Global Investment Behavior During Uncertainty: Safe Havens or Risk-Taking?

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Abstract

This project looks at how investors behave during uncertain times: do they play it safe or still bet on bold, high-risk startups? Using global startup data from Crunchbase and economic indicators from the World Bank, we explored patterns in funding across sectors, countries, and time. The analysis shows that investors don't abandon risk—they just become more selective. Safer industries like biotech get steady support, while scalable ventures still attract funding, especially when supported by strong policies or open markets. Machine learning models helped spotting nonlinear correlations that traditional methods missed, showing how real-world investment decisions adapt to shifting economic conditions.

Keywords: Economic Big-data tools; Startup investments; Global Financial Crisis; Macroeconomics

1 Introduction

Periods of economic uncertainty—whether due to financial crises, pandemics, or geopolitical shocks—often lead investors to reassess their strategies. Venture capital, as one of the most risk-tolerant investment mechanisms, offers a unique lens into how economies navigate uncertainty: do investors seek refuge in safer, well-established sectors, or double down on high-risk, high-reward ventures that promise scalability?

When the economy takes a downturn, investors tend to rethink where they put their money. Some evidence suggests a retreat into capital-preserving investments(Rajan, 2011), for example healthcare and infrastructure, which considered as "safe heavens", while others highlight counter-cyclical opportunities in innovative startups. (Nanda & Rhodes-Kropf, 2013) With less copetition and lower valuations, recessions could also considered as a great opportunities for long-term investors to get in early on new ideas. The possibility of getting extra high-returns may attract investors to invest even more. Gompers and Lerner (2001) describe the venture capital is not just reactive–but surprisingly adaptable. Another recent studies by Samila and Sorenson (2011) and Chemmanur et al. (2014) find that investor behavior shifts significantly during uncertainty, but the balance between risk-aversion and risk-seeking is sector- and region-dependent.

This study contributes to that conversation by modeling how startup investment varies across sectors, regions, and funding stages during uncertain periods. We examine whether capital allocation reflects a flight to "safe bets" (e.g., health, infrastructure) or an appetite for "scalable risk" (e.g., AI, fintech). Using exploratory analysis, regression modeling, and machine learning (regression trees and random forests), we test whether investor preferences lean toward safety or scalability under macroeconomic stress. Additionally, we enrich our dataset through web scraping to contextualize economic conditions and sector dynamics, offering a real-time economic layer to the analysis.

2 Data and Method

The analysis was done based on the Startup Investment dataset originally complies from Crunchbase's 2013 Snapshot, with public data of startups from 1966 to 2013. The dataset was published on Kaggle by Cirtautas (2019), including information on organizations, investors, funding rounds, acquisitions etc. Other datasets containing macro-economic indicators of countries from WorldBank open data was used to merge with the original dataset. After cleaning and merging the dataset together by unique IDs, country names, and year, the data used for this project contains totaling over 15,000 entities on startups that received funding between 2000 to 2013. The funding amount were analyzed in US dollars nominal terms as provided.

This paper uses Python libraries such as pandas, matplotlib, seaborn, statsmodels, geopandas, sklearn etc., to create figure visualizations, maps, OLS regressions, classification tree, and machine learning. Results were interpreted with an economic lens, focusing on analyzing long-term trends of investment. This paper applies a range of Python libraries to carry out the full analysis pipeline–from data cleaning and visualizations to statistical modeling and machine learning. Libraries such as pandas and **geopandas** were used to load, filter, and merge large datasets, including startup investment records from Crunchbase and macroeconomic indicators from the World Bank. **Matplotlib** and seaborn were key tools for creating clear and insightful visualizations, including bar charts, line plots, distribution maps, and correlation heatmaps. To explore statistical relationships, the **statsmodels** library was used to run Ordinary Least Squares (OLS) regressions, helping identify how economic variables like interest rates, market openness, and government subsidies affect funding outcomes. For predictive modeling, scikit-learn (**sklearn**) was used to implement both regression trees and classification trees, allowing us to uncover non-linear patterns and thresholds in investment behavior—patterns that standard linear models might miss.

