.

Interpretation ...

Investors give entrepreneurs a reality check about their market size. If investors aren't there to break through entrepreneurs reality distortion field, eventually the market teaches them the true size in stage 3 and 4 as by stage 4 both funded and unfunded startups have the same expectations about the size of market they're tackling.


Average % User Growth in Last Month by Helpfulness of Investors
30%
25%
20%
15%
10%
5%
0%
Investors aren't helpful for daily business
Investors are helpful for daily business
startupgenome.cc

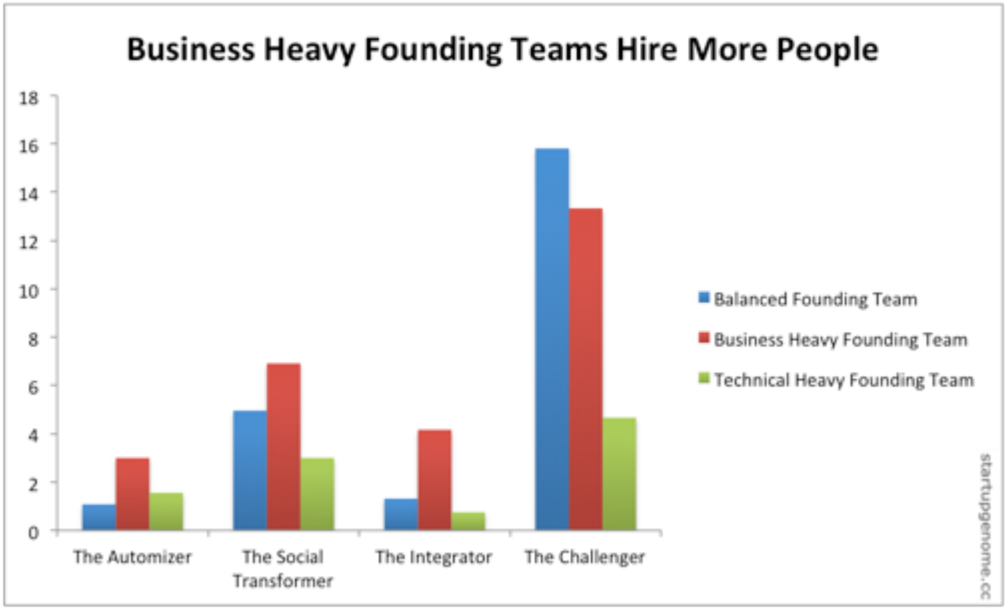

Avg. Funding Raised by Helpfulness of Investors
$2,500,000
$2,000,000
$1,500,000
$1,000,000
$500,000
$-
Investors aren't helpful for daily business
Investors are helpful for daily business
startupgenome.cc

