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EVERYONE STEPS BACK? THE WIDESPREAD RETRACTION OF CROWD-FUNDING SUPPORT FOR MINORITY CREATORS WHEN MIGRATION FEAR IS HIGH

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Everyone Steps Back? The Widespread Retraction of Crowd-Funding Support for Minority Creators when Migration Fear is High
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ABSTRACT

We study funding gaps on Kickstarter across multiple ethnic groups from 2009-2021. Scaling the concept of racially salient events, we quantify the close co-movement of minority funding gaps in crowd-funding to inflamed political rhetoric surrounding migration. The funding gap for minorities more than doubles in the most inflamed periods compared to baseline. Results are especially acute for Hispanic creators. Distant, mostly white backers are typically important for projects reaching a critical threshold of funding support. Retractions in support for minority creators during tense periods are even spatially, as present in liberal cities as conservative ones.

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1. Introduction

Crowd-funding is an important tool for pursuing creative projects and new ventures. It allows early validation of product demand and a path for those with lower risk tolerances to test ideas (Hvide and Panos 2014). Projects aid new ventures via product signaling (Sewaid et al. 2021) and attracting follow-on investment (Roma et al. 2021). Mollick and Kuppuswamy (2014) show the creation of gaming ventures following a successful campaign, and Yu and Fleming (2022) link crowd-funding to growth-oriented regional entrepreneurship. Given these benefits, many hope crowd-funding will "democratize" access to finance.[1] And to some degree, it has a weaker "home bias" for investment in local areas.[2]

Many studies document large racial funding gaps in entrepreneurial finance[3], which has unfortunately carried through to crowd-funding. Younkin and Kuppuswamy (2018) first document racial bias on Kickstarter, showing reduced success for Black creators among projects with videos posted during 2012-2014. Their experiments show the bias is likely unconscious, and they argue bias can be lowered through endorsements, prior success, and removing race indicators like photos. Further work suggests this racial bias can be exacerbated. Gorbatai et al. (2023) use three laboratory experiments to show racially salient events raise biases against Black creators. The success gap on Kickstarter for Black creators grows by about 10% in a 30-day window after publicized police shootings.

Our research contributes to this nascent literature through a platform that captures multiple ethnic groups (Black, Hispanic, and Asian creators) using names and photos for 2009-2021. Scaling the concept of racially salient events, we quantify the close co-movement

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[1] Examples include Agrawal et al. (2014), Mollick (2014), Mollick and Robb (2016), and Younkin and Kashkooli (2016).
[2] For example, Agrawal et al. (2015), Kim and Hann (2014), and Lin and Viswanathan (2016).
[3] Prominent early examples include Fairlie and Robb (2007) and Chatterji and Seamans (2012). Recent contributions include Cook et al. (2022), Hamilton et al. (2022), Fairlie et al. (2022), and Marx et al. (2024). Ewens (2023) provides a comprehensive review.

of racial funding gaps on Kickstarter with inflamed political rhetoric using the Migration Fear Index developed by Baker et al. (2016).[4] Across quarters, a one standard deviation increase in the Migration Fear Index connects to a 1.9% lower success rate for minority creators, compared to a 48.8% baseline average. The index fluctuated by more than four standard deviations during the campaign and early years of the Trump administration, representing as much as a 15% decline in relative terms. Non-linear estimations calculate that the minority success gap more than doubles in the most inflamed periods.

These findings are remarkably robust, including using matched creator samples and a repeat creator panel.[5] Indeed, a core contribution of this work is to confirm findings like Gorbatai et al. (2023) in large samples and multiple settings, including spillovers across ethnic groups. Political rhetoric captured in the Migration Fear Index naturally links most closely to a worsening bias against Hispanic creators, and we also trace out smaller impacts on Black and Asian creators. While we show robustness to other metrics, our use of the Baker et al. (2016) index is intentional. This macro-sentiment variable captures important information and could be a useful lever for studies examining racial differences in financial access and the real effects of finance (King and Levine 1993).

Increased racial funding gaps could be due to changes on the supply of projects from creators or changes on the demand side from backers. On the supply side, the political climate may affect the rate at which minorities list projects on Kickstarter compared to white creators or influence how minorities present their projects. Exploring these, we do not observe

[4] The online supplement provides a full literature review, including extensive work linking public discourse and opinions on immigration to attitudes toward racial and ethnic groups.

[5] The verification that racial bias on Kickstarter worsens in tense periods is important, as other work finds different responses. Black-owned restaurants received sympathetic responses and greater traffic after George Floyd's murder and during Black Lives Matter movements, with digital signals of Black ownership deemed beneficial (Mitkina et al. 2023, Aneja et al. 2023, Agarwal et al. 2023). The frequent non-pecuniary motivation of backers (Boudreau et al. 2021) makes responses theoretically ambiguous.

significant changes across quarters in minority creator shares nor their product categories. We also construct metrics of project quality using machine learning techniques, generative AI tools, and human grading. These metrics are highly predictive of project success but do not explain our main findings. Thus, while there may be an important role for project supply beyond what our observational data captures, the supply side does not appear capable of explaining the heightened racial gap among listed projects.

Turning to the demand side of project backers, it is initially puzzling why crowd-funding could reduce geographic constraints, allowing creators throughout the U.S. to equally court backers in New York or Seattle, but still feature strong racial biases. Yet, we show that the racial shortfalls are not due to a localized retraction of support among backers closest to minority creators, either in racial or geographic terms. Indeed, most financial backers on Kickstarter live far away from the creators they support, tending to reside in big coastal cities. Most backers are also white, and the most critical shortfalls of support occur in the range of achieving 10-20 backers. Thus, white backers distant from the project creator must play a significant role in widening racial gaps. One hypothesis is that this retraction would be more severe in very conservative areas.[6] Yet, we show that the spatial distributions of backers in low and high periods of the Migration Fear Index are quite similar. The withdrawal of support is uniform, as present in liberal cities as conservative ones. This broad-based weakening is consistent with unconscious bias worsening (Younkin and Kuppuswamy 2018).

This pervasive, macro retraction among project backers is novel compared to what is often described for racial gaps in finance (e.g., biases among local loan officers in bank lending). Crowd-funding can be democratizing geographically but still exhibit biases, racial and potentially otherwise, if "everyone steps back".

[6] For example, reactions against Asians were stronger in Trump-leaning counties after Trump referred to Covid-19 as the "Chinese Virus" (Cao et al. 2022, Huang et al. 2023).

2. Data Development for Projects and Creators

Kickstarter is a large crowd-funding platform where creators and entrepreneurs disclose their plans and funding needs for a "creative" project via a web page that contains a main body (comprised of video, images, and text), funding status, and reward tiers. Projects are grouped into 15 categories: Art, Comics, Crafts, Dance, Design, Fashion, Film & Video, Food, Games, Journalism, Music, Photography, Publishing, Technology, and Theater. In exchange for monetary pledges, creators promise nonbinding "rewards" like finished products, early-stage prototypes, or early access to services (e.g., Krishnan et al. 2017). If the sum of pledges received during the funding period—between one and 60 days, with 30 days being most common—meets the funding goal, then the project goes forward. Otherwise, backers are released (i.e., "all or nothing" funding).

We focus on U.S.-based projects and drop cases where the creator's name field contains non-name elements (e.g., "Dark Elf's Games", "Carole's Candy Shop"). We infer creators' racial ethnicity through NamePrism, which uses a naïve Bayes model based upon first and last names. An indicator variable *Minority* is equal to one if the highest inferred probability belongs to a Black, Hispanic, or Asian category. The Migration Fear Index counts the number of newspaper articles with at least one term from defined Migration and Fear term sets and then divides by the total count of contemporaneous articles.

Our main dependent variable is an indicator variable *Success*, which is equal to one if a project reached its target. *Pledges/Goal* measures the total amount of dollars pledged to the project, scaled by the initial goal. This metric can exceed one, as projects can be oversubscribed, and some creators leave projects open to continue outreach. We thus cap the ratio at 125% of goal, with about 20% of the sample at this top code. Finally, ln(*Backers)* is the log number of backers.[7]

After preparation, we have 150,282 project observations between 2009q2 and 2021q1. The average success rate is 48.8%, projects average pledges equal to 60.2% of initial goal, and the mean number of backers is 78.6. Minority creators account for 9.3% of projects, significantly less than their share of the U.S. population, and the sample is skewed toward men. Black, Hispanic, and Asian creator shares are 1.1%, 5.1%, and 3.2%, respectively.

Our online supplement describes the Kickstarter data and their preparation, including summary stats. Section 4 will describe our backer data.

3. Empirical Analysis for Racial Success Gaps

Table 1 provides a visual portrait. The red dashed line is the Migration Fear Index, which jumps with the launch of Trump's campaign and continued success to win the Republican nomination. The sharp dip in 2016q2 coincides with a quiet quarter after Trump and Hillary Clinton have secured their party nominations but before the general election begins. The index further rises with Trump's win and the enactment of the "Muslim travel ban". The peak in 2017q3 is the summer of Trump's first year in office and includes events like the Unite the Right rally in Charlottesville, VA. The 2018 rebound coincides with Trump's criticism of immigration from "sh##hole" countries, the announcement of "zero tolerance" policies on the border that included family separations, and his threats to revoke birthright citizenship. The index remains elevated through most of Trump's presidency but declines by late 2019 to near its initial level.

[7] Stanko and Henard (2017) link number of backers, beyond funds raised, to future performance.

The solid green line with circles shows the success difference of white- vs. minority-created projects scaled by the total rate of project success: (success rate for white creators – success rate for minority creators) / (total success rate). White creators are generally more likely to reach funding goals. Prior to 2015, the differential is 10% or less. Commencing in 2015, however, the differential is rarely less than 20% until 2020. While the co-movements are not perfectly synchronized, the tight visual linkage foreshadows the strength of regressions.[8]

The lower panel uses regressions of the form,

$$
\begin{aligned}
&Funding\ outcome_i \\
&\quad = \beta_1 Minority_i + \beta_2 Minority_i \times Fear_{tq} + \beta_3 Fear_{tq} \qquad (1) \\
&\quad + \Omega\, Controls_i + \lambda\, Fixed\ Effects_{c,s,t} + \varepsilon_i
\end{aligned}
$$

where i, q, and t index projects, quarters, and years, respectively. $Minority_i$ is an indicator variable for the creator being a minority. $Fear_{tq}$ is the Migration Fear Index for quarter q and year t. We include fixed effects for the project category and state of the creator. Year effects account for macroeconomic conditions and restrict identification to quarterly variation.

Regressions control for project-level traits using an indicator for female creator, log project target funding, log project description length, log project duration, the number of projects launched by the same creator in the same quarter, and an indicator variable for whether the creator is self-mentioned in project description. These controls follow Gafni et al. (2019, 2021) and capture quality differences over postings. Reflecting the two sources of variation in the interaction term $Minority_i \times Fear_{tq}$, we two-way cluster standard errors by

[8] The supplement shows that the spike after 2020 is due to challenges encountered by Chinese creators during the worst periods of Asian Hate. This episode is perhaps more closely linked to politically charged xenophobia during the pandemic than the migration fear focused upon in the core of this project. Bias during this episode may have been more conscious among potential backers as well.

creator and quarter, reporting t-statistics. We weight regressions so that each creator-quarter carries the same importance.

Column (1) shows higher values of the Migration Fear Index correspond with reduced success for minorities. With a coefficient of -0.032, a one standard deviation increase in the index (0.601) translates to a decline of 1.93% in minority success compared to a baseline average of 48.8% (a relative effect of 3.9%). This decline in minority success is comparable to the baseline gap of -2.1% measured with the main effect of $Minority_i$. The main effect of the fear index is weak, indicating limited change in project success for white creators. When using a non-parametric specification, we measure the racial gap of 4.4% present in the bottom two quartiles of values of the fear index more than doubles to 9.2% for the top quartile. Columns (2) and (3) show comparable funding shortfalls.

Our baseline analysis provides an overall portrait that combines minority ethnic groups. As elaborated upon in the supplement, the baseline racial bias against Hispanic creators is about half of what Black creators face, while Asian creators at baseline have slightly higher success rates than white creators. From this baseline level, the success decline with a one standard deviation increase in the index is most severe and precisely estimated for Hispanic creators (-2.4%), compared to Black (-1.4%) and Asians (-1.5%). This reflects that much of the discourse and uncertainty linked to Trump focused on Hispanic migration.

An important question is whether minorities present less fundable or weaker projects during heightened periods of anxiety. We investigate in several ways. First, the supplement reports regressions that use features of postings (e.g., readability/mistakes, presence of photos, or self-mentions) as outcome variables with model (1), generally finding the focal interaction term to be quite small and not statistically significant.

Second, **Table 2** evaluates projects from 2013 and onwards in the presence of two quality metrics. The first metric uses a machine learning algorithm trained on projects from 2009-2012 to predict project success for listings during 2013-2021. The second metric uses estimate project quality from an enterprise ChatGPT scoring. Both metrics (described in the supplement) are very predictive of funding success and boost the adjusted R^2, but the measured interaction term remains very strong.

The supplement reports alternative specifications and sample restrictions (e.g., excluding projects with minimal or extreme support). Considering the supply side of projects, there is no evidence for lower participation of minority creators nor minority backers when fear spikes. Minority creators increase from around 7% of creators in 2009 to typically 11% or above in recent years, and this growth is steady quarter-to-quarter. The distributions of projects across categories are also stable. Additionally, the results are not linked to general economic uncertainty nor reflect migration uncertainty in other countries. We find similar results when using Google Search Values and state-level indices. We still measure minority differentials when extending model (1) to include city x year x quarter or product category x year x quarter fixed effects. Results are robust to employing different name algorithms or using pictures to infer race.