Throughout the whole research process, each result was interpreted mainly through an economic lens, focusing not just on predictive accuracy but on real-world investor behavior. This allows the significance of this study to go beyond the academic, but deal more with real-world application. The aim was to trace how funding patterns shifts over time, particularly on the role that the economic downturns has played in this shift. By combining big data tools with economics, the analysis offers key insights into long-term investment trends.

3 Results

3.1 Investment behavior over time

Our analysis reveals that while the overall volume of startup funding increased steadily from 2000 to 2013, the allocation of that funding shifted obviously during periods of economic downturn. Software and biotech led in total investment during this time period, but average funding per startup was often lower in these ”safer” industries. This strategy—often referred to as “quantitative spraying”—involves distributing many smaller investments across perceived low-risk sectors, rather than placing fewer, high-stake bets. It reflects a behavioral pivot where investors prioritize portfolio diversification and downside protection over maximizing returns from a few standout startups.

This behavior aligns with known psychological biases in financial decision-making, particularly in the context of uncertainty. The investment market differs from traditional consumer markets in that both the products (startups) and the customers (investors) are highly sensitive to perceived volatility. Unlike in standard markets, where choices are largely driven by product utility or quality, investment decisions are often influenced by sentiment, emotion, and narrative framing. As noted by Chen (Aug 05, 2024), investors exhibit loss aversion—they tend to fear losses more than they appreciate gains of equal size. During downturns, this fear becomes more acute, leading investors to preserve capital by moving into sectors perceived as more stable, such as healthcare, clean energy, and logistics, even if those sectors offer lower upside potential.

This pattern is illustrated clearly in Figure 1, which compares the distribution of raised funding in high-risk and low-risk sectors. The histogram shows the the investment of low-risk are more tightly clustered and consistent. In contrast, high-risk sectors has a wider and more skewed distribution, with a longer right tail emphasizing that it have more extreme high values on funds. However, these are only exceptions, but not general rules.

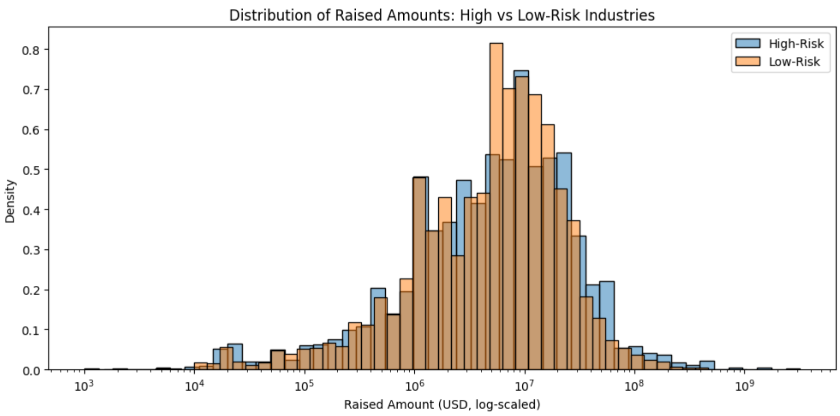

Figure 1: Distribution of funds–High vs. low risk industries: This histogram illustrates more clearly the differences between the high and low risk investment markets. Low-risk investments have a more concentrated distribution of amounts, while high-risk investments have more extreme outlier.

Recessions play a pivotal role in shaping how investment strategies evolve over time. Periods of economic downturn, such as the 2008–2010 financial crisis, often act as stress tests that expose the fragility of certain investment models while reinforcing the resilience of others. Higher-risk investments are more sensitive to the general economic climate and exhibit a very volatile investment curve, while lower-risk investments have been showing a relatively smooth and consistent rising trend. In early-stage funding, traditionally scalable sectors like mobile, biotech, and analytics maintained consistent funding levels. Conversely, late-stage funding remained relatively strong across sectors, with notable support for nano-tech, clean-tech, and software — likely reflecting investor preference for scaling ventures already showing traction, rather than funding early, untested ideas during periods of heightened risk.