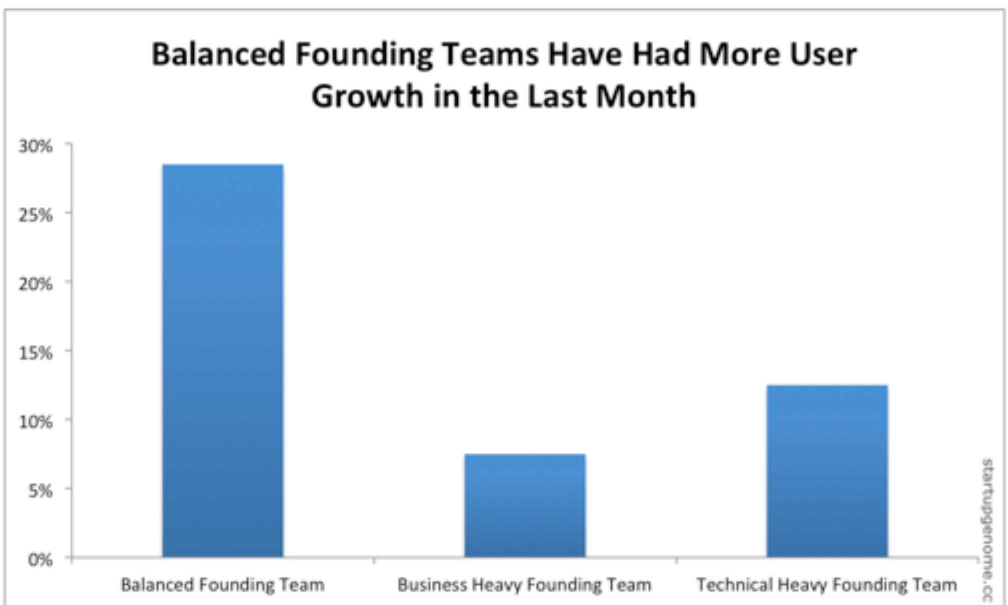


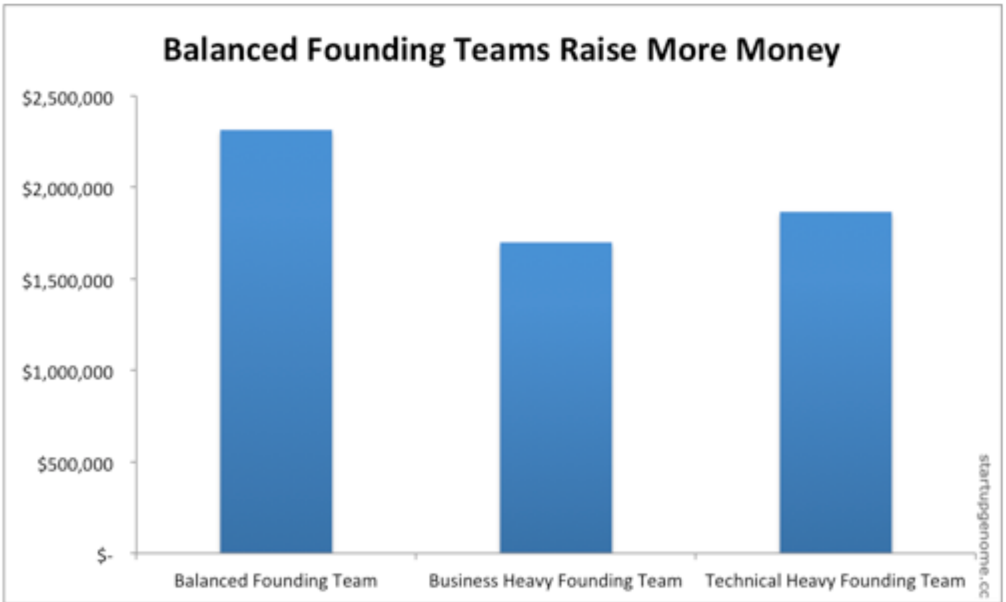
We asked entrepreneurs if their investors were helpful for their daily business. Surprisingly, whether they had helpful investors or not, had almost zero effect on performance. There is almost no difference in user growth, funding raised and the likelihood of being inconsistent. But earlier in the report we showed that startups that said they had a nonzero amount of helpful mentors performed much better than startups who didn't.

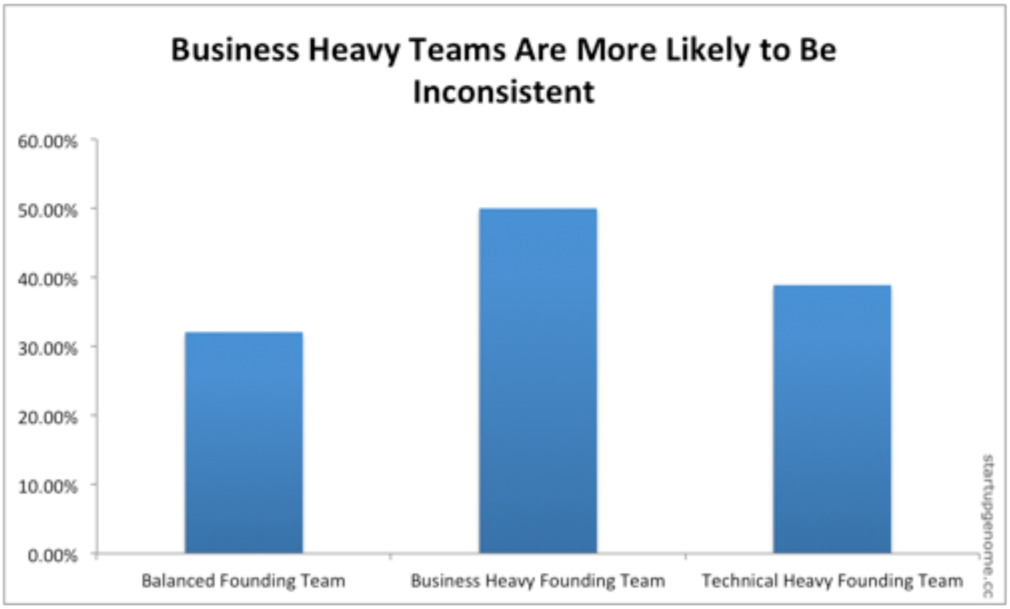
We think this may be because investors' main value add is their ability to increase the valuation in future rounds, and get larger exit sizes. Their help on a daily basis, which consists mostly of introductions and help with recruiting is not that significant because great entrepreneurs will find a way to get introduced to the people they want to hire and build a great team even if their investors don't help. Whereas the people startups consider helpful mentors probably help with something more domain specific than introductions and recruiting.

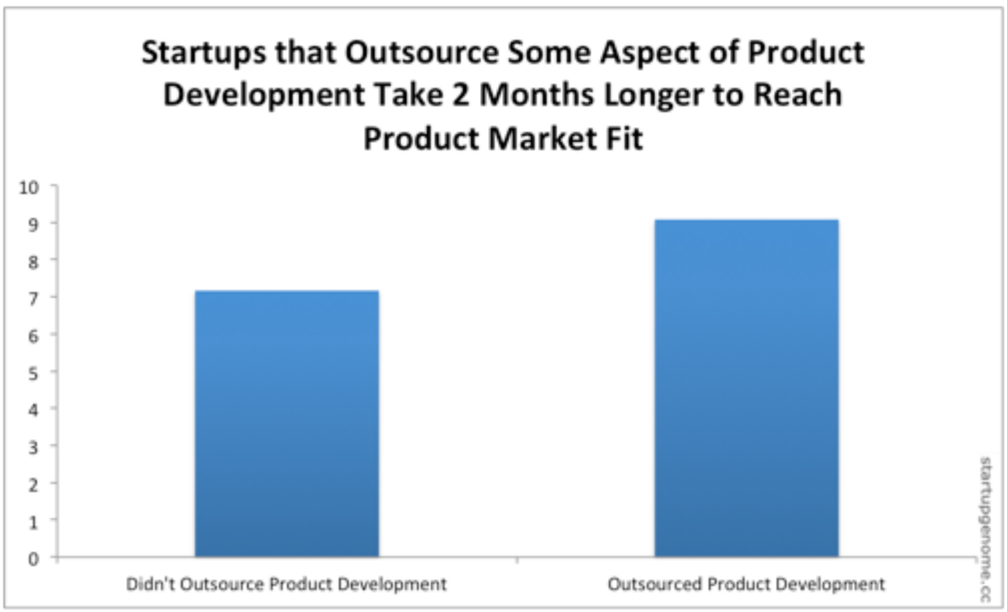
Here are a few more self explanatory graphs that you might find interesting:

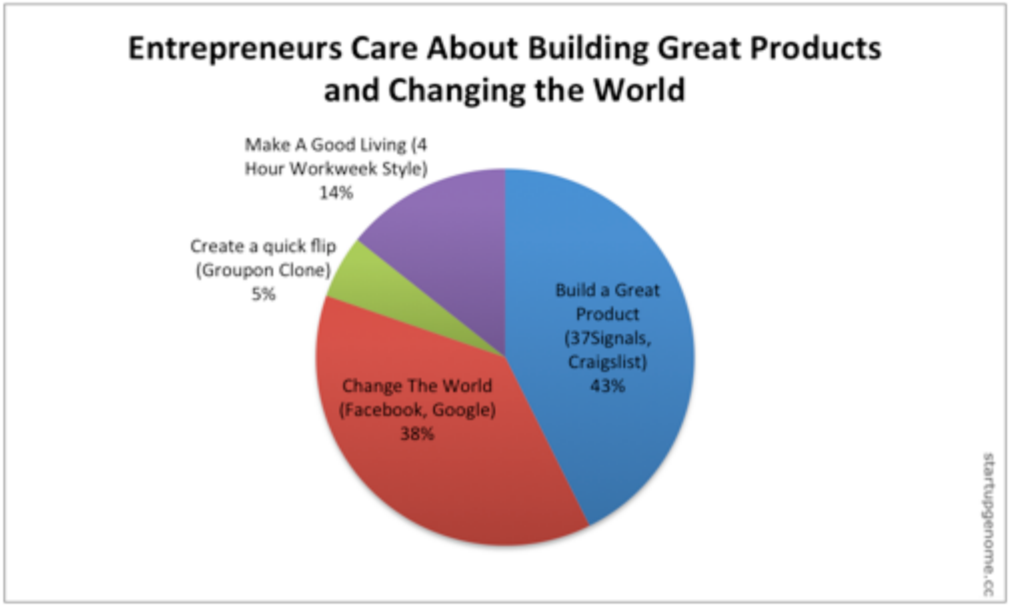


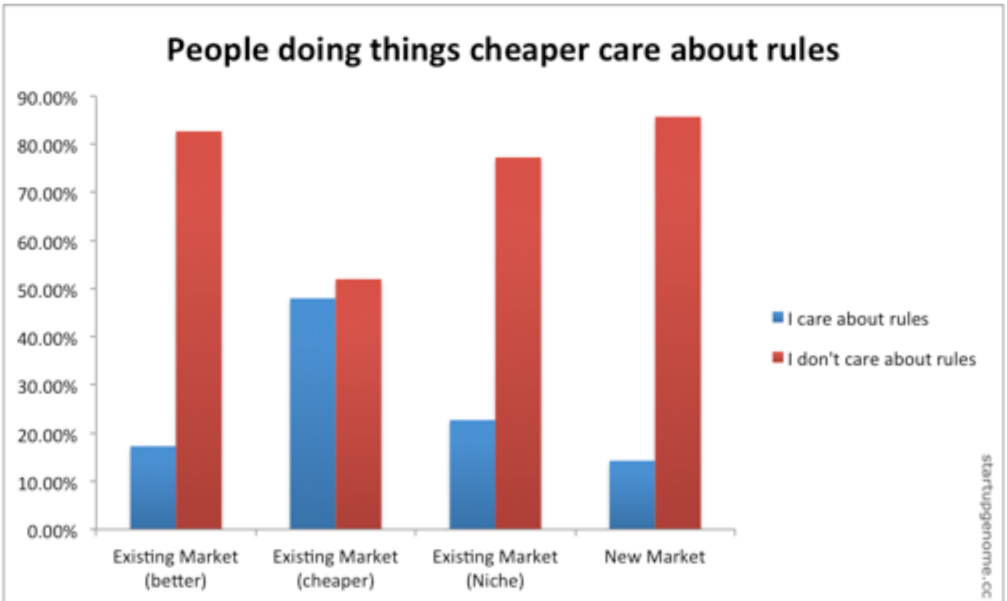



Balanced Founding Teams Raise More Money
$2,500,000
$2,000,000
$1,500,000
$1,000,000
$500,000
$-
Balanced Founding Team
Business Heavy Founding Team
Technical Heavy Founding Team
startupgenome.cc