Kickstarter has a "Staff Picked" designation for about 10% of projects, raising their visibility to potential backers. Repeating specification (1) with a (0,1) indicator for being Staff Picked as the dependent variable yields a main effect for $Minority_i$ of 0.0037 (t-stat=0.56) and an interaction effect for $Minority_i \times Fear_{tq}$ of -0.0094 (t-stat=-2.25). In other words, while the projects of minority creators are equally likely to be Staff Picked as those of white creators in quarters when the index is low, minorities are less likely to be Staff Picked during tense times. This may be due to less early momentum for minority projects being reinforced by the algorithm. To ensure this exposure is not driving our results, we show similar outcomes when excluding Staff Picked projects.

Tables 3a and 3b present two auxiliary samples. Table 3a uses a matched sample that identifies similar projects that were listed within 12 months of each other but during very low vs. high anxiety levels. These matched projects are all sourced from 2015-2017 due to the extreme fluctuations during those years. Panel A considers the matched projects of minorities, estimating a one standard deviation increase in the Migration Fear Index corresponds to a 1.6% lower likelihood of success. Panel B does not show a similar effect among matched projects for white creators. These results suggest comparable projects of minorities are experiencing different outcomes based upon external conditions.

Table 3b isolates 40,729 projects from 14,722 creators with two or more projects. We add creator fixed effects to specification (1), finding a relative effect of 2.7% that is comparable to 3.9% in the full sample. While we favor estimations that incorporate the ubiquitous single-time creators, the intensive margin shows a comparable magnitude.

The supplement shows the results in Tables 3a and 3b also hold when including the ML and ChatGPT quality metrics; for a smaller subset of the matched sample, we also show robustness to including a quality metric developed by a human grader.

4. Data Development for Project Backers

To consider further the relative roles of supply and demand of projects in racial funding gaps, we develop additional metrics related to project backers. For all projects, Kickstarter reports the count of backers and total pledge amounts. Once a project reaches ten or more backers, Kickstarter further reveals the city location(s) of backers, with up to ten locations and the number of backers per location provided.

Project success typically requires achieving support of at least 20 backers. There is a 5% success rate for projects with 10 or fewer backers, 58% success rate with 11-20 backers, and 86% success rate with 21+ backers. By contrast, average pledge amounts do not vary much. Thus, while projects in total average 78.6 backers as some exceed 1000+ backers, the success deterioration for minorities during tense times is more due to projects that would have received, for example, 25 backers instead only getting 15.

We define a "local backer" as being within 50 miles of the creator. On average, 36.1% of backers are local; 20% if weighting projects by backer count. This need to appeal to distant backers is true at small funding amounts—the local share of observed backers for projects with 10-15 backers is 28%.

Finally, most backers are white. Kickstarter does not publish backer names, but Gafni et al. (2021) collected backers from April 2009 to March 2012, which they generously shared. Minorities account for 6.2% of backers from this period, with Black, Hispanic, and Asian shares of backers being 0.4%, 2.9%, and 2.7%, respectively. The average minority backer share for a minority creator is 11% compared to 4% for a white creator. If conditioning on project and creator traits, the share of backers who are minorities is about 10% higher for minority creators.

In sum, project success typically hinges on building a critical mass of 20 or more backers, most of whom will be white and distant from the creator.

5. Empirical Analysis for Backer Reduction

The supplement contains four analyses that confirm that minority funding gaps are not due to reduced support among those closest to them.

- One analysis shows that declines in support for minorities are among locations and products where they disproportionately depend on the support of white backers.
- A second analysis uses project blurbs to show that the decline is not due to weaker interest in projects with a distinctive ethnic component (e.g., “texmex” cuisine).
- A third analysis shows the declines are not concentrated among projects with local geographic appeal (e.g., for a local bakery).
- A final analysis shows that minority success gaps are evident among quite large projects with goals of $5000 or more, as well as smaller ones.

These tests confirm the racial success gap is widespread and follows upon the weakening of support among distant white backers.

Table 4 thus considers the local racial and political climate around the creator. While studies often identify larger negative effects from polarizing political events in conservative areas, the prevalence of Kickstarter backers in larger and more liberal cities may dampen this for crowd-funding. Table 4 uses data generously provided by Howell et al. (2023). Using county locations of creators, we map time-invariant measures of the county’s average Implicit Association Tests (IAT) bias results, average racially charged Google search, and average vote share for Republican candidates in Presidential elections since 2012 (see supplement for more information). Each pair of columns splits the sample at the median of these time-invariant metrics, and we repeatedly find evidence of reduced support for minorities on both sides. The differences are not statistically significant and suggest a balanced retraction in support regardless of where a creator lives.

Table 5 focuses on projects with 10-20 backers, given the critical role of reaching 20 backers for success. The top panel shows the distribution of backers across the 96 cities that account for at least 0.1% of Kickstarter's backers. The distributions are visually quite similar in times of low and high anxiety, and the bottom panel formally tests this conclusion. The share equality test considers whether the cumulative share of backers accounted for by the top 18, 96, or 166 cities, respectively, are the same across low and high fear states. The distribution equality test alternatively measures whether the spatial layout of support within the indicated city band is similar across fear states.

None of these tests reject the null hypothesis of spatial equality. The supplement shows these results when expanding to even smaller cities or when considering all projects. Additional tests that combine Table 4's location-based attributes with backer distributions also confirm that the declines in support are broad-based.

6. Conclusion

Crowd-funding democratizes access to financial capital spatially, yet racial funding gaps still exist. Our analysis shows macro-sentiment plays an important role in financing, and a widespread retraction in backer support can best explain minority financing gaps during periods of political animosity regarding migration. In our work, these funding challenges were especially true for Hispanic creators. These results appear consistent with the unconscious bias documented in experimental studies, but changes in the supply of projects may also play a role, too.

Useful interventions are possible. Even if they do not directly collect race data, crowd-funding platforms could use techniques like ours to monitor project success by ethnic groups in real-time. Their algorithms could then give a bit more attention to projects disadvantaged by the macro environment. Most of the shortfalls come from rather small differences in backers—for example, not getting from 12 to 20 backers, or not getting sufficient momentum to get Staff Picked. Platforms could potentially "lean against the wind" and provide added visibility to minority creators during tense moments. For public policy, we believe awareness is the most important issue for now. Especially to the degree that this effect is observed in other forms of entrepreneurial finance, concerned policymakers can intervene to support minority ventures when the macro environment is hostile.

We hope future research explores these dynamics for bank loans, angel financings, and other types of crowd-funding and investigates additional real impacts of the impaired finance channel. Even if a spike in negative sentiment quickly fades, it may have longer-lasting consequences if fewer minority projects and businesses take root.

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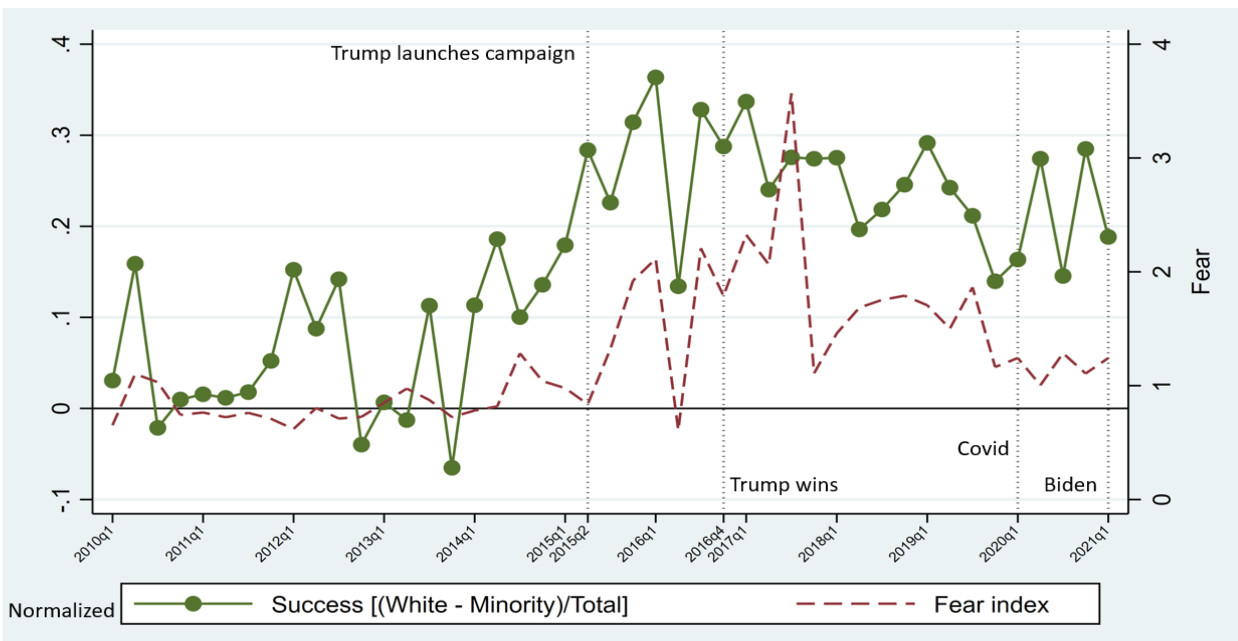
Table 1: Migration fear and minority funding outcomes

The top panel displays the quarterly co-movement of the relative success of white- vs. minority-created projects on Kickstarter (scaled by the total rate of project success) and the Migration Fear Index first developed by Baker et al. (2016), divided by 100. The accompanying table reports coefficient estimates from a regression sample of 150,282 projects. We regress three funding outcome variables on the interaction of Minority and the Migration Fear Index. Success is an indicator equal to one if the project is successfully funded. Pledges/Goal is equal to total funding pledges scaled by project goals, capped at 125%. ln(Backers) is equal to the natural logarithm of the number of project backers. Minority is an indicator variable equal to one if a project creator is a minority. Regressions control for project-level traits using an indicator for female creator, log project target funding, log project description length, log project duration, the number of projects created by the same creator in the same year-quarter, and an indicator variable for whether the creator is self-mentioned in project description. Specifications include year, state and category fixed effects. Regressions are weighted so that each creator-quarter receives equal weight. Standard errors are two-way clustered by creator and quarter, with t-statistics reported in parentheses. +, ++, and +++ indicate significance at the 10, 5, and 1% levels, respectively.



	Success	Pledges/Goal	ln(Backers)
	(1)	(2)	(3)
Minority × Fear	**-0.032+++**	**-0.038+++**	**-0.147+++**
	(-4.90)	**(-4.69)**	**(-4.40)**
Minority	-0.021+	-0.025+	-0.104++
	(-1.96)	(-1.99)	(-2.11)
Fear	-0.010	-0.012	-0.042
	(-0.74)	(-0.79)	(-0.75)
Mean of Outcome Var.	0.488	0.602	2.860
Impact of 1 SD of Fear	-0.019	-0.023	-0.088
Impact Relative to Mean	-3.94%	-3.79%	-3.09%

Table 2: Specifications with quality assessments

See Table 1. Columns (2)-(5) restrict the sample to 116,590 projects in 2013 and afterwards and for which ML and ChatGPT quality metrics could be developed. Columns (3) and (5) add a metric of likely project success developed by training a machine learning algorithm on projects before 2013. Columns (4) and (5) add a metric of project quality developed by ChatGPT scoring. Estimations include Project Controls and Year, State, and Category Fixed Effects.

	Baseline estimation for Success	Restricting sample to observations with quality metrics	Including ML prediction of success	Including ChatGPT metric of quality	Including both metrics
	(1)	(2)	(3)	(4)	(5)
Minority × Fear	**-0.032+++**	**-0.029+++**	**-0.026+++**	**-0.024+++**	**-0.023+++**
	(-4.90)	**(-3.93)**	**(-4.05)**	**(-3.82)**	**(-3.80)**
Minority	-0.021+	-0.025+	-0.024++	-0.024++	-0.023++
	(-1.96)	(-1.99)	(-2.04)	(-2.06)	(-2.07)
Fear	-0.010	-0.010	-0.008	-0.007	-0.007
	(-0.74)	(-0.76)	(-0.76)	(-0.70)	(-0.70)
Quality Metric ML			0.234+++		0.187+++
			(51.00)		(38.74)
Quality Metric ChatGPT				0.120+++	0.097+++
				(45.52)	(37.98)
Observations	150282	116590	116590	116590	116590
Adj. R^2	0.218	0.218	0.268	0.271	0.301

Table 3a: Specifications using matched sample from 2015-2017

See Table 1. This table constrasts matched projects. Matched projects must have been posted within 12 months of each other and have the same creator ethnicity, gender, and project category. We only include first-time creators and projects that were not Staff Picked. Among candidates matching all criteria, we select projects with the most similar funding goals and allow multiple matches. Estimations include Project Controls and Year, State, and Category Fixed Effects.

	Success	Pledges/Goal	ln(Backers)
	(1)	(2)	(3)
A. Minority creator matched sample			
Fear	-0.027+++	-0.039+++	-0.148+++
	(-3.51)	(-3.86)	(-3.87)
Observations	2317	2317	2317
Adj. R^2	0.146	0.167	0.084
Mean of Outcome Var.	0.216	0.283	1.776
Impact of 1 SD of Fear	-0.016	-0.023	-0.089
Impact Relative to Mean	-7.51%	-8.28%	-5.01%
B. White creator matched sample			
Fear	0.009	0.007	0.013
	(1.14)	(0.71)	(0.38)
Observations	20672	20672	20672
Adj. R^2	0.177	0.204	0.112
Mean of Outcome Variable	0.302	0.387	2.122
Impact of 1 SD of Fear	0.005	0.004	0.008
Impact Relative to Mean	1.79%	1.09%	0.37%

Table 3b: Specification using sample of creators with multiple projects

See Table 1. This table considers panel variation among creators. Estimations include Project Controls and Year, State, and Category Fixed Effects. Estimations additionally add Creator Fixed Effects.