Altogether, this section highlights a key insight: uncertainty doesn't eliminate investment—it changes its timing and target. In recessionary periods, capital tends to shift from early risk-taking to later-stage confirmation, favoring ideas that are already in motion. The market rewards startups that show both scalability and resilience, and investors respond by concentrating their funding into those that can bridge innovation and reliability, even during economic stress.

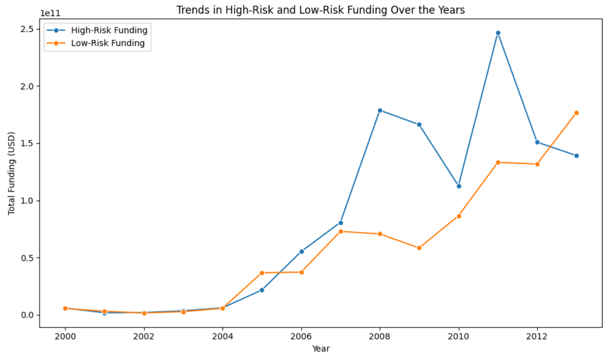

Figure 2: Funding trends: High risk vs. Low risk: The blue line representing high-risk funding over year have greater fluctuation, especially during 2008-2010 Great Recession period

3.2 Regression analysis

The OLS method was used to examine the effect of macroeconomic indicators and venture capital dynamics to startup funding. The regression equation referring to Table 1 is:

$$log(Funding_i) = \beta_0 + \beta_1 \times VF_i + \beta_2 \times VF_i^2 + \beta_3 \times IR_i + \beta_4 \times TS_i + \beta_5 \times MO_i + \epsilon_i \quad (1)$$

$$log(Funding_i) = 5.562 + 0.119 \times VF_i - 0.005 \times VF_i^2 - 0.041 \times IR_i + 0.554 \times TS_i + 0.557 \times MO_i + \epsilon_i \quad (2)$$

where $Funding_i$ is the total funding for startup i, TF_i= Total venture funding in the ecosystem, TF_i^2= Squared term (captures diminishing returns), IR_i= Real interest rate (%), TS_i = Transfers and subsidies (index), MO_i= Market openness (index)

This result points to some noteworthy conclusions, providing evidence for the shift to safer bets. First, the positive value of β_1 and negative value of β_2 suggest that an increase in venture capital investment significantly boosts up the startup funding, usually due to the fact that venture capital invests for a relatively large amount compared to other investors. At the same time, the negative value of β_2 suggests a diminishing returns on high-level investments. Over time, as the new industry or company becomes more mature and attracts more investment, the market becomes saturated. Therefore, the return on investment will decline and eventually level off.

This regression also supports the hypothesis that monetary tightening during the financial crisis pushes the investors towards safer bets. This matches with the risk aversion strategies taken by investors due to the fear of loss.(Chen, Aug 05, 2024) In contrast, the policy variables such as government transfers and subsidies, and market openness level of countries were both strongly and highly significant, which interprets that with government support and protection policies, the startup ecosystem of the country will be more stable. This reduces perceived risk, encouraging more consistent and stable investment even when the economy is highly uncertain.

Overall, the regression model reinforce our expectations of the effect that macroeconomic interprets will have on the funding amounts and patterns.