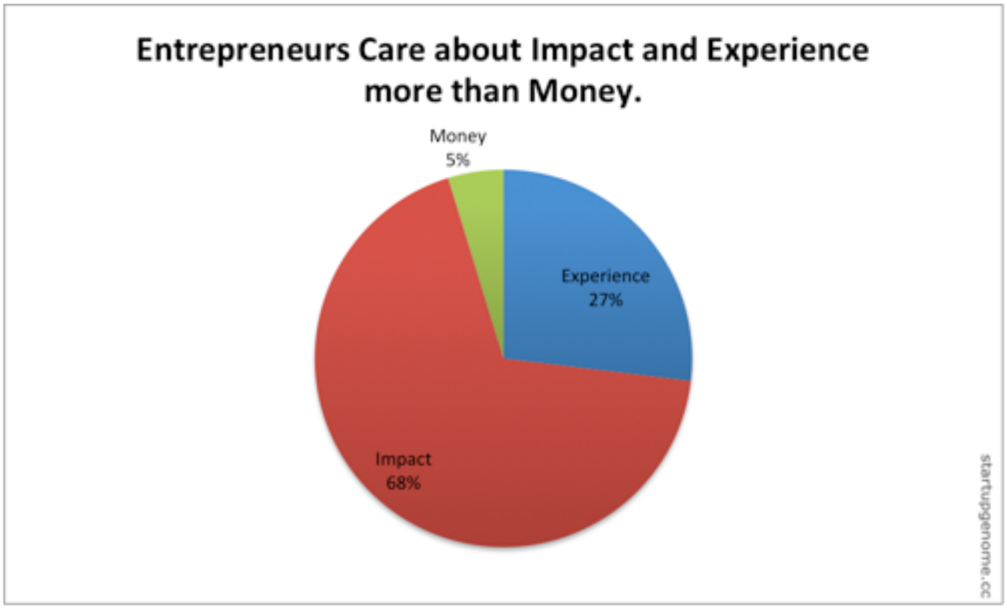

Business Heavy Teams Are More Likely to Be Inconsistent
60.00%
50.00%
40.00%
30.00%
20.00%
10.00%
0.00%
Balanced Founding Team
Business Heavy Founding Team
Technical Heavy Founding Team
startupgenome.cc

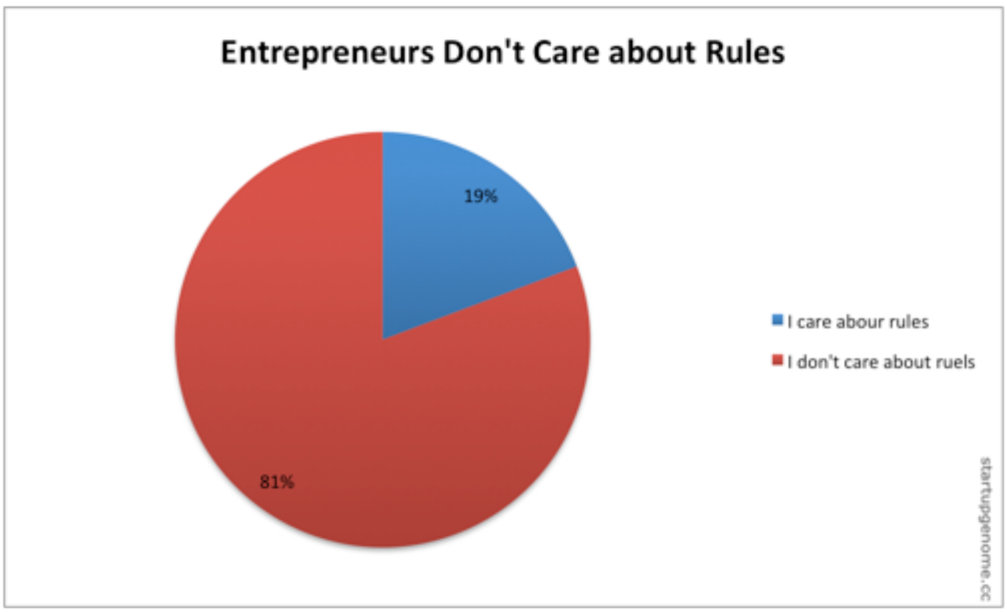

Startups that Outsource Some Aspect of Product Development Take 2 Months Longer to Reach Product Market Fit
10
9
8
7
6
5
4
3
2
1
0
Didn't Outsource Product Development
Outsourced Product Development
startupgenome.cc


Entrepreneurs Care About Building Great Products and Changing the World
Make A Good Living (4 Hour Workweek Style) 14%
Create a quick flip (Groupon Clone) 5%
Build a Great Product (37Signals, Craigslist) 43%
Change The World (Facebook, Google) 38%
startupgenome.cc


People doing things cheaper care about rules
90.00%
80.00%
70.00%
60.00%
50.00%
40.00%
30.00%
20.00%
10.00%
0.00%
Existing Market (better)
Existing Market (cheaper)
Existing Market (Niche)
New Market
I care about rules
I don't care about rules
startupgenome.cc


Most Entrepreneurs Think They Are Doing Something New
Existing Market (better) 26%
New Market 39%
Existing Market (cheaper) 10%
Existing Market (Niche) 25%
startupgenome.cc


Entrepreneurs Care about Impact and Experience more than Money.
Money 5%
Experience 27%
Impact 68%
startupgenome.cc


Entrepreneurs Don't Care about Rules
19%
81%
I care abour rules
I don't care about ruels
startupgenome.cc