	Success	Pledges/Goal	ln(Backers)
	(1)	(2)	(3)
Minority × Fear	**-0.028++**	**-0.027+**	**-0.112+++**
	(-2.16)	**(-1.96)**	**(-3.14)**
Fear	-0.003	0.000	0.012
	(-0.64)	(0.01)	(0.87)
Observations	40729	40729	40729
Adj. R^2	0.613	0.707	0.827
Mean of Outcome Variable	0.632	0.789	3.452
Impact of 1 SD of Fear	-0.017	-0.016	-0.067
Impact Relative to Mean	-2.66%	-2.06%	-1.95%

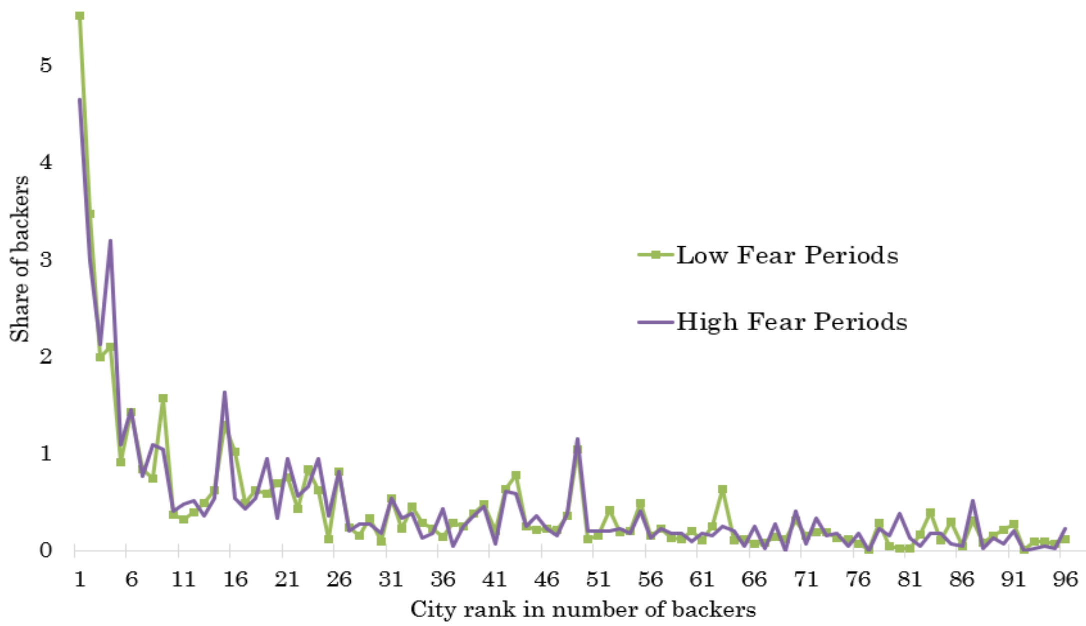
Table 4: Specifications with split sample by local racial/political climate

See Table 1. This table considers the local racial/political climate around the project creator. Columns (1)-(2) split the sample based upon local Implicit Association Tests (IAT) bias metrics, with higher values indicating more typical implicit racial bias [median=0.356]. Columns (3) and (4) split the sample based upon average racially charged Google search rates, with higher values indicating more typical racial animus [median=62.15]. See Howell et al. (2023) regarding these measures. Columns (5) and (6) split the sample based upon average Republican vote shares in Presidential elections since 2012 [median=37.0%]. Estimations include Project Controls and Year, State and Category Fixed Effects.

	Implicit Associate Test racial bias of creator county		Google racial search term animus		Republican vote share in Presidential elections	
	Median and above	Below median	Median and above	Below median	Median and above	Below median
	(1)	(2)	(3)	(4)	(5)	(6)
Minority × Fear	**-0.029+++**	**-0.033+++**	**-0.037+++**	**-0.027+++**	**-0.022+**	**-0.035+++**
	(-3.00)	**(-3.67)**	**(-4.40)**	**(-3.01)**	**(-2.01)**	**(-3.78)**
Minority	-0.026	-0.022	-0.016	-0.031++	-0.039++	-0.021
	(-1.54)	(-1.60)	(-1.26)	(-2.08)	(-2.15)	(-1.52)
Fear	-0.008	-0.017	-0.008	-0.015	-0.012	-0.012
	(-0.61)	(-1.24)	(-0.55)	(-1.11)	(-0.92)	(-0.92)
Observations	66258	66780	66388	64418	66059	65954
Adj. R^2	0.229	0.190	0.228	0.212	0.219	0.203
	Linear Diff:	0.005	Linear Diff:	-0.009	Linear Diff:	0.053
		(0.50)		(-0.91)		(1.07)
Mean of Outcome Var.	0.411	0.568	0.499	0.487	0.413	0.566
Impact of 1 SD of Fear	-0.017	-0.020	-0.022	-0.016	-0.013	-0.021
Impact Relative to Mean	-4.24%	-3.49%	-4.46%	-3.33%	-3.20%	-3.72%

Table 5: Spatial distribution of backers among projects with 10-20 backers

The top panel displays the share of backers for minority projects across cities for projects with 10-20 backers. This range of backers is the critical region where project success emerges. Cities are ranked by their total share of backers, with the 96 cities that account for at least 0.1% of backers included. The purple line with no marker shows the distribution in quarters with a Migration Fear Index value of 1.75 or higher; the green line with marker shows the distribution in quarters when the index is less than 1.75. The very tight overlay suggests declines in backer support for minorities are relatively uniform spatially. The accompanying table reports formal equality tests of city backer distributions among projects with 10 or more backers. Share equality tests consider if the total creator shares for a given racial group in the indicated city set are equal across fear states. Distributional equality tests consider if the city distributions for backers are equal across fear states, using Kaplan (2019) simulated p-value function.



	City distribution restricted to 18 cities with >1% total backer share	City distribution restricted to 96 cities with >0.1% total backer share	City distribution restricted to 166 cities with >0.05% total backer share
	(1)	(2)	(3)
Cumulative share of all backers	0.211	0.418	0.496
White creators low fear	0.210	0.419	0.496
White creators high fear	0.205	0.405	0.485
p-value: share equality test	0.813	0.453	0.565
p-value: distribution equality test	0.777	0.799	0.876
Minority creators low fear	0.242	0.452	0.532
Minority creators high fear	0.239	0.450	0.520
p-value: share equality test	0.848	0.932	0.615
p-value: distribution equality test	0.995	0.995	0.354

ONLINE SUPPLEMENT: DATA AND EMPIRICS

1. Data, Sample, and Key Empirical Measures

Our main data come from Kickstarter.com. Since inception, Kickstarter has enjoyed wide popularity; by 2022, more than 21 million people have backed a project, and the total dollars pledged to Kickstarter projects has exceeded $7 billion.[1] Kickstarter projects focus on creative endeavors and businesses, and it does not contain the hardship appeals for financial support common on platforms like GoFundMe. In 2018, reward-based crowd-funding was estimated to be $871 million, lying in-between equity crowd-funding ($1.5b) and donation-based crowd-funding ($629m) according to Cambridge Centre for Alternative Finance (2020).[2]

Figure S1 provides an example project that raised funds for a debut album from Joey Garcia, entitled Woke Up Running. As of March 2022, the drive had raised $4095 against an initial goal of $3700. Pledges of $20 or more received a signed hard copy of the album and a JG sticker, while pledges of $1600 or more received several rewards, including Garcia writing and recording a song "about you or for you." Garcia lives in Plymouth, IN, and his bio reads: "I'm small-town people trying to do something I love doing for a living. It's a dream that most fail but I refuse to give up. I have a full-time job but music is my life. I've fallen to the bottom but just get right back up." Twelve of Garcia's 92 backers came from Plymouth, while three backers were overseas. Garcia posted 7 updates during the campaign.

To download data on Kickstarter projects, we use https://webrobots.io, which is a web crawling company that extracts information from public websites.[3] These data include information about project creators, number of project backers, project descriptions, locations, goals (target amount to be raised), pledges (the amount that has been donated), whether

[1] Statistics retrieved from https://www.kickstarter.com/help/stats (December 2022).

[2] Alternative sources (e.g., Statista) can give different estimates of total market sizes but generally agree that reward-based funding is of comparable magnitude to equity-based models.

[3] We download Kickstarter datasets starting from January 2016, and these downloads contain retrospective project information tracing back to Kickstarter's initial launch on April 28, 2009. Starting from December 2015, Webrobots' web scraping algorithm collected all the sub-categories of Kickstarter data, giving a comprehensive view of projects. Since March 2016, the scraping frequency has been monthly. See https://webrobots.io/kickstarter-datasets/ and https://webrobots.io/about-us/.

projects are classified under a "Staff Picked" category[4], and project launch dates and deadlines.

From this initial downloaded data, we drop suspended/canceled projects and projects with missing text or incomplete creator name fields. In 7.3% of cases, the creator's name field contains only non-name elements (e.g., "Dark Elf's Games", "Vibrant Sounds"); an additional 0.5% of projects combine a name with non-name elements ("Saxophonist Ted Allen", "Carole's Candy Shop"). To identify these cases, one author and two Upwork freelancers manually reviewed all creator names to flag non-name elements. We drop these cases from our estimations, and our results are robust to including cases with some name-related elements or including all projects with additional interactions for non-name entities. Finally, to increase the precision of minority status of creators, we drop a small share of projects with more than one creator.

To infer creators' racial ethnicity, we primarily use NamePrism (https://www.name-prism.com/), a nationality and ethnicity classification tool based on name embeddings created by Ye et al. (2017) and Ye and Skiena (2019). NamePrism makes available their APIs for academic and non-commercial purposes, supporting hundreds of research projects.[5] NamePrism's algorithm uses a naïve Bayes model which depends on first and last names, inferring ethnic probabilities for six categories: White; Black; Hispanic; Asian and Pacific Islander (API, hereafter Asian); American Indian and Alaska Native (AIAN); and More than Two Race (2PRACE). We create an indicator variable *Minority* which is equal to one if the highest inferred probability belongs to a Black, Hispanic, or Asian category, and zero otherwise.[6] Robustness checks consider the cumulative probability that a creator is non-white and two other name classification algorithms and a picture-based method.

Our main explanatory variable is the Migration Fear Index first developed by Baker et al. (2015, 2016). The index counts the number of newspaper articles with at least one term from each of the Migration and Fear term sets, and then divides by the total count of newspaper articles (in the same calendar quarter and country). The Migration word list

[4] Staff Picked was changed to Projects We Love in 2016. Kickstarter has a team that reviews live projects to identify "standout" ones. https://www.kickstarter.com/blog/introducing-projects-we-love-badges. https://help.kickstarter.com/hc/en-us/articles/115005135214-How-can-my-project-get-featured-or-selected-as-a-Project-We-Love.

[5] Prominent work using names to identify or signal minority status include Bertrand and Mullainathan (2004), Fryer and Levitt (2004), and Kline et al. (2021).

[6] There are very few AIAN and 2PRACE cases (collectively summing to 0.03% of sample), which we leave in the baseline category with white creators when modelling indicator variables for minorities.

includes “border control”, “open borders”, migrant, migration, asylum, refugee, immigrant, immigration, assimilation, Schengen, and “human trafficking”, while the Fear terms include anxiety, panic, bomb, fear, crime, terror, worry, concern, and violent.[7]

Table S1 provides additional details on variable construction.

Table S2a provides summary statistics on our data.

Table S2b analyzes whether minorities present their projects differently during anxious periods. The analysis uses the regression framework from Table 1, with column headers indicating specified trait of projects. Columns (1)-(5) show limited difference in terms of ex ante traits. Minority creators are weakly more likely to have longer project depictions or include a picture with higher fear states, but the sizes of the two effects are very small (a relative effect of 0.47% and 1.24%, respectively, vs. -3.94% in for Success in Table 1). There are no measured differences in terms of self-mentioning, mistakes as a share of word count[8], or number of Frequently Asked Questions (FQAs) provided. By contrast, Columns (6)-(7) consider the number of updates provided (by the creator) or comments generated (by interactions of backers and the creator). These two ex post measures depend upon the momentum generated by the project and are significantly fewer for minorities during elevated fear states. The relative size of these latter effects (-4.15% and -6.23%) are of the same magnitude as the Success shortfall.

Table S2c continues by showing regressions with six indices regarding the readability of project’s description. These metrics combine in various ways the number of easy or difficult words, sentence length, and similar metrics to quantify how accessible the text is. A description of these indices is available from the authors. As we do not have any reason to favor one index over others, we present all six. We use a 2% winsorization to guard against outliers from very short texts. For five of the six measures, no difference is evident statistically or in relative terms. The sixth, the Dale Chall index, measures a statistical difference but is still very small in relative terms at -0.41%, roughly one-tenth of the Success

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[7] The index is built upon media news articles, but we do not parse the exact role of the media. The media may only be reflecting the underlying concerns of audiences (perhaps invoked by politicians), be causing their audiences’ concerns through their reporting, or a combination of these. With political discourse and identity politics revolving around national issues and media outlets, the role of media is tightly wound up with these other factors.

[8] The share is calculated as misspelled words divided by total number of words, excluding stop words. This calculation can be biased against names (human, characters, places, etc) or special characters in postings, and we have confirmed this metric (and its null effect) is not overly influenced by categories like art and literature.

magnitude in Table 1. In summary, Table S2b and S2c indicate that the postings of projects by minorities in times of elevated concern do not appear materially different at their start, but the subsequent interactions (comments, updates) highlight they receive less engagement commensurate with their lower likelihood of funding success.

Table S2d provides the distributions of project categories by white and minority creators across fear states (divided at an index value of 1.75). The distributions are overall stable, with Cramer's V statistics for the distribution differences low at 0.12.