Table 1: Impact of Economic and VC Funding Factors on Total Funding

Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**
const	14.295***	14.286***	12.852***	5.562***
	(0.016)	(0.016)	(0.117)	(0.214)
venture_funding_sum	0.141***	0.137***	0.119***	
	(0.039)	(0.039)	(0.039)	
venture_funding_sum_sq	-0.005***	-0.005***	-0.005***	
	(0.002)	(0.002)	(0.002)	
Real interest rate (%)		-0.021***	-0.041***	
		(0.005)	(0.005)	
Transfers and subsidies			0.242***	0.554***
			(0.020)	(0.021)
Market openness				0.557***
				(0.014)

Note: Standard errors in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

3.3 Geography Insight

Geography also plays a key role. While early-stage innovation is rising globally—especially in Southeast Asia, South America, and Africa—actual funding remains concentrated in the U.S., Canada, and Western Europe. China stands out as a notable exception, maintaining high growth even during the financial crisis (Instone, 2018). The main reasons for this are the different political and economic policies (taxes and subsidies), the environment of startup ecosystem (total number of startups, percentage of high/low-risk firms), and the degree of development of different industries in different countries. All of which will change the investor's confidence in investing, and thus the amount of investment will vary.

The maps highlights that developing regions such as South America, Southeast Asia, and parts of Africa host a high proportion of early-stage startups. However, the corresponding map reveals that total early-stage funding is still heavily concentrated in advanced economic countries. This disparity reflects a long-observed trend in venture capital geography: while new ventures are forming everywhere, meaningful investment flows disproportionately to a handful of financial hubs.(Samila & Sorenson, 2011)

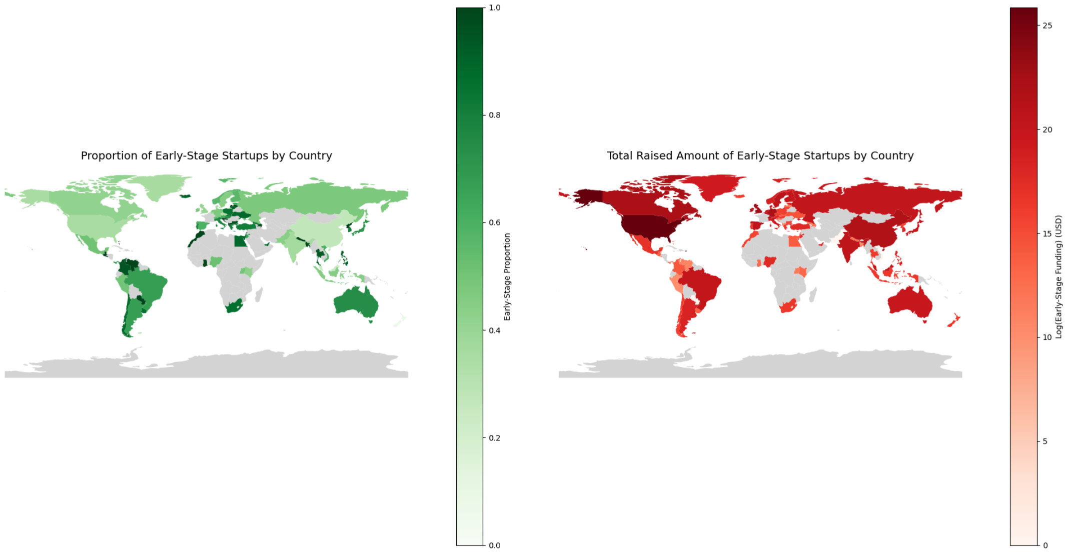

Figure 3: Early stage startup proportion and total funds received

Until recent years, by scraping and visualizing data from Crunchbase (2023) that contains 451 emerging unicorn companies of each continent of 2023. North America(especially the U.S.) is still considered as both a scalable and "safer" ecosystem for startups. This is due to the mature financial and innovation systems. This aligns with investor behavior that seeks scalable risks not only during the economic downturns.