VI. Final Thoughts

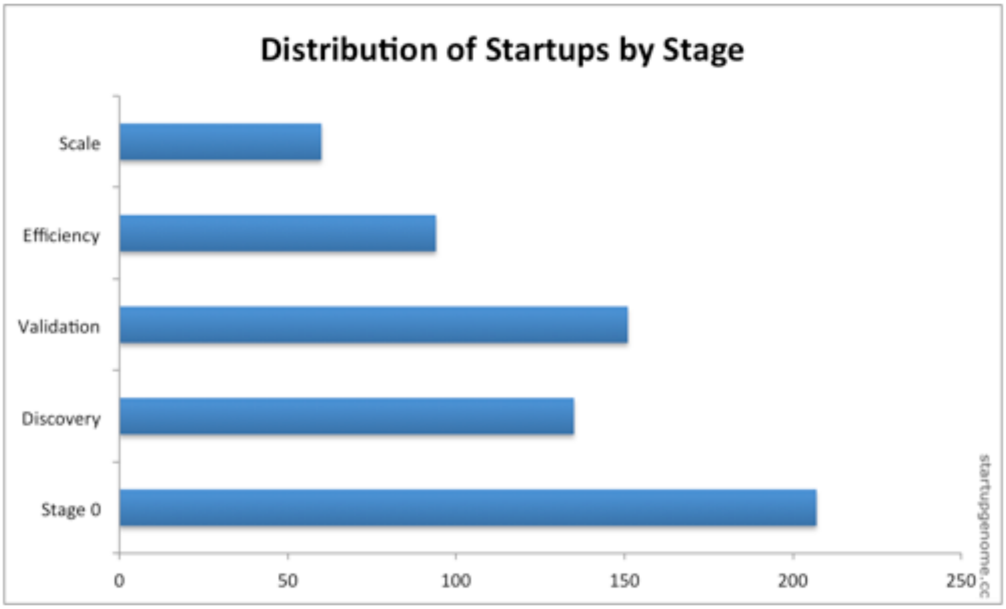
One of our key focuses in the next few months will be developing a more intricate ontology to map the progress of startups along many more dimensions and to get a deeper understanding of the metrics and their corresponding thresholds that determine stages. This should drastically increase our ability to test hypotheses and organize data.

We've started with Customer Development as the primary dimension because we believe it is a leading indicator for what level of progress other dimensions should have. In addition to Customer Development we've classified 5 other first order dimensions of the ontology: Product Development, Team, Financials, Business Models, and Market.

We hope you found this report eye opening and thought provoking. While we don't think we're far enough along to deem any of our findings conclusive we think we've found clear trends that prove a lot of common wisdom and turn some on its head. While our first data set wasn't as granular as we hoped, this is only our first report and you can expect to see our methodology refined and our data points grow as we move forward.

C. Appendix

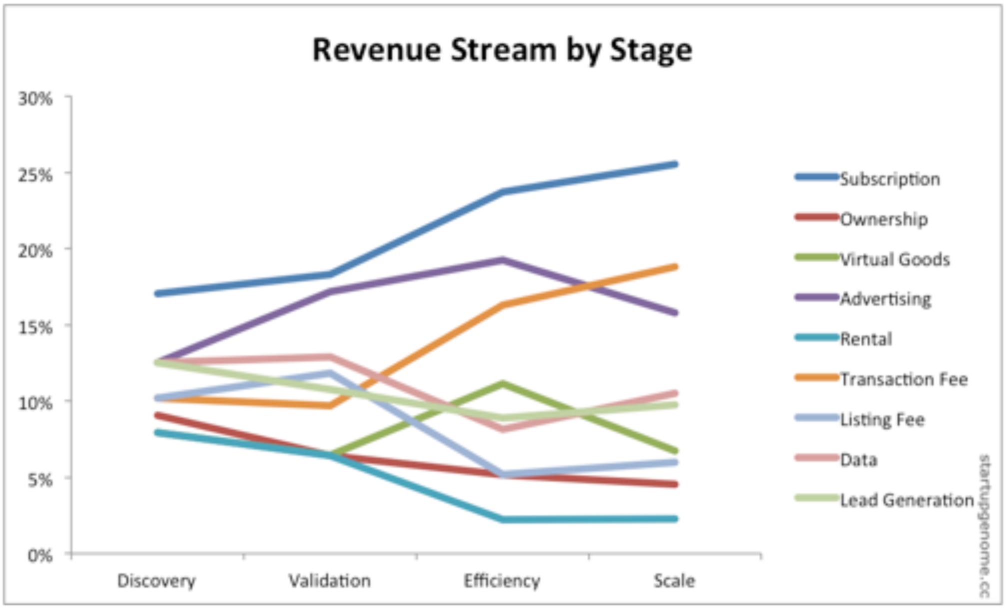
I. Stages



Here you can see the distribution of the 600+ startups that filled out the survey. Startups were marked as stage 0 if they did not fill out enough of the survey for us to identify what stage they were. Most startups that we were able to identify were at stage 2. While it would be reasonable to expect a smooth slope through the stages, we believe we had more startups at stage 2 than stage 1 because:

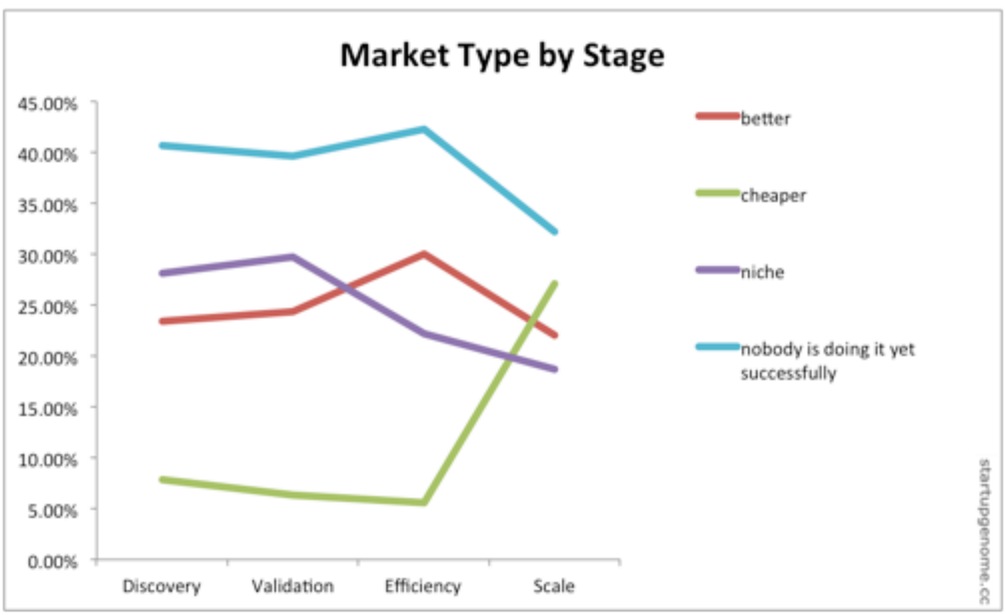
- Threshold for passing through stage 1 is low, people do it quickly
- We aren't that good at assessing stage 1 in a fine grained way since it's very qualitative
- Startups that limp through stage 1 are just more likely to get stuck at 2 and need to pivot back through stage 1
- Startups that don't spend enough time in stage 1 require a lot more pivots

We don't yet have longitudinal data to show what stage startups spend most of their time. So if we know a startup is in stage 2 and has been working for 10 months we don't know if it's 1 month is stage 1 and 9 months in stage 2 or the reverse. But it will be interesting to see if startups that move too quickly through stage 1 are more likely to get stuck in stage 2 or pivot.



filter: only consistent startups working full time

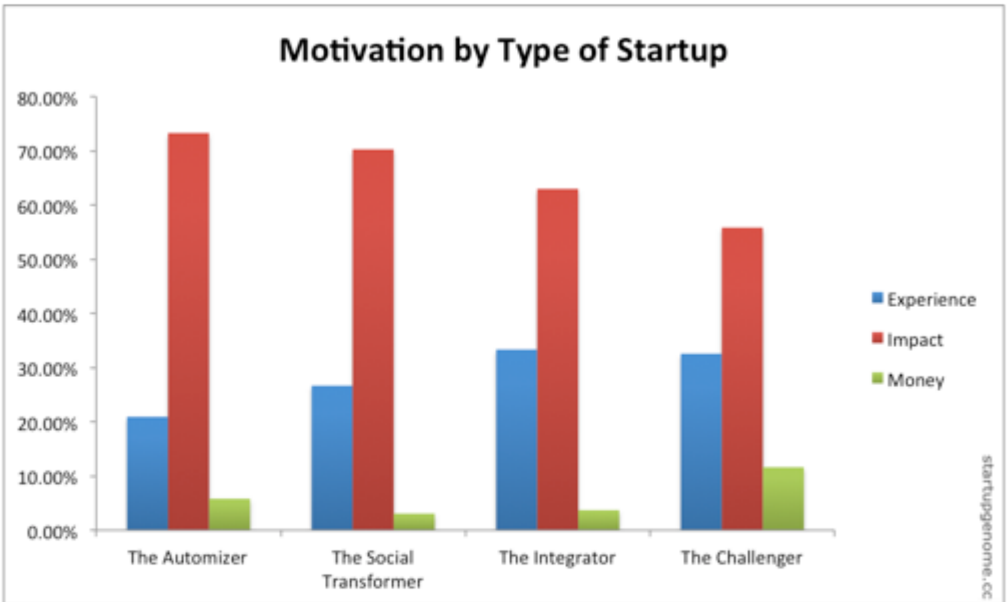
Subscription and Transaction Fees are by far the most common type of revenue streams. It's interesting to see what revenue streams startups think will work in stage 2 but have considerable drop off with startups that have actually made it to stage 4. Virtual Goods, Advertising and Data all have major drop offs.



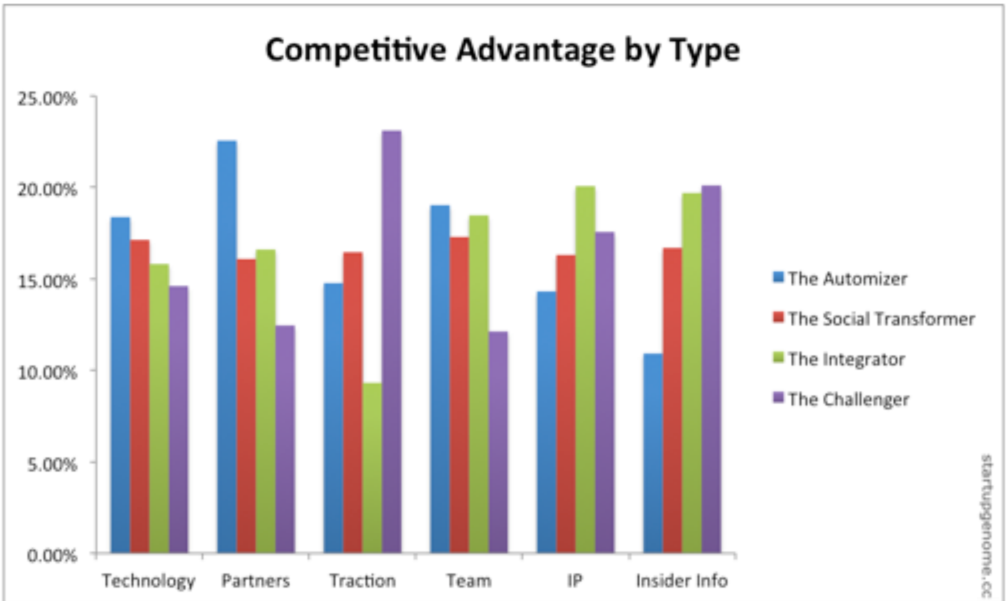
filter: only consistent startups working full time