Figure S2 shows two features of the Kickstarter data that influence our estimation design. First, minority creators steadily increase from around 7% of creators in 2009 to typically 11% or above in recent years. While this a relative growth of 50% or more, it is consistently accumulating quarter to quarter. This steady growth suggests a limited role for the extensive margin in terms of minority creators being differentially likely to post projects. We thus focus on rates of success for posted projects, with matched sample exercises to complement. Second, from a small initial start, the number of projects on Kickstarter grew to peak in 2014-2015, subsequently diminishing steadily over time. This peak period and its reversion were accompanied by a macro dip in the general rate of success for projects by all ethnic groups. We show this period does not influence our estimates in robustness checks.[9]

Figure S3 shows raw funding success rates. The figure included in Table 1 abstracts from macro shifts in project success rates common to all creators through its normalization.

2. Additional Analysis of Racial Success Gap

Table 1 of the main text presents our core estimates. **Table S3a** reports coefficients for the control variables. The magnitude of the backer estimate depends upon how one treats very high backer counts. **Tables S3b and S3c** consider setting the Pledges/Goal cap at the 90th percentile level (176.6%) or using log values conditional on pledges.

Table S3d tests for non-linear effects by introducing indicators for *Minority x Fear Medium* and *Minority x Fear High*, where we define *Fear Medium* and *Fear High* to be a Migration Fear Index value between [1.040, 1.685) and [1.685, max], respectively. These

[9] The growth and peak in postings coincide with a change that allowed direct posting of projects by creators with reduced human pre-review by Kickstarter staff. While shifting from human to algorithmic lending decisions can reduce racial lending bias (Howell et al. 2023), we have not identified implications of the easier posting of projects beyond the growth in posted projects (for creators of all ethnicities). Minority shortfalls in funding success are stable during this period.

points correspond to the 50th and 75th percentiles, respectively, of the index from Table S2a. The main effect on *Minority* captures the likelihood of a funding shortfall when the Migration Fear Index is below its median value, estimating a 4.4% lower success rate. As the index rises to third quartile values (*Fear Medium*), the funding gap for minorities expands but is not statistically different from base levels. For quarters with the Migration Fear Index at its highest levels (*Fear High*), the minority gap more than doubles to 9.2%, adding together the main effect and the interaction term. These swings represent large declines in funding success occurring within calendar years and conditional on controls.

Table S3e separates Black, Hispanic, and Asian creators. Black creators have the largest baseline gaps, with an 11.4% lower likelihood of success, and show marginal further declines when the Migration Fear Index is high. Hispanic creators have a smaller main effect, with a 4.5% lower likelihood of success at baseline, but they experience the most deterioration when the index is high. This reflects that much of the discourse and uncertainty linked to Trump focused on Hispanic migration. Finally, Asian creators have positive main effects, but this advantage also declines when the Migration Fear Index is elevated.[10] The declines for Black and Asian creators capture some broader spillovers from general migration concern, although some instances focused explicitly on these two groups (e.g., Trump's references to "sh##hole" countries were widely interpreted to encompass Black migrants as well).

Figure S4 graphs the baseline success gap and the estimated change with a three standard deviation increase in the fear index for each minority group.

Table S4a provides robustness checks about the use of the Migration Fear Index. Each row corresponds to a separate estimation. We report the coefficients for *Migration x Fear* and, in a few cases, additional interactions introduced. In all cases where we add a potential explanatory variable, we include both a main effect for the added variable (not reported) and an interaction term with minority creators (reported). The sample size may change modestly if a variable's series ends before the baseline Migration Fear Index in 2021q1. All other regression details remain the same as in Column (1) of Table 1.

[10] While many features of this study appear aligned with the unconscious bias described in experimental work, this may not be true for Asian creators. They have a positive main effect in funding success, and their deteriorations in funding success were most prominent in the highly visible Asian Hate period after the pandemic started. The evidence for an unconscious bias with respect to Black and Hispanic creators is much stronger. The Asian Hate period may also more closely link to politically charged xenophobia than the Migration Fear Index focused upon in the core of this project.

Rows B-D contrast the Migration Fear Index with other measures of economic and policy uncertainty, to ensure that our focus on the Migration Fear Index is not capturing a broader uncertainty beyond migration fear. We include from Baker et al. (2015, 2016) the Economic Policy Uncertainty Index in Row B and the Economic Policy Uncertainty Index (News) in Row C. In Row D, we include an Uncertainty Index based upon Twitter. While the added metrics show some negative coefficients, they do not diminish the main interaction.

Row E next turns to a pre-post analysis of the surprising election of Trump in November 2016, as he was predicted by most forecasters to lose the election to Clinton. We restrict the sample period to 2015q4 – 2017q4 and replace the *Fear* index with an indicator variable *After*, which is set equal to one for the 4 quarters in year 2017. Row E reports the key interaction term that captures the differential change in funding outcomes between minority and white creators in 2017 compared to the period right before. Minority creators experienced a decrease in funding success probability in this analysis after the election.

Row F provides an alternative to the design of the Baker et al. (2015, 2016) indices, created using Google Search Values (Law and Zuo 2021). The news media in the United States have biases (Groseclose and Milyo 2005), and this extension helps confirm that our findings are not particular to this metric's design. This extension confirms the baseline test, and Row G further shows similar results with state-level indices. We prioritize the Baker et al. (2015, 2016) indices for our explanatory regressors given their independent construction.

Rows H-J compare the Migration Fear Index in the United States to those of the United Kingdom, Germany, and France. The backlash against migration is not exclusive to the United States. Immigration was a key factor in Brexit voting, and migrant concerns (e.g., refugees) have spiked in Germany and France. These political movements are correlated across countries, and nations also report upon each other's news, leading to a macro index correlation above 0.5 across the four nations. Yet, due to the quarterly variation that we isolate, the link to the U.S. Migration Fear Index strongly prevails over alternatives.

Row K includes a Bartik-style control for expected racial success that combines the distribution of minority projects across detailed product categories prior to 2013 with realized success rate by category in subsequent years. This specification continues to show a strong interaction term for minority creators and the fear index.

Row L shows robustness to dropping 37k projects with very minimal support of 0-2 backers. At the other extreme, Row M shows similar outcomes when excluding the top 5% of projects in terms of pledges relative to goal (threshold level of 2.9935 for pledges/goal).[11]

Row N shows outcomes where we add an additional interaction for whether migration fear is rising through the calendar year. Year fixed effects restrict variation to differences across quarters within a calendar year. This additional interaction measures if there is a difference during time of escalating vs subsiding fear (e.g., the early vs later parts of the Trump presidency). Seven of 13 years in sample have escalating fear, six have declines. The null effect on the interaction term suggests the impact is independent of the macro trend.

Table S4b shows additional robustness checks and extensions on the design. Row B shows results when excluding all project- and creator-level controls. Controlling for features like description length and self-mentions helps ensure that shifts in project quality or posting behavior are not responsible for the reduced minority success rate, but these features are also endogenous. Our estimate grows modestly without these controls. Row C shows very similar results when interacting all controls with the Migration Fear Index. Rows D and E show similar results when excluding sample weights or weighting estimates such that each creator receives the same overall weight, respectively.

Our baseline model allows estimation of the main effect of the Migration Fear Index using quarterly variation within years. Rows F and G show robustness to instead modeling city x year x quarter fixed effects and product category x year x quarter fixed effects, respectively, in equation (1) of the main text. In either strategy, we no longer estimate the main effect for the Migration Fear Index given the quarterly dimension to the fixed effect, but the key interaction term with minority creators remains.

Row H shows similar outcomes when excluding Staff Picked projects.

Row I shows very similar outcomes when excluding the Kickstarter spike period.

Row J drops 2016 to confirm the results are not due only to the spike.

Names are noisy proxies for race, especially for identifying Black individuals (e.g., Cook et al. 2022, Greenwald et al. 2023), and the remainder of Table S4b considers robustness. Row K first repeats our baseline estimation with creators who have projected ethnicity accuracy higher than the median of 95.6%. In this half of the sample, we observe a somewhat stronger effect. The interpretation of this increase is ambiguous. The stronger effect could

[11] See Crosetto and Regner (2018) for a discussion of momentum cascades for crowd-funding.

follow from reduced measurement error that downward biased the original interaction term. Alternatively, a focus on more distinctive ethnic names could upwardly bias the estimate from the true sample-wide treatment effect of race.

The last three rows of Table S4b use alternative ways to define racial minorities. Following Law and Zuo (2021), Row L reports results using the cumulative probability that the project creator is non-white, rather than a binary variable. Row M shows similar results with an alternative ethnicity classifier, Ethnicolr (Ambekar et al. 2009), that uses deep learning techniques to classify names into ethnic groups trained on a Census Bureau dataset about the racial distribution of last names. We also find similar results when we require the name classifiers agree on race (interaction term of -0.039, t-stat=-5.00). In general, while techniques differ and may influence some measures, the interaction term that we emphasize in this study builds upon multiple ethnic groups and is robust.

Finally, for about 46% of our sample [n=72,854], we have a low-resolution picture of the creator posted on Kickstarter. Using machine learning algorithms that designate ethnicity from pictures, we create an alternative code for minority status. Two limitations are important. First, visual inspection by the authors concluded that the algorithm was most accurate for Black creators, whereas the Hispanic and Asian ethnicity designations were more debatable. Additionally, the same creator can be classified differently across projects based upon different pictures. Nonetheless, we find quite similar results in Row N, which is very comforting for our primary effort using name-based algorithms.

Tables S5a and S5b provide full results similar to Tables 1 and S3e for the picture-based sample. The results are quite comparable, with a notable difference being a stronger interaction of the Black creator dummy and the Migration Fear Index. We also find similar results when combining name and picture techniques. There is no strong time trend for creators including a picture, with the lowest rate of 39% in 2010 and the highest rate of 49% in 2016. There is a 0.23 correlation in binary assignments that is statistically significant.

The next tables extend our quality analysis of Table 2. Measures of quality were developed using project proposal descriptions that lacked pictures (due to data and computation limitations), information on funding outcomes (by design), and names of creators (by design). We developed the ML metric using a multi-class classifier using Error-Correcting Output Codes (ECOC) with linear learners. The algorithm was trained on project funding success during 2009-2012 and applied to 2013+ proposals. The ChatGPT metric was developed using an enterprise ChatGPT 4o account. Due to ChatGPT memory limitations, projects were analyzed in batches of about 50,000 projects (thus, three batches per run of our full sample) and with explicit instructions to ChatGPT to analyze the projects in sub-batches of 5,000. Through 12 upload iterations, each project received four scores. Two scores were developed with uploaded projects kept in sequential order; the other two scores were from iterations where the projects were uploaded in a randomized order. After each batch process, the full prompt history was closed/deleted and a new memory prompt opened with identical prompt text.[12] The final score given to a project is the average of four scores provided by ChatGPT during separate iterations.[13]

Table S6a considers the matched 2015-2017 sample from Table 3a, again observing a strong robustness to incorporating measures of project quality from the ML model or ChatGPT scoring.

In **Table S6b**, we randomly selected from Table 3a's matched sample 50% of the minority created projects and 1000 white creator projects for human grading. A small number of these projects that lacked key fields were dropped. We again removed name and funding information. We then tasked an Upwork freelancer to grade project quality on a five-point scale similar to ChatGPT. Table S6b shows robustness in this narrow sample to including the Upwork quality metric alongside the ML and ChatGPT metrics.

Finally, **Table S6c** shows robustness to including the quality metrics in Table 3b's repeated creator panel.

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[12] The prompt text:
"The zip file contains [[filled in with count of upload, e.g., 50,000]] project proposals that were listed on a crowdfunding website. The original proposals contained pictures, but these files contain the text only. The title of each file contains the project id.
Proposed projects vary in quality. Some depictions are lengthy and rich in information, where the project creator has invested time in the proposal. Others are short and without much information.
Please prepare an excel spreadsheet where you do the follow:
Column 1: List the project id from the title of each file
Column 2: Rate the project on a five-point scale for overall quality. Define "5" to be the best quality and "1" to be the worst quality. If a proposal lacks text completely, please place into the worst quality bin. Please place approximately 20% of projects into each quality bin.
There is a large amount of data in this request. Please plan to process the files in smaller sets of 5000 projects at a time so that the computational workload is manageable. Please be consistent across the smaller sets in how you score projects. You do not need to interact with me between each set. Combine all work into a single final excel file."

[13] We have implemented quality analysis as a control variable, and it is noteworthy that measured quality does not decline with higher fear states.

3. Additional Analysis of Backer Data and Mechanisms

We measure the spatial distance of creators to backers using the geographic centroids of cities and the Haversine flat earth formula. **Table S7** provides complete tabulations.[14] Across categories, Food, Music, and Comics are the least localized, while Photography and Journalism are the most. This need to appeal to non-local backers is true at small funding amounts. The local share of observed backers for projects with 10-15 backers is 28%. By even this small level of support, 13% of backers are typically located in one of the top 18 cities on Kickstarter in terms of backing (excluding the creator's own city if she is in a top city).

The main text reports the ethnic distribution of backers using the Gafni et al. (2021) data for projects from April 2009 to March 2012. On the creator side, the Gafni et al. (2021) data are 1.3% Black, 2.7% Hispanic, and 2.2% Asian. The Hispanic and Asian shares for this earlier period are lower than our full sample due to the growth of minority creators over time as a share of Kickstarter creators, shown in Figure S2.

The impact of challenging times for the level of minority backer support for minority creators is theoretically ambiguous. Support might increase if communities rally around minority creators in difficult moments, such as the "activist homophily" documented by Greenberg and Mollick (2017) for gender-based crowd funding. However, anxious conditions might lead potential minority backers to be cautious and limited in the financial support they provide to causes. **Table S8** explores if funding declines are more prominent among types of projects that typically depend heavily on minority support. While this group cannot explain all the shortfall observed, it provides insight into whether declines in success likely embody retractions of support from potential backers close to the creator.