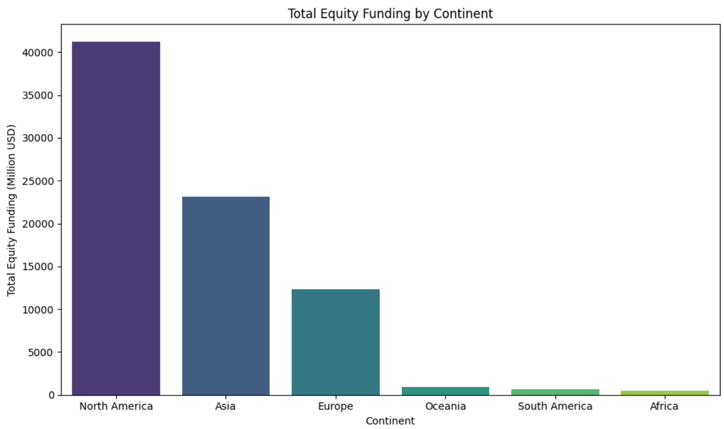

Figure 4: Total equity funding of Unicorns of each continent: North America is still favored by investors in 2023

3.4 Machine Learning models

To better understand how investors behave during uncertain times, we used machine learning models—specifically a regression tree and a classification tree—to uncover patterns that a standard regression couldn't reveal. The regression tree showed that investor decisions aren't just about more or less money—they're shaped by clear tipping points. For instance, startups in countries with open markets or lower interest rates tended to receive significantly more funding, highlighting how broader economic conditions influence investor confidence.

The objective function of the regression tree of this project is:

$$\min_{j,s}\left[\sum_{i:\text{MarketOpenness}_i\leq s}\left(\log(\text{RaisedAmount}_i)-\hat{y}_{R1}\right)^2+\sum_{i:\text{MarketOpenness}_i>s}\left(\log(\text{RaisedAmount}_i)-\hat{y}_{R2}\right)^2\right]$$

Where :

- R_1 and R_2 are the left and right child nodes
- $\hat{y}_{R1}, \hat{y}_{R2}$ are the average predictions in each

The classification tree helped us see who's likely to receive "high" versus "low" funding. It turns out that early-stage, high-risk startups without policy support were almost always underfunded, while those with strong public backing and more maturity stood a better chance. The model correctly predicted funding outcomes over 75% of the time, compared to the much weaker performance of a traditional regression, which struggled to explain the data. Together, these models paint a clearer picture: during times of uncertainty, investors don't avoid risk entirely—they just become more selective. They look for signals of safety—like government support or economic openness—before placing bigger bets. The key takeaways of the classification tree is that high government subsidies and late-stage startups increase the chance of receiving high funding, whereas low-risk startups tend to receive lower funding. This suggests that the scalable risk attracts investors during recovery. According to these interpretations, we could summarize certain conclusions:

- Low-risk industries have a larger number of investors, while high-risk industries have a smaller number of investors but a larger amount of individual inputs.
- Rather than simply analyzing the shift in investor bias between sectors with different risk profiles, there is a greater tendency to invest strategically in startups that are supported by the government. Local governments tend to provide more are support to later-stage, lower-risk companies.