In stage 1 most startups think they are doing something new. By stage 4 the market as either matured or startups decided it was more effective to position themselves in an existing market or as resegmenting a market. In stage 4 there is a very large increase in the number of startups positioning themselves as cheaper than the alternatives.

II. Types

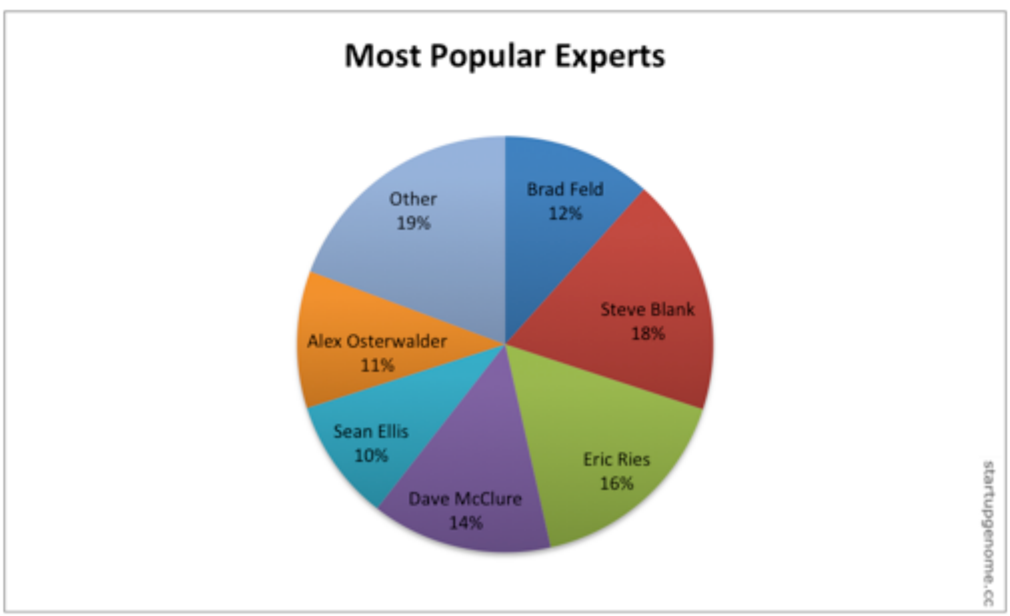


Across the board entrepreneurs are motivated more by Impact and experience than money. Though money as a motivation is higher in Type 3 (The Challenger) startups.



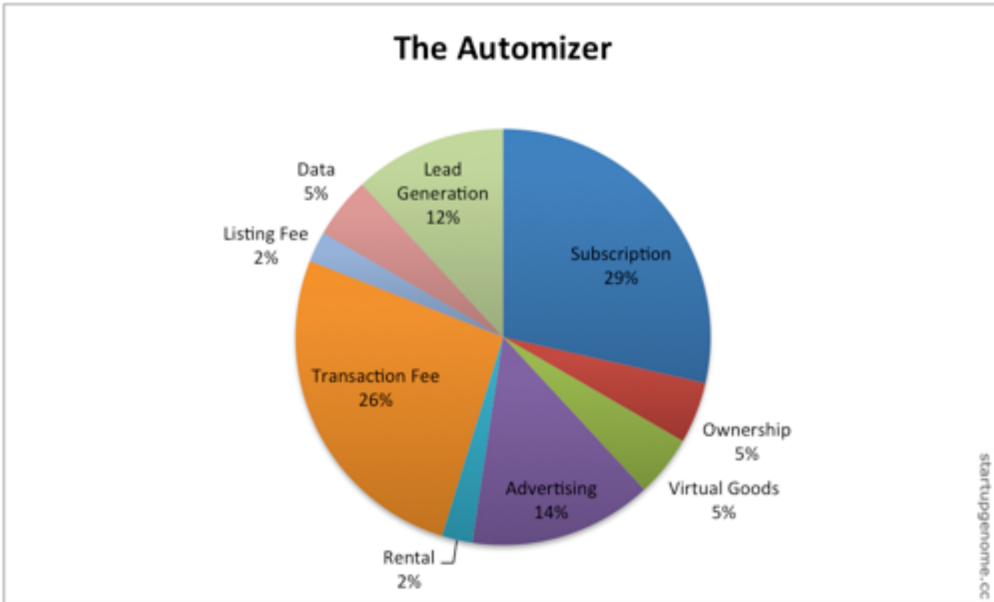
filter: only consistent startups working full time