While we lack data on project backers after 2012, we use the initial period to segment the full sample by the degree to which it is likely that minority backers are important.[15] Columns (1)-(2) of Table S8 report results with splitting the sample at the median anticipated

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[14] Local share reported in the main text use the top 10 backer locations for a project and are likely upper bounds on the total share of backers who are local. Sorting cities by their count of backers for a project, the top ranked city is local in 60.1% of cases, the second ranked city is local in 31.2% of cases, and the shares decline monotonically to 7.5% for the tenth ranked city. Thus, unobserved backers for a project in cities outside of the top 10 are more likely to be non-local.

[15] We first separately calculate the average minority backer share by product category and by state with the Gafni et al. (2021) data from 2009-2012 for projects with a minority creator. These components describe the products and states where minority creators were more supported by minority backers in the initial period. We then interact these two components for a product x state index of anticipated dependency across the full sample. By using this interaction approach, we calculate anticipated dependency for the full sample even if a given {product, state} pair was not observed in 2009-2012.

minority backing. The strongest declines in minority success when fear spikes are found among the lower part of the distribution where minority backing was less likely. The linear difference of the interaction terms of Columns (1) and (2) is small, and we do not reject that the results are the same. The relatively small share of backers who are minorities made it unlikely that the large success differentials for minority creators could be explained by reduced minority backer support. This analysis confirms this intuition and provides further evidence that minority backers may soften funding shortfalls for minority creators.

A second test evaluates whether project blurbs signal ethnicity-related work (e.g., the blurb from the example in Figure S1 is "Woke Up Running. My first album of my thoughts and sometimes harsh reality of life. https://m.facebook.com/jgdreams"). Placing blurbs into lower case, we mark likely ethnic references in product depictions through the presence of any one of a set of key word stems in the blurb.[16] Stems capture multiple variations of a word family (e.g., "mexic" captures "mexico" and "mexican"). When we exclude these from our analysis, the results strengthen to an interaction term of -0.036+++ (t-stat=-5.65). While this analysis is not perfect (e.g., we do not observe pictures, more word stems could be added), it strongly suggests reactions by backers towards ethnicity-related projects are not behind these results.

Projects on Kickstarter range from local to global in appeal. A project to revive a local dance studio in Boston might only be funded by local residents and former customers, with little appeal to backers in Kansas City. By contrast, a project that proposes an audio book version of a popular comic book might garner national interest. Local projects could factor into funding declines if minority creators are more likely to draw localized support (including white backers) and, perhaps, these types of projects become less desirable when fear spikes.

We test these features by splitting the sample based upon the degree to which backers for a product tend to be localized. Kickstarter's categories are mostly orthogonal to the local-global dimension, as described above, and so we develop a project-level classification. For projects with 10+ backers, we can calculate directly a "local" project as one that has 50% or more of its observed backers within 50 miles of the creator's city. For projects with fewer than 10 backers, we predict this likelihood by training a machine learning algorithm on the project blurbs. The total estimated local share is 47% of projects with this approach.

[16] Stems are {africa black, excepting where white is also present as in "black and white photography"}; {bolivi brazil cuba dominica hispanic guatema hondura latino mexic peru salvador taco texmex, excepting tacoma}; and {asia china chinese india japan korea vietnam, excepting fantasia}. 2.36% of postings carry one or more of these stems.

The sample of non-local projects in Column (3) of Table S8 delivers very similar results to the full sample. The decline in minority success for local projects in Column (4) is smaller in absolute terms, with the difference to non-local projects being borderline statistically significant. However, as local projects have lower baseline success rates, the relative effect is in fact larger. Declines in local backer support do not appear to be a significant driver of the crowd-funding gaps for minorities during high levels of fear.[17]

Thus, it appears unlikely that a deterioration in "friends and family" or community support is responsible for the outcomes, although there are dimensions of affinity we cannot observe. Columns (5)-(6) of Table S8 provide one further split to consider whether the declines are isolated among projects with small funding goals, where affinity is most likely to be influential. We divide the sample at the median project goal of $5000. Projects with small targets show larger declines in funding success, but the results are also quite strong among projects with goals of $5000 or more. These results again speak to a widespread effect.

Table 4 of the main text considered the local racial and political climate around the creator using data generously provided to us by Howell et al. (2023). Xu et al. (2014) provide the original metrics on a county's average Implicit Association Tests (IAT) bias results, Stephens-Davidowitz (2013) measure the average racially charged Google search, and the MIT Election Lab (https://electionlab.mit.edu/data) provides average vote share for Republican candidates in Presidential elections since 2012.

Table S9 provides an extended version of Table 5 in the main text. Panel A shows the work with projects having 10-20 backers. The fourth column extends the inclusion threshold to 597 cities with at least 0.01% of backers. We are cautious regarding ever larger city spans due to two challenges in the equality test.[18] Nonetheless, the test results remain comparable.

Panel B shows comparable distributions with backers from all projects. These distributions are dominated by projects that garner many backers, increasingly skewing

[17] These estimates define projects as local if more than 50% of observed backers are in nearby cities, and we find similar results if parsing projects by known local share of all backers (including those outside of the top 10 who are in unknown location). The sharpest funding deteriorations for minorities are in Comics, Games, Music, and Publishing, which are among the most global categories.

[18] We employ the distribution comparison of Kaplan (2019). The test identifies deviations at points along the distribution and calculates a simulated p-value for overall distributional equality. The long tail is populated with cities that have just one or two instances of backers, and thus the null hypothesis will always be rejected when testing that distributions are the same across all cities due to this lumpiness. The theoretical basis for the procedure is also uncertain in the presence of many ties, which one repeatedly encounters among smaller cities.

them towards the biggest cities. The results are mostly similar, with most tests continuing to fail to reject a null hypothesis of spatial equality. Two differences are present. The first is that there is less backer support among the largest cities for minority creators that diminishes as the city span widens. For white creators, we also find some parts of the city distribution are different in Columns (3) and (4) when the distribution reaches 166+ cities.

A final test considers for backers the city-level implicit bias, racial search animus, and Republican vote share measures used in Table 4 of the main paper. We create for each project a weighted average of these location-based metrics by combining the backer count in each U.S. city with the city's average racial/political metric. For projects with 20 backers or fewer, where success typically does or does not emerge, we do not discern any shifts when this composite metric is used as the outcome variable using specification (1) of the main paper. For example, the interaction term of a minority creator and the fear index shifts the weighted-average IAT score metric by 0.021 (t-stat=0.60) standard deviations. The other two measures are even smaller, and similar null results hold for cutoffs of 50 or 100 backers.[19]

4. Case Study of Asian Hate

The Covid-19 pandemic was first reported in the city of Wuhan, Hubei Province, China, in December 2019. On March 18, 2020, President Trump called SARS-CoV-2 virus, the original virus that causes the Covid disease, the "Chinese virus". The origins of the virus, coupled with the enflamed political rhetoric, led to an increase in acts and displays of Sinophobia, as well as prejudice, discrimination, violence, and racism against people of Asian descent in the United States and elsewhere (Cao et al. 2022). Anti-Asian hate crimes surged 145% in 2020 relative to 2019, while overall hate crimes dropped 6%. In New York City, one of the hardest hit cities in the early phase of the pandemic in 2020, Anti-Asian hate crimes increased by 833% relative to the previous year. These hostilities were widely reported[20] and ultimately led to counter efforts to "Stop Asian Hate."

This episode is an important case study to complement our main analysis. **Figure S5** shows simple descriptive evidence for the success rate of white vs. Asian creators during the

[19] There is some suggestive evidence that the backer distributions shift (on net) towards locations of historical bias or conservative voting at high backer levels due to comparatively less support from the biggest cities. We hesitate to make too strong of an interpretation because projects at this level are virtually all successful and the limitation to the top 10 locations of backers becomes more severe in this part of the distribution.

[20] E.g., https://www.wsj.com/articles/asian-americans-feel-the-hate-11617661203

Covid period. Whereas Asian creators have slightly higher success rates than white creators before Covid, there is sharp reversal in the second quarter of 2020 that remains elevated until the first quarter of 2021. Changes are not observed for Black and Hispanic creators.

We use the ethnic name algorithms of Kerr and Lincoln (2010) to provide sub variation in the Asian group. Creating a sample from 2019q1 to 2021q1 [n= 16,420], we model an indicator variable for the pandemic period and interact it with indicator variables for being Chinese, Indian, other East Asian (Japanese, Korean, Vietnamese), and Hispanic, with effects measured against other ethnicities. **Table S10** shows a 17.9% decline in success for Chinese creators during the pandemic period; by contrast, the other null interactions suggest the retraction of support during the pandemic was mostly localized for Chinese creators.

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Figure S1: Example of Kickstarter Campaign

KICKSTARTER

Joey Garcia`s debut Album- Woke Up Running

Woke Up Running. My first album of my thoughts and sometimes harsh reality of life.https://m.facebook.com/jgdreams

Created by

Joey Garcia

92 backers pledged $4,095 to help bring this project to life.

Last updated October 13, 2015

Story

My first album!! I NEED YOUR HELP MY FRIENDS. I`m currently working with some talented musicians on this new project! We hope to be in the studio as soon as this project is funded and be done with the album in two months or close to it. Your help is needed and greatly appreciated. This will showcase some of my best work and hope to do my hometown proud!

Risks and challenges

If any challenges get in my way I'm ready to face them head on. The songs are already there in my head, on paper, and partially recorded. We may run into mishaps but we are very prepared and confident that we will succeed together.

Learn about accountability on Kickstarter

Questions about this project? **Check out the FAQ**

Pledge $100 or more

Will get you everything in the $50 pledge plus a digital download of the album and a bonus song not on the album

ESTIMATED DELIVERY Oct 2015

SHIPS TO Anywhere in the world

5 backers

Pledge $200 or more

You will receive everything in the previous pledges plus I will make a small piece of hanging art for you and a personal video thanking you

ESTIMATED DELIVERY Oct 2015

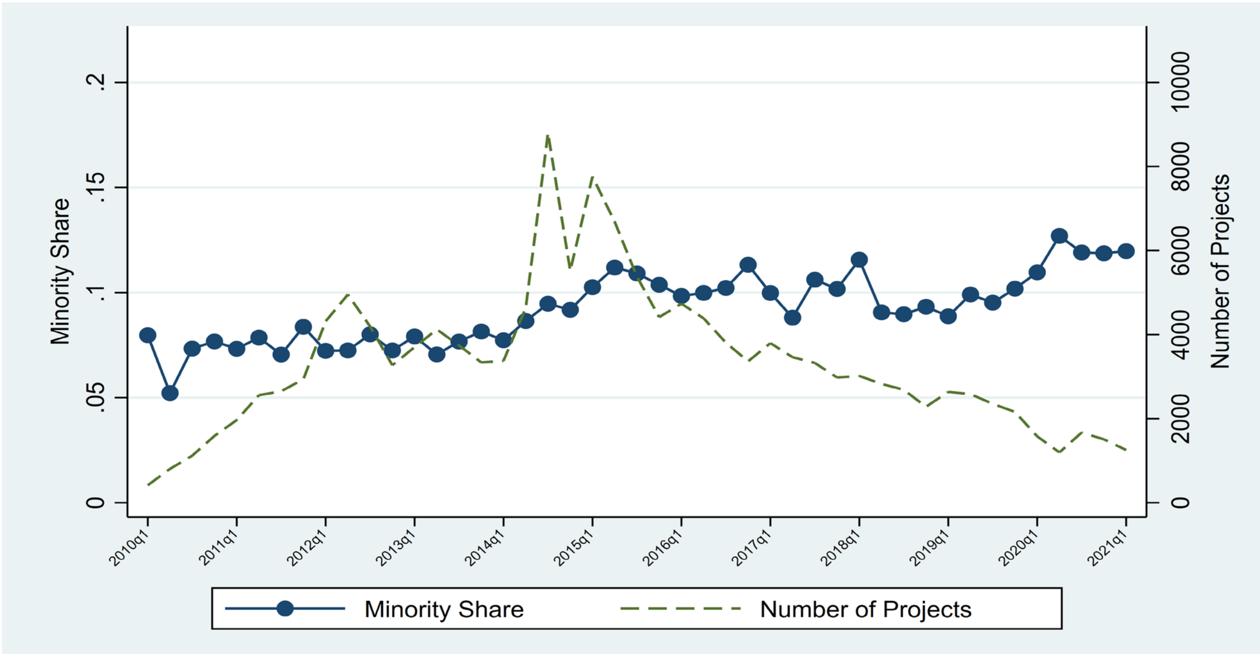
SHIPS TO Anywhere in the world

2 backers

Limited (6 left of 8)

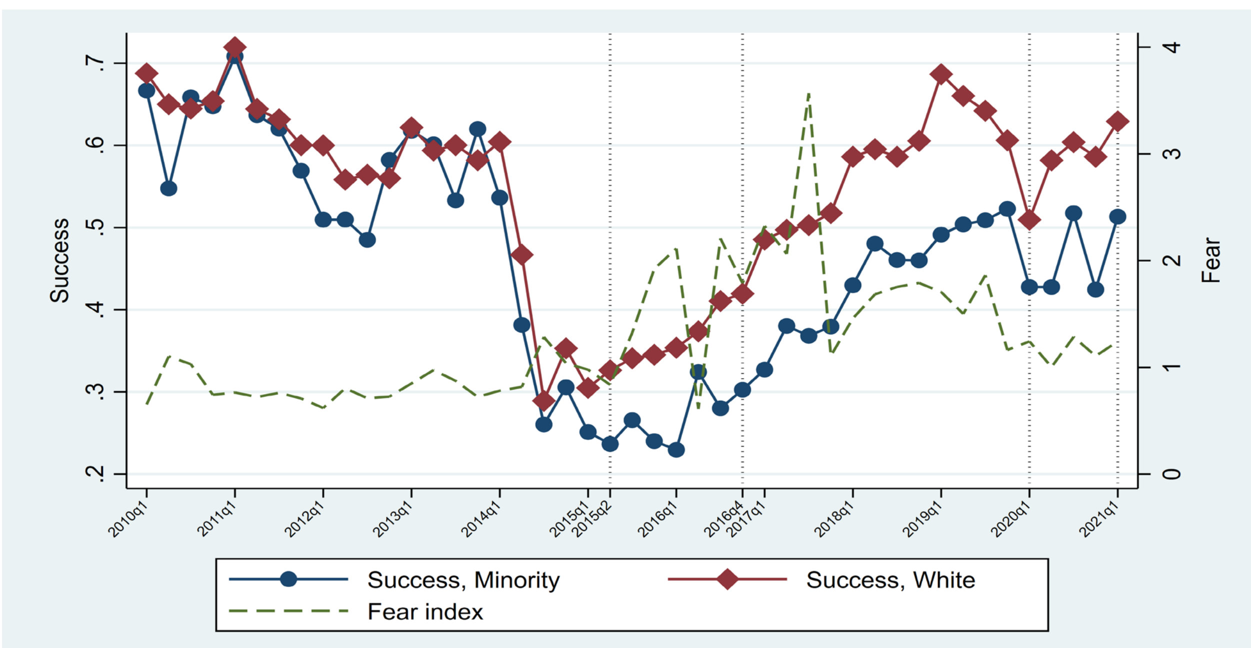
Source: https://www.kickstarter.com/projects/jgmusic/joey-garcia-s-debut-album-woke-up-running?ref=discovery&term=garcia (accessed March 2022).