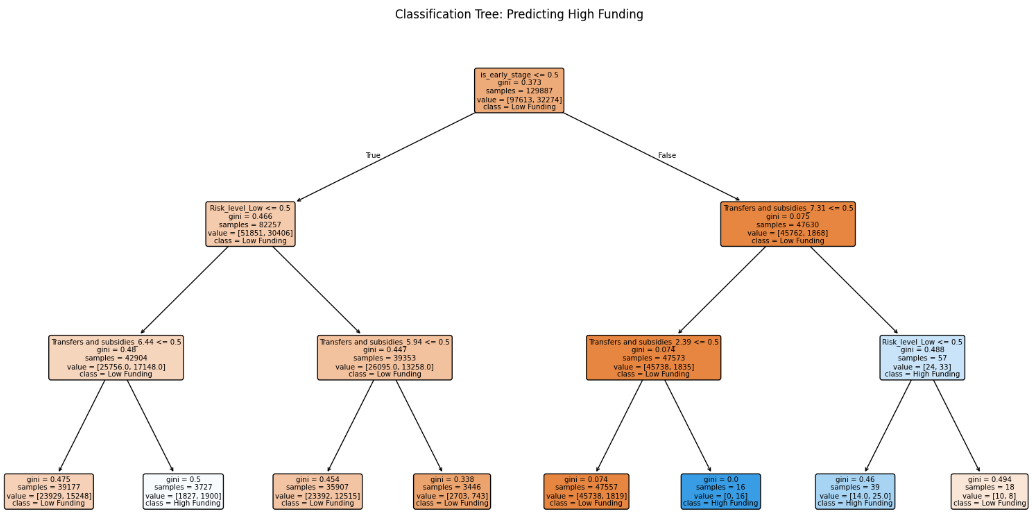

Figure 5: Classification Tree: Predict who's likely to receive high vs low funding

With refer to table 2, the error rate could be calculated using following steps:

$$\text{Error rate} = \frac{FalsePositive + FalseNegatives}{TotalObservations} \approx 24.6$$

$$Gini = 1 - \sum_{i=1}^{C} (p_i)^2 p_i : proportionofsamplesofclassiinthenode$$

Table 2: Classification Report: Predicting High Funding

Label	**Precision**	**Recall**	**F1-Score**	**Support**
False (Low Funding)	0.7605	0.9821	0.8572	24,451
True (High Funding)	0.5128	0.0573	0.1032	8,021
Macro Average	0.6367	0.5197	0.4800	32,472
Weighted Average	0.6993	0.7537	0.6710	32,472

3.5 Compare OLS with Machine learning

In order to see which models best explain how funding decisions are made during uncertain times, a comparison was done between the performance of the classification tree, regression tree, and traditional OLS regression. The classification tree did a solid job, correctly predicting whether a startup would receive high or low funding about 75% of the time. This suggests that investor decisions can often be boiled down to a few key traits—like risk level, stage, and government support. When predicting actual funding amounts, the regression tree outperformed OLS by producing lower error, and it also revealed more useful patterns. For example, it showed that funding tends to increase sharply once interest rates drop below a certain level or when market openness is high. In contrast, the OLS model struggled–its R^2 value converge to zero, meaning it couldn't explain much of the variation in funding at all. Overall, these results show that machine learning models, especially trees, are much better at capturing the real-world complexity behind investor decisions. Rather than relying on simple, linear trends, they adapt to the way investors think—balancing risk, timing, and policy signals when deciding where to put their money.

Table 3: Model Comparison: Classification Tree, Regression Tree, and OLS Regression

Model	**Accuracy**	**MSE**	R^2
Classification Tree	0.7537	–	–
Regression Tree	–	1.3344	0.0326
OLS Regression	–	1.3674	0.0087

4 Conclusion

There is little doubt that major economic downturns—such as the 2008 financial crisis—reshape the landscape of startup investment. (Conti, 2019) However, their impact is not primarily a reduction in the total volume of investments. Rather, these events shift how investors assess and allocate capital, changing both the strategy and criteria used to evaluate startups. This study examined how venture capital responds to uncertainty, asking whether global investors favor safer industries or remain drawn to scalable, risk-intensive ventures during economic downturns. Our analysis found a consistent pattern: in periods associated with economic stress, funding became more concentrated in capital-intensive but elastic sectors like biotechnology and enterprise software–suggesting a tilt toward safer bets. These industries offer a combination of stability and long-term value, making them appealing when risk tolerance shrinks, suggesting that investors remain open to scalable risk, particularly when startups demonstrate strong market potential, technological differentiation, or policy alignment.One possible explanation for this dual behavior lies in the psychology of investing. In uncertain environments, the promise of high returns from breakthrough technologies may still entice investors, even if those opportunities come with greater risk. This reflects a common tension in investor behavior: the desire to minimize losses while still capturing rare, high-reward opportunities.

Ultimately, our analysis supports a hybrid conclusion: economic downturns do not eliminate risk appetite—they recalibrate it. Investors become more selective, directing capital toward ventures that not only show promise but also signal resilience. Rather than avoiding entirely from uncertainty, they adapt it—treating it as a filter for more disciplined and strategically timed risk-taking.

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