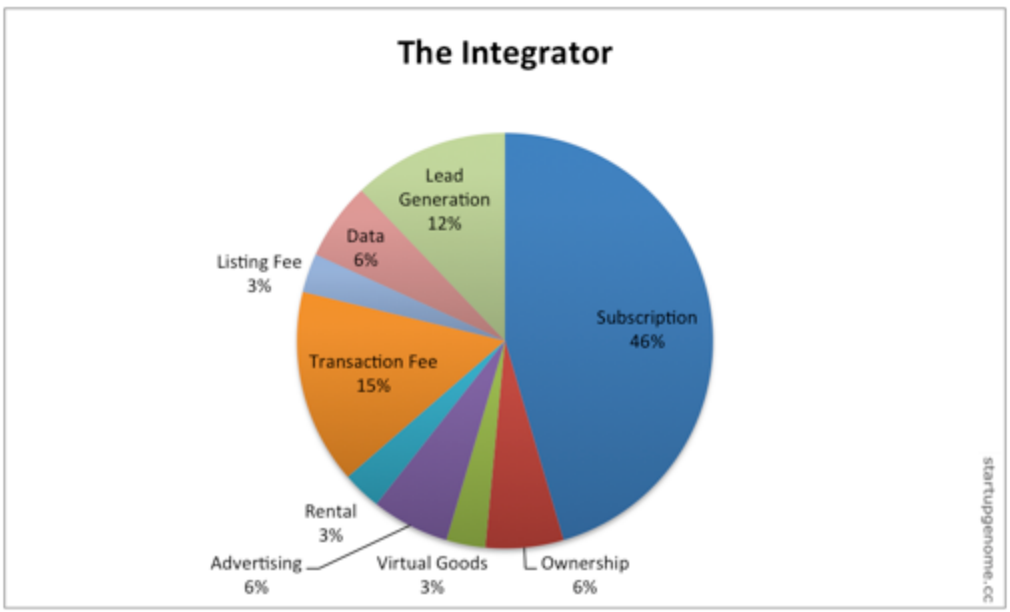
All startups equally consider technology, team and IP competitive advantages. Insider info is slightly more important for Type 2 (The Integrator) and Type 3 (The Challenger), which are usually B2B startups. Whereas traction is by far the key competitive advantage for Type 3 (The Challenger) startups since winning key customers can often act as a large barrier to entry.

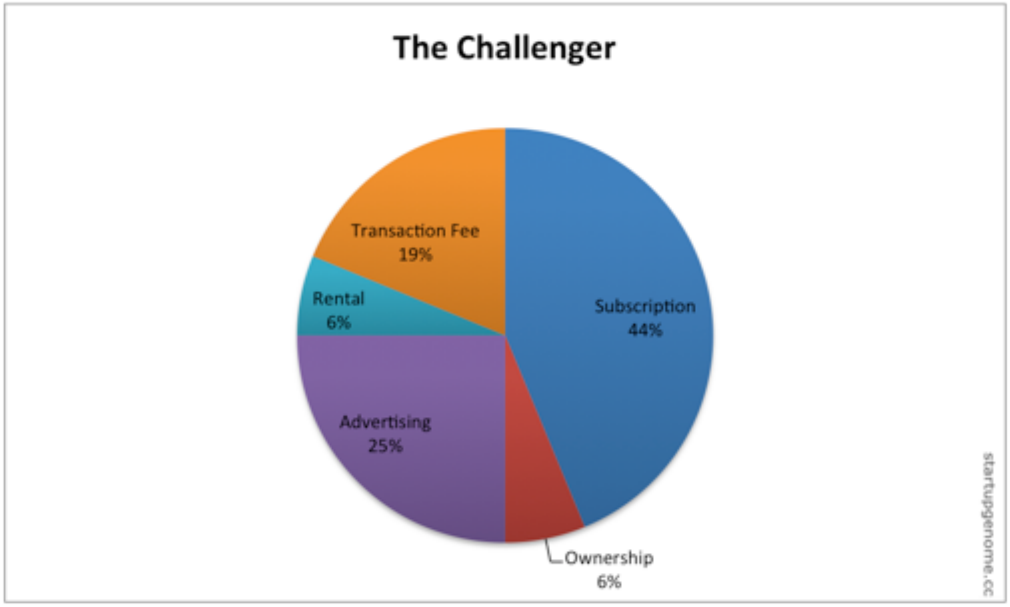


The most popular experts listed in “other” were Paul Graham, Fred Wilson, Guy Kawasaki and Seth Godin. They will not be write-in candidates in the next survey.

Revenue Streams by Type







filter: only consistent startups working full time

D. Acknowledgments & Sources

Authors:
Max Marmer, Bjoern Lasse Herrmann, Ron Berman

Supporters:
Chuck Eesley, Steve Blank, Fadi Bishara

Methodology:
In order to not bias the startups taking the survey we will not publish the thresholds and milestones we use for the stage assessment.

Our tools of choice were Markov Models, Cross Tabulations and Microsoft Excel.

If you would like to learn more about our methodology please read this post, our collaborator Ron Berman wrote on our research process: http://www.systemmalfunction.com/2011/05/deciphering-genome-of-startups.html or contact us at startupgenome@blackbox.vc

Sample sizes:
- Total number of startups: 663
- Startups that were consistent with the Marmer stages: 334
- Startups that raised $50k+ funding (with specific amount disclosed): 104
- Startups that had funding but not disclose the amount: 108
- All startups were web startups

List of traditional indicators of success:
- user growth
- funding raised
- team size
- market size
- time spent working
- % of user base being paid

List of indicators of success based on the Startup Lifecycle:
- stages
- consistency
- premature scaling
- laggards
- pivots
- uncertainty

Inspiration:

Steve Blank, Dave McClure, Sean Ellis, Eric Ries, Paul Graham, Joel York