Figure S2: Project count and minority share by quarter



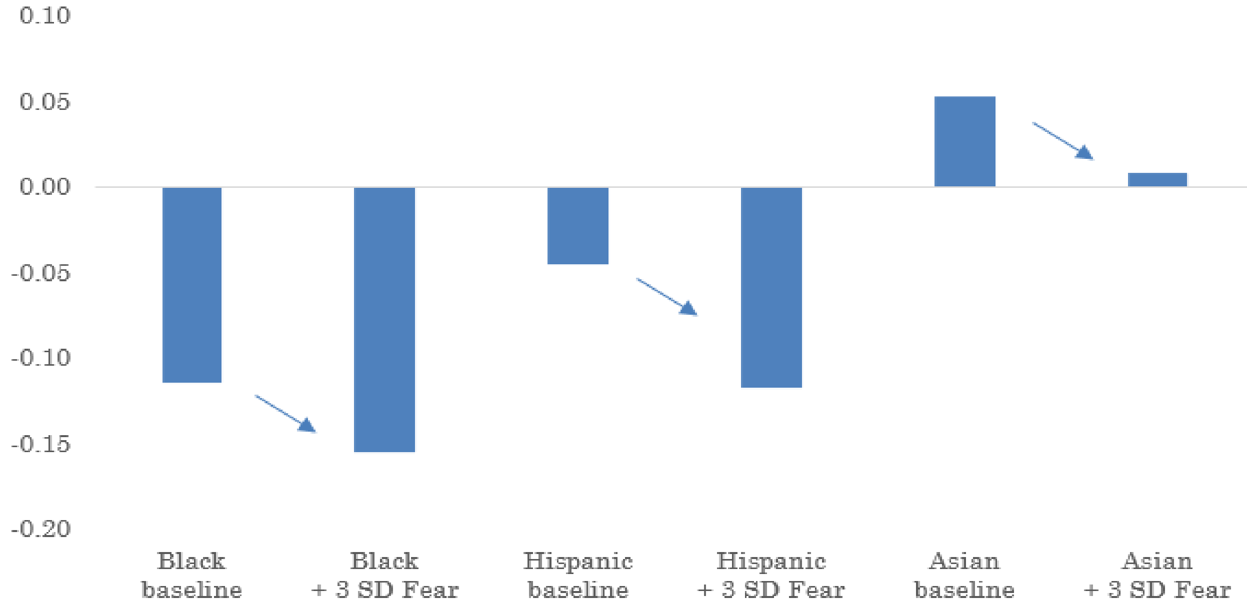
Notes: See Table 1.

Figure S3: Raw success rates by minority status



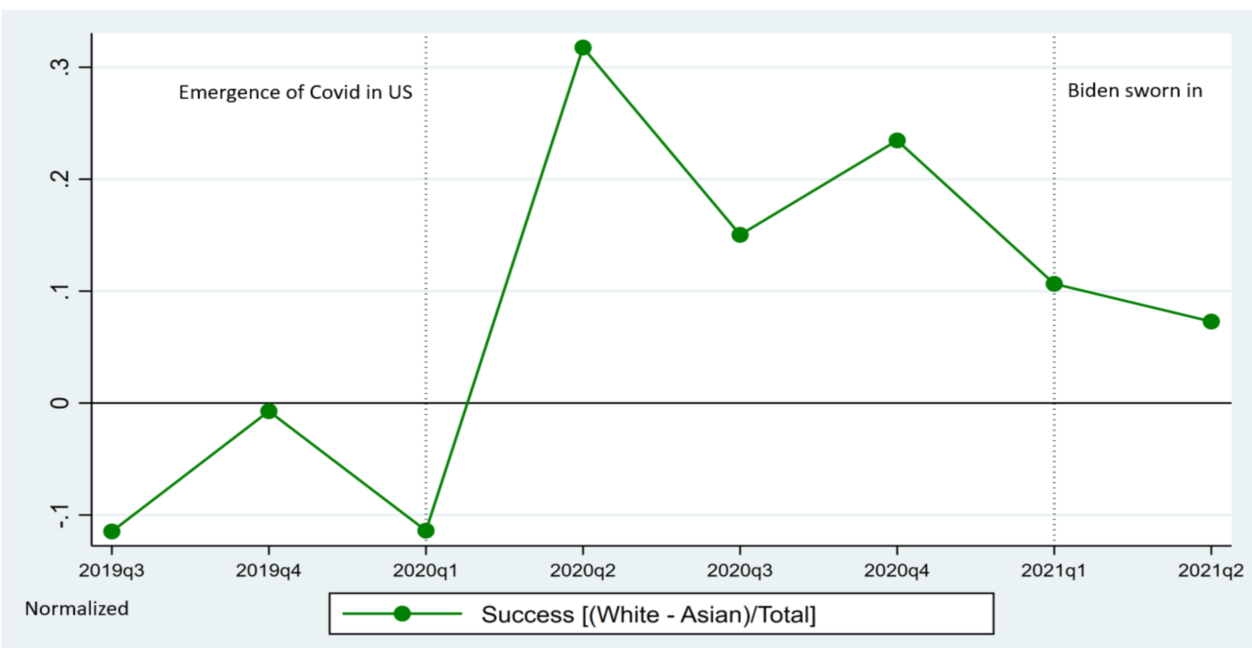
Notes: See Table 1.

Figure S4: Success difference by ethnic group relative to white creators, conditional on controls, with 3 SD fear index change



Notes: See Table S3e.

Figure S5: Success difference of white vs. Asian creators during pandemic



Notes: See Table 1.

Table S1: Variable definitions

Crowd funding outcome	
Success	An indicator equal to one if the project is successfully funded.
Pledges/Goal	Total amount pledged to the project, scaled by the project goal. A cap is set at 125%.
Backers	Total number of backers who pledged any amount to the project.
Creator characteristics	
Minority	An indicator equal to one if the project creator is Black, Hispanic or Asian. It is inferred by using NamePrism algorithm.
Black, Hispanic, Asian	An indicator equal to one if the inferred probability is the largest among all ethnic groups.
Pr(Minority)	The probability inferred by NamePrism algorithm that the project creator is a minority summed over minority groups.
Census Minority	An indicator equal to one if the project creator is Black, Hispanic or Asian. It is inferred by using ethnicity classifier developed by Ambekar et al. (2009; known as Ethnicolr). Calibrated using the Census data, the method uses a deep learning method to classify names into ethnic groups. Specifically, the Census Bureau provides data on the racial distribution of last names. A LSTM (long short-term memory) model is trained to assign race to names in proportion to how names are distributed across racial groups. More information at https://github.com/appeler/ethnicolr.
Female	An indicator equal to one if the project creator is Female. It is inferred by matching the creator name with the gender data published on https://github.com/lmullen/gender by Lincoln Mullen.
Creator characteristics	
Fear	Migration Fear Index created by Baker, Bloom, and Davis (2015, 2016) divided by 100. The index represents the total number of newspaper articles including any of the predefined terms, scaled by the total number of newspaper articles in the same calendar quarter. Predefined terms: "immigration, migration, assimilation, migrant, immigrant, asylum, refugee, open borders, border control, Schengen, human trafficking" falls under the migration term set; "anxiety, panic, bomb, fear, crime, terror, worry, concern, violent" in the fear term set. See https://www.policyuncertainty.com/immigration_fear.html.
Google SVI	The decile score of Google Search Volume Index that is calculated by using Google Trends. The index is based on the query frequency of ten most related words of each chosen keyword of the Migration Fear Index. The index is the first component of principal component analysis of 110 keywords (Law and Zuo 2021; Da et al. 2014).

Table S1: Variable definitions, continued

Project characteristics	
Goal	The target amount of funding determined by the project creator.
Horizon	The duration that the project will be kept posted for funding on Kickstarter.
Total projects	Total number of projects submitted by the same creator in the same year-quarter.
Length	The length of the project description.
Self mention	An indicator equal to one if the project creator self-mentioned himself/herself in the project description.
Staff picked	An indicator equal to one if the project is staff picked.

Table S2a: Descriptive statistics of Kickstarter sample

This table reports descriptive statistics on the 2009-2021 regression sample.

	Mean	SD	p25	Median	p75
	(1)	(2)	(3)	(4)	(5)
Crowd funding outcome					
Success	0.488	0.500	0	0	1
Black Creator	0.290	0.454	0	0	1
Hispanic Creator	0.360	0.480	0	0	1
Asian Creator	0.513	0.500	0	1	1
White Creator	0.496	0.500	0	0	1
Pledges/Goal (cap of 1.25)	0.602	0.548	0.010	0.546	1.153
Black Creator	0.369	0.506	0.0002	0.026	1.016
Hispanic Creator	0.451	0.531	0.001	0.073	1.058
Asian Creator	0.634	0.545	0.014	1.000	1.175
White Creator	0.612	0.548	0.011	0.728	1.162
Backers	78.6	194.5	3	19	69
Black Creator	44.3	135.4	1	4	31
Hispanic Creator	49.8	141.5	1	7	41
Asian Creator	93.6	213.2	3	24	83
White Creator	80.1	196.8	3	19	70
ln(Backers)	2.860	1.828	1.386	2.996	4.248
Creator characteristics					
Minority	0.093	0.290	0	0	0
Black	0.011	0.104	0	0	0
Hispanic	0.051	0.219	0	0	0
Asian	0.031	0.174	0	0	0
Pr(Minority)	0.142	0.243	0.014	0.048	0.117
Census Minority	0.115	0.319	0	0	0
Female	0.255	0.436	0	0	1
Immigration fear					
Fear	1.254	0.601	0.804	1.040	1.685
Google SVI	0.548	0.296	0.333	0.556	0.778
Google SVI State Level	0.516	0.316	0.222	0.556	0.778
Project characteristics					
ln(Goal)	8.432	1.551	7.439	8.517	9.393
ln(Horizon)	3.479	0.359	3.434	3.434	3.584
ln(Total Projects)	0.033	0.147	0.000	0.000	0.000
ln(Length)	4.665	0.347	4.595	4.812	4.883
Self Mention	0.076	0.265	0	0	0
Staff Picked	0.103	0.304	0	0	0

Table S2b: Specifications with measures of project presentation

See Table 1. This table considers measures of project presentation. Estimations include Creator controls (an indicator for female creator, the number of projects created by the same creator in the same year-quarter) and Year, State and Category Fixed Effects.

						Dependendent on project's level of uptake/activity	
	Length of project text	Includes picture	Includes self mention of creator	Mistakes as share of word count	Number of FAQs provided	Number of updates provided	Number of comments generated
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Minority × Fear	**0.867+**	**0.010+**	**-0.005**	**0.029**	**-0.005**	**-0.373+++**	**-0.836++**
	(1.95)	**(1.98)**	**(-1.37)**	**(1.17)**	**(-0.31)**	**(-3.13)**	**(-2.05)**
Minority	-2.571+++	-0.032+++	-0.008	0.102+++	-0.082+++	-0.483++	-1.320
	(-4.12)	(-3.39)	(-1.35)	(2.75)	(-3.55)	(-2.29)	(-1.61)
Fear	-0.749++	-0.001	-0.001	-0.012	-0.001	-0.123	-0.024
	(-2.11)	(-0.33)	(-0.31)	(-0.81)	(-0.10)	(-0.82)	(-0.08)
Observations	150282	150282	150282	150282	150282	150282	150282
Adj. R^2	0.081	0.021	0.062	0.077	0.058	0.119	0.186
Mean of Outcome Var.	111.39	0.485	0.0762	1.915	0.407	5.405	8.067
Impact of 1 SD of Fear	0.521	0.006	-0.003	0.017	-0.003	-0.224	-0.502
Impact Relative to Mean	0.47%	1.24%	-3.94%	0.91%	-0.74%	-4.15%	-6.23%

Table S2c: Specifications with measures of text readability

See Table 1. This table considers the readability of the text. Estimations include Project Controls and Year, State and Category Fixed Effects.

	Gunning Fog Readability Index	Flesch Kincaid Reading Grade Level	Coleman Liau Readability Index	Dale Chall Readability Index	Automated Readability Index	Linsear Write Readability Index
	(1)	(2)	(3)	(4)	(5)	(6)
Minority × Fear	**0.048**	**0.002**	**-0.042**	**-0.062+++**	**0.006**	**0.042**
	(1.45)	**(0.07)**	**(-1.41)**	**(-3.54)**	**(0.14)**	**(0.89)**
Minority	0.041	0.128++	0.101+	0.134+++	0.080	0.070
	(0.77)	(2.27)	(1.87)	(4.34)	(1.12)	(0.92)
Fear	0.014	0.014	-0.014	0.001	0.015	0.020
	(1.07)	(0.82)	(-0.49)	(0.05)	(0.65)	(1.17)
Observations	137375	137375	137375	137375	137375	137375
Adj. R^2	0.058	0.055	0.078	0.065	0.049	0.039
Mean of Outcome Var.	11.757	9.695	9.435	9.005	10.028	12.234
Impact of 1 SD of Fear	0.029	0.001	-0.025	-0.037	0.004	0.025
Impact Relative to Mean	0.25%	0.01%	-0.27%	-0.41%	0.04%	0.21%

Table S2d: Project category descriptive statistics

This table reports descriptive statistics on the 2009-2021 regression sample. High fear states are index values of 1.75 and higher.

	White creators		Minority creators	
	Low fear	High fear	Low fear	High fear
	(1)	(2)	(3)	(4)
Art	9.56	8.81	9.81	8.39
Comics	4.08	6.31	4.05	6.01
Dance	1.14	0.92	1.24	1.17
Design	3.36	4.15	4.29	3.52
Fashion	4.89	7.36	7.58	10.97
Food	6.17	8.15	6.56	8.95
Film & video	16.85	13.17	17.89	15.46
Games	6.57	8.56	5.85	5.57
Journalism	1.68	2.08	1.37	2.29
Music	15.99	10.73	12.26	8.10
Photography	2.59	2.46	2.37	2.58
Technology	6.88	9.79	11.17	14.46
Theater	2.38	1.99	1.67	1.35
Publishing	15.60	12.29	11.81	8.62
Crafts	2.27	3.24	2.08	2.55
Cramer's V statistic	0.124		0.120	

Table S3a: Full regression results for Table 1

See Table 1.

	Success	Pledges/Goal	ln(Backers)
	(1)	(2)	(3)
Minority × Fear	**-0.032+++**	**-0.038+++**	**-0.147+++**
	(-4.90)	**(-4.69)**	**(-4.40)**
Minority	-0.021+	-0.025+	-0.104++
	(-1.96)	(-1.99)	(-2.11)
Fear	-0.010	-0.012	-0.042
	(-0.74)	(-0.79)	(-0.75)
Female	0.072+++	0.076+++	0.264+++
	(20.60)	(20.22)	(19.64)
ln(Goal)	-0.069+++	-0.088+++	0.122+++
	(-19.63)	(-22.89)	(10.08)
ln(Horizon)	-0.135+++	-0.150+++	-0.376+++
	(-16.96)	(-15.79)	(-11.22)
ln(Total Projects)	-0.184+++	-0.173+++	-0.544+++
	(-9.76)	(-8.44)	(-7.77)
ln(Length)	0.026+++	0.029+++	0.140+++
	(4.60)	(4.41)	(5.16)
Self-mention	0.122+++	0.143+++	0.524+++
	(20.34)	(21.25)	(20.94)
Observations	150282	150282	150282
Adj. R^2	0.218	0.243	0.193
Project Controls	Y	Y	Y
Year, State and Category FE	Y	Y	Y

Table S3b: Table 1 with variations on pledged scaled cap

See Table 1.

	Baseline Pledges/Goal with 125% cap	Pledges/Goal with cap at 90th percentile (176.6%)	ln(Pledges/Goal) conditional on positive pledges
	(1)	(2)	(3)
Minority × Fear	**-0.038+++**	**-0.048+++**	**-0.274+++**
	(-4.69)	**(-5.00)**	**(-4.04)**
Minority	-0.025+	-0.022	-0.062
	(-1.99)	(-1.51)	(-0.72)
Fear	-0.012	-0.013	-0.071
	(-0.79)	(-0.76)	(-0.88)
Observations	150282	150282	134534
Adj. R^2	0.243	0.244	0.284
Project Controls	Y	Y	Y
Year, State and Category FE	Y	Y	Y

Table S3c: Distribution of pledges relative to goal

See Table 1.

	Minority creators	White creators
	(1)	(2)
[0%, 20%)	52.6%	43.1%
[20%, 50%)	5.2%	5.8%
[50%, 75%)	1.4%	1.2%
[75%, 100%)	1.7%	1.7%
[100%, 125%)	23.9%	27.9%
[125%, 150%)	5.7%	6.6%
[150%, 175%)	2.9%	3.2%
[175%, 200%)	1.5%	1.8%
[200%, max]	5.0%	8.7%

Table S3d: Non-linear specifications

See Table 1. Regressions remove the linear interaction of Minority x Fear and instead introduce two indicator variables for Minority x Fear High and Minority x Fear Medium, with Fear High and Fear Medium defined to be a Minority Fear Index value between [1.685, max] and [1.040, 1.685), respectively. These chosen points correspond to approximately the 50th and 75th percentiles, respectively, of the index from Table S2.

	Success	Pledges/Goal	ln(Backers)
	(1)	(2)	(3)
Minority × High Fear	**-0.048+++**	**-0.058+++**	**-0.234+++**
	(-4.80)	**(-5.52)**	**(-6.66)**
Minority × Medium Fear	**-0.019**	**-0.020**	**-0.036**
	(-1.03)	**(-1.07)**	**(-0.63)**
Minority	-0.044+++	-0.053+++	-0.218+++
	(-6.03)	(-6.26)	(-7.07)
High Fear	-0.014	-0.018	-0.073
	(-0.64)	(-0.70)	(-0.85)
Medium Fear	-0.048	-0.058	-0.260+
	(-1.43)	(-1.49)	(-1.90)
Observations	150282	150282	150282
Adj. R^2	0.218	0.243	0.193
Project Controls	Y	Y	Y
Year, State and Category FE	Y	Y	Y

Table S3e: Funding outcomes by minority ethnic group

See Table 1. This table extends the regression in Table 1 to separately consider the funding outcomes of Black, Hispanic, and Asian creators.

	Success	Pledges/Goal	ln(Backers)
	(1)	(2)	(3)
Black × Fear	**-0.023**	**-0.037++**	**-0.095**
	(-1.26)	**(-2.12)**	**(-1.49)**
Black	-0.114+++	-0.119+++	-0.518+++
	(-4.85)	(-4.79)	(-5.29)
Hispanic × Fear	**-0.040+++**	**-0.046+++**	**-0.174+++**
	(-5.30)	**(-4.88)**	**(-4.25)**
Hispanic	-0.045+++	-0.057+++	-0.234+++
	(-3.34)	(-3.60)	(-3.62)
Asian × Fear	**-0.025+**	**-0.028+**	**-0.132++**
	(-1.98)	**(-1.95)**	**(-2.33)**
Asian	0.053+++	0.063+++	0.265+++
	(3.04)	(3.15)	(3.32)
Fear	-0.010	-0.012	-0.042
	(-0.74)	(-0.79)	(-0.75)
Black:			
Mean of Outcome Var.	0.290	0.369	2.113
Impact of 1 SD of Fear	-0.014	-0.022	-0.057
Impact Relative to Mean	-4.77%	-6.03%	-2.70%
Hispanic:			
Mean of Outcome Var.	0.360	0.451	2.331
Impact of 1 SD of Fear	-0.024	-0.028	-0.105
Impact Relative to Mean	-6.68%	-6.13%	-4.49%
Asian:			
Mean of Outcome Var.	0.512	0.634	3.057
Impact of 1 SD of Fear	-0.015	-0.017	-0.079
Impact Relative to Mean	-2.93%	-2.65%	-2.60%

Table S4a: Specification checks on Table 1

See Table 1. Each panel reports focal interaction term(s) from separate regressions

Specification Check	Interaction Term(s)	Success
A: Baseline analysis	Minority x Fear	-0.032+++ (-4.90)
B: Including Economic Policy Uncertainty Index	Minority x Fear Minority x EPU-Index	-0.033+++ (-4.86) -0.003 (-0.14)
C: Including Economic Policy Uncertainty Index (News)	Minority x Fear Minority x EPU-News	-0.034+++ (-4.95) -0.010 (-0.51)
D: Including Twitter-Based Uncertainty Index	Minority x Fear Minority x Uncert-Twitter	-0.033+++ (-4.79) -0.006 (-0.45)
E: Using pre-post on election of President Trump (sample period of Q4 2015 – Q4 2017)	Minority x Post	-0.045+++ (-3.98)
F: Using alternative Google Search Value Index developed by authors	Minority x Google SVI	-0.060+++ (-3.36)
G: Using alternative Google Search Value Index at state level	Minority x Google SVI State	-0.038+++ (-2.83)
H: Including Migration Fear Index for United Kingdom	Minority x Fear Minority x Fear-UK	-0.023+++ (-2.98) -0.007 (-1.51)
I: Including Migration Fear Index for Germany	Minority x Fear Minority x Fear-DEU	-0.027+++ (-4.23) -0.002 (-1.00)
J: Including Migration Fear Index for France	Minority x Fear Minority x Fear-FRA	-0.033+++ (-4.46) -0.001 (-0.12)
K: Including Bartik-style control for expected racial success	Minority x Fear	-0.026+++ (-2.77)
L: Dropping projects with 0-2 backers	Minority x Fear	-0.037+++ (-3.75)
M: Dropping the top 5% of project in pledges/goal (>2.99x)	Minority x Fear	-0.016+++ (-2.80)
N: Including interaction for rising trend in Fear during year	Minority x Fear Minority x Fear x Rising	-0.032+++ (-4.95) -0.003 (-0.34)

Table S4b: Specification checks on Table 1

See Table 1. Each panel reports focal interaction term(s) from separate regressions

Specification Check	Interaction Term(s)	Success
A: Baseline analysis	Minority x Fear	-0.032+++ (-4.90)
B: Excluding all project controls	Minority x Fear	-0.038+++ (-5.03)
C: Interacting all project controls with Fear index	Minority x Fear	-0.032+++ (-4.78)
D: Excluding sample weights	Minority x Fear	-0.033+++ (-4.59)
E: Weighing each creator equally	Minority x Fear	-0.025+++ (-3.97)
F: Including City x Year x Quarter Fixed Effects	Minority x Fear	-0.032+++ (-3.00)
G: Including Category x Year x Quarter Fixed Effects	Minority x Fear	-0.022+++ (-3.62)
H: Excluding Staff Picked projects	Minority x Fear	-0.030+++ (-4.84)
I: Dropping Kickstarter spike period of Q2 2014 – Q3 2015	Minority x Fear	-0.035+++ (-4.62)
J: Dropping 2016	Minority x Fear	-0.031+++ (-4.19)
K: Keeping creators with above-median ethnic name accuracy of 95.6% and higher [n=75,141]	Minority x Fear	-0.043+++ (-3.56)
L: Using alternative name algorithm 1 to classify minority	Minority x Fear	-0.040+++ (-5.08)
M: Using alternative name algorithm 2 to classify minority	Minority x Fear	-0.027+++ (-4.40)
N: Using picture to classify minority status [n=72,854]	Minority x Fear	-0.029+++ (-3.71)

Table S5a: Table 1 using picture-based sample

See Table 1.

	Success	Pledges/Goal	ln(Backers)
	(1)	(2)	(3)
Minority × Fear	**-0.029+++**	**-0.034+++**	**-0.143+++**
	(-3.71)	**(-4.88)**	**(-6.55)**
Minority	-0.051+++	-0.063+++	-0.244+++
	(-4.60)	(-5.78)	(-6.69)
Fear	-0.004	-0.006	-0.021
	(-0.27)	(-0.38)	(-0.40)
Observations	72854	72854	72854
Adj. R^2	0.221	0.245	0.197
Project Controls	Y	Y	Y
Year, State and Category FE	Y	Y	Y

Table S5b: Table S3e using picture-based sample

See Table 1.

	Success	Pledges/Goal	ln(Backers)
	(1)	(2)	(3)
Black × Fear	**-0.026++**	**-0.035+++**	**-0.192+++**
	(-2.18)	**(-3.12)**	**(-4.99)**
Black	-0.184+++	-0.216+++	-0.750+++
	(-10.76)	(-12.43)	(-12.43)
Hispanic × Fear	**-0.037+++**	**-0.040+++**	**-0.110+++**
	(-3.14)	**(-3.32)**	**(-2.82)**
Hispanic	-0.026	-0.038++	-0.231+++
	(-1.52)	(-2.15)	(-4.21)
Asian × Fear	**-0.022++**	**-0.025+++**	**-0.109+++**
	(-2.49)	**(-3.28)**	**(-4.60)**
Asian	-0.010	-0.015	-0.068+
	(-0.83)	(-1.26)	(-1.85)
Fear	-0.005	-0.007	-0.025
	(-0.33)	(-0.45)	(-0.47)
Observations	72854	72854	72854
Adj. R^2	0.228	0.253	0.207
Project Controls	Y	Y	Y
Year, State and Category FE	Y	Y	Y

Table S6a: Specifications using matched sample and quality metrics

See Table 2 and Table 3a.

	Baseline estimation for Success	Including ML prediction of success	Including ChatGPT metric of quality	Including all metrics
	(1)	(2)	(3)	(4)
A. Minority creator matched sample				
Fear	**-0.027+++**	**-0.022++**	**-0.028+++**	**-0.024+++**
	(-3.51)	**(-3.41)**	**(-4.05)**	**(-3.89)**
Quality Metric ML		0.152+++		0.114+++
		(5.17)		(4.33)
Quality Metric ChatGPT			0.094+++	0.081+++
			(6.98)	(7.17)
Observations	2317	2317	2239	2239
Adj. R^2	0.146	0.177	0.193	0.210
B. White creator matched sample				
Fear	**0.009**	**0.007**	**0.010**	**0.009**
	(1.14)	**(1.10)**	**(1.64)**	**(1.54)**
Quality Metric ML		0.194+++		0.155+++
		(18.41)		(17.54)
Quality Metric ChatGPT			0.099+++	0.081+++
			(25.19)	(24.95)
Observations	20672	20672	20211	20211
Adj. R^2	0.177	0.220	0.222	0.247

Table S6b: Specifications using narrow sample with human grader quality assessment

See Tables 2 and 3a. Sample considers 1121 minority and 996 white creator projects selected at random from matched sample. This sample was graded for quality by a freelancer hired on Upwork.

	Baseline estimation for Success	Including ML prediction of success	Including ChatGPT metric of quality	Including human grader metric of quality	Including all metrics
	(1)	(2)	(3)	(4)	(5)
A. Minority creator matched sample					
Fear	**-0.038++**	**-0.034++**	**-0.031++**	**-0.041+++**	**-0.034++**
	(-3.37)	**(-3.21)**	**(-3.10)**	**(-3.71)**	**(-3.40)**
Quality Metric ML		0.153+++			0.113++
		(4.53)			(3.19)
Quality Metric ChatGPT			0.099+++		0.051+
			(5.46)		(2.27)
Quality Metric Human Grader				0.112+++	0.076+++
				(8.89)	(5.07)
Observations	1121	1121	1121	1121	1121
Adj. R^2	0.133	0.164	0.186	0.196	0.225
B. White creator matched sample					
Fear	**0.013**	**0.015**	**0.017**	**0.012**	**0.015**
	(0.64)	**(0.72)**	**(0.84)**	**(0.69)**	**(0.85)**
Quality Predictor ML		0.211+++			0.161+++
		(8.12)			(8.12)
Quality Predictor ChatGPT			0.096+++		0.042
			(4.62)		(1.87)
Quality Metric Human Grader				0.111+++	0.070+++
				(9.19)	(3.52)
Observations	996	996	996	996	996
Adj. R^2	0.198	0.248	0.239	0.251	0.286

Table S6c: Specifications using creator panel with quality assessments

See Table 2 and 3b.

	Baseline estimation for Success	Restricting sample to observations with quality metrics	Including ML prediction of success	Including ChatGPT metric of quality	Including both metrics
	(1)	(2)	(3)	(4)	(5)
Minority × Fear	**-0.028++**	**-0.028++**	**-0.027+**	**-0.028+**	**-0.028+**
	(-2.16)	**(-2.05)**	**(-2.03)**	**(-2.04)**	**(-2.02)**
Fear	-0.003	-0.002	-0.003	-0.003	-0.003
	(-0.64)	(-0.53)	(-0.64)	(-0.61)	(-0.69)
Quality Metric ML			0.033+++		0.026+++
			(5.98)		(4.59)
Quality Metric ChatGPT				0.030+++	0.028+++
				(10.45)	(9.60)
Observations	40729	30394	30394	30394	30394
Adj. R^2	0.613	0.635	0.636	0.637	0.638

Table S7: Descriptive statistics of Kickstarter backers

This table reports descriptive statistics by levels of backers in projects. For projects with 10 or more backers, Kickstarter releases information on the top 10 backer locations and counts of backers in those 10 locations.

					Calculations using top 10 backer locations data		
Backer count	Project count	Project success rate	Minority creator share	Average pledge	Share of backers within 50 miles	Share of projects with more than 50% of backers with 50 miles	Share of backers in 18 largest Kickstarter backer cities (excl. own city)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
0-4	48008	0.015	0.115	42.1	n.a.	n.a.	n.a.
5-9	13180	0.156	0.093	67.2	n.a.	n.a.	n.a.
10-14	8448	0.378	0.088	79.9	0.280	0.230	0.134
15-19	6800	0.555	0.086	83.3	0.302	0.257	0.129
20-24	5699	0.644	0.085	84.8	0.326	0.298	0.132
25-29	5136	0.702	0.084	84.0	0.346	0.337	0.140
30-34	4598	0.760	0.082	81.9	0.366	0.375	0.144
35-39	3984	0.785	0.085	86.4	0.373	0.379	0.158
40-44	3638	0.826	0.079	85.1	0.394	0.413	0.162
45-49	3149	0.829	0.082	83.1	0.399	0.419	0.176
50-74	12388	0.873	0.077	84.9	0.425	0.460	0.192
75-99	7809	0.901	0.076	86.1	0.438	0.474	0.229
100-249	17146	0.939	0.076	81.4	0.411	0.421	0.309
250-499	5790	0.967	0.083	74.9	0.310	0.259	0.479
500-999	2606	0.985	0.074	67.1	0.208	0.116	0.631
1000+	1903	0.989	0.065	123.3	0.120	0.017	0.771
Total	150282	0.488	0.093	71.8	0.361	0.354	0.239

Table S8: Specifications with split sample by likelihood of minority or local backer support

See Tables 1 and 4. Columns (1)-(2) split the sample based upon the likelihood that significant minority backing exists for a minority creator using data from Gafni et al. (2021) to make {State, Product} predictions [median=0.019]. Columns (3) and (4) split the sample by whether 50% or more of backers are within 50 miles of the creator or likely to be so. Columns (5) and (6) split the sample by median funding goal [median=$5000]. Estimations include Project Controls and Year, State and Category Fixed Effects.

	Split by likelihood of significant minority backing		Split by likelihood of significant local backing		Split by size of funding goal	
	Median and above	Below median	Majority distant	Majority local	Median and above	Below median
	(1)	(2)	(3)	(4)	(5)	(6)
Minority × Fear	**-0.023+++**	**-0.031+++**	**-0.030+++**	**-0.015++**	**-0.025+++**	**-0.045+++**
	(-3.27)	**(-2.79)**	**(-4.28)**	**(-2.37)**	**(-3.01)**	**(-4.89)**
Minority	-0.019	-0.043++	-0.005	-0.013	-0.022	-0.013
	(-1.56)	(-2.46)	(-0.48)	(-1.25)	(-1.58)	(-0.95)
Fear	-0.011	-0.011	-0.014	-0.004	-0.011	-0.007
	(-0.71)	(-0.83)	(-1.43)	(-0.46)	(-0.99)	(-0.45)
Observations	70335	70233	79368	70686	78704	71578
Adj. R^2	0.237	0.203	0.187	0.185	0.224	0.150
	Linear Diff:	0.006	Linear Diff:	-0.016+	Linear Diff:	0.020+
		(0.51)		(-1.72)		(1.79)
Mean of Outcome Var.	0.5023	0.4866	0.731	0.216	0.387	0.598
Impact of 1 SD of Fear	-0.014	-0.019	-0.018	-0.009	-0.015	-0.027
Impact Relative to Mean	-2.75%	-3.83%	-2.47%	-4.17%	-3.88%	-4.52%

Table S9: Distribution analysis for backers

See Table 5. This table reports measures of city backer distributions among projects with 10 or more backers. High fear states are quarters with a Migration Fear Index value of 1.75 or higher. Share equality tests consider if the total creator shares for a given racial group in the indicated city set are equal across fear states. Distributional equality tests consider if the city distributions for backers are equal across fear states, using Kaplan (2019) simulated p-value function.

	City distribution restricted to 18 cities with >1% total backer share	City distribution restricted to 96 cities with >0.1% total backer share	City distribution restricted to 166 cities with >0.05% total backer share	City distribution restricted to 597 cities with >0.01% total backer share
	(1)	(2)	(3)	(4)
A. Projects with 10-20 backers				
Cumulative share of all backers	0.211	0.418	0.496	0.690
White creators low fear	0.210	0.419	0.496	0.689
White creators high fear	0.205	0.405	0.485	0.679
p-value: share equality test	0.813	0.453	0.565	0.592
p-value: distribution equality test	0.777	0.799	0.876	0.194
Minority creators low fear	0.242	0.452	0.532	0.730
Minority creators high fear	0.239	0.450	0.520	0.718
p-value: share equality test	0.848	0.932	0.615	0.651
p-value: distribution equality test	0.995	0.995	0.354	1.000
B. All projects				
Cumulative share of all backers	0.572	0.768	0.818	0.907
White creators low fear	0.563	0.760	0.812	0.903
White creators high fear	0.584	0.780	0.827	0.911
p-value: share equality test	0.492	0.506	0.631	0.801
p-value: distribution equality test	0.500	0.311	0.009	0.001
Minority creators low fear	0.628	0.805	0.848	0.928
Minority creators high fear	0.532	0.746	0.797	0.901
p-value: share equality test	0.007	0.136	0.200	0.499
p-value: distribution equality test	0.468	0.959	0.603	0.277

Table S10: Asian crowd-funding success during the pandemic

See Table 1. Regressions consider projects from 2019q1 to 2021q1, and we model an indicator variable After for the Covid period and interact it with indicator variables for creators being Chinese, South Asian (Indian), Other East Asian (Japanese, Korean, Vietnamese), Hispanic, and Black.

	Success	Pledges/Goal	ln(Backers)
	(1)	(2)	(3)
Chinese x After	**-0.179+++**	**-0.163+++**	**-0.250**
	(-5.07)	**(-3.75)**	**(-1.37)**
Chinese	0.086++	0.078+	0.223
	(2.44)	(1.92)	(1.55)
South Asian x After	-0.073	-0.040	0.254
	(-1.10)	(-0.54)	(0.93)
South Asian	-0.020	-0.022	-0.277++
	(-0.41)	(-0.45)	(-2.38)
Other East Asian x After	0.023	0.071	0.449++
	(0.39)	(1.25)	(2.34)
Other East Asian	-0.011	-0.006	0.005
	(-0.20)	(-0.11)	(0.03)
Hispanic x After	0.049+	0.046+	0.207+
	(2.19)	(2.04)	(2.13)
Hispanic	-0.103+++	-0.113+++	-0.387+++
	(-4.71)	(-5.25)	(-4.18)
Black x After	-0.014	-0.019	-0.157
	(-0.36)	(-0.43)	(-1.01)
Black	-0.110+++	-0.141+++	-0.422+++
	(-7.07)	(-8.53)	(-6.19)
After indicator	0.067+++	0.086+++	0.154+++
	(9.94)	(14.88)	(8.60)
Observations	16420	16420	16420
Adj. R^2	0.294	0.331	0.278
Project Controls	Y	Y	Y
Year, State and Category FE	Y	Y	Y

ONLINE SUPPLEMENT: LITERATURE REVIEW

1. Extended Literature Review

Our work builds upon and contributes to two literatures: 1) the evidence on biases against minorities in entrepreneurial finance and on crowd-funding sites and 2) studies of how migration fear builds upon and exacerbates biases against minorities.

Biases in Entrepreneurial Finance and Crowd-Funding Platforms

A deep literature documents the severe challenges of minorities for raising finance (Ewens 2023). Blanchflower et al. (2003) find that Black-owned small businesses are twice as likely to be denied credit as non-minorities, and Blanchard et al. (2008) further identify discrimination for Hispanic-owned businesses. Multiple studies of racial differences in self-employment note the important role of capital access (Fairlie and Robb 2007), including recent work by Hamilton et al. (2022) and Fairlie et al (2022). These differences in access to financial capital can preclude individuals from entering new businesses and projects altogether or require them to start at a suboptimal size (Evans and Jovanovic 1989, Hurst and Pugsley 2018). More recently, Howell et al. (2023) and Chernenko and Scharfstein (2022) document how Black-owned businesses were less likely during the Covid-19 pandemic to obtain a Paycheck Protection Program loan and instead utilize fintechs.[1]

A complementary literature examines the rise of crowd-funding, following upon Mollick (2014). A prominent hope of crowd-funding is that it will "democratize" access to finance (e.g., Agrawal et al. 2014, Mollick and Robb 2016, Younkin and Kashkooli 2016), and to some degree crowd-funding weakens the "home bias" for investment in local areas (e.g., Agrawal et al. 2014, 2015, Kim and Hann 2014, Lin and Viswanathan 2016). Social capital plays an important role in raising support among backers (Eiteneyer et al. 2019, Manikandan 2020, Josefy et al. 2017). Projects on Kickstarter aid the launch of a business via product signaling (Sewaid et al. 2021) and attracting follow-on investment (Roma et al. 2017, 2021). Crowd-funding allows early validation of product demand and may be a path for those with

[1] See also Fairlie (1999), Asiedu et al. (2012), Bayer et al. (2018), Flam et al. (2020), Begley and Purnanandam (2021), Cassel et al. (2021), Li (2022), Bennett and Robinson (2023), and Agrawal and Lim (2023). Da Rin et al. (2013) and Robb and Robinson (2014) provide an overview of start-up capital. Kerr et al. (2014) and Lerner et al. (2018) evaluate early-stage financing and venture success.

lower risk tolerances to test ideas and enter (Hvide and Panos 2014). Mollick and Kuppuswamy (2014) show the creation of gaming ventures following a successful campaign, and Yu and Fleming (2022) and Yu et al. (2017) link crowd-funding to growth-oriented regional entrepreneurship.[2]

Yet, racial and gender biases have carried over to crowd-funding. Younkin and Kuppuswamy (2018) document racism on Kickstarter against Black creators due to unconscious bias. These authors argue this bias can be lowered through endorsements, prior success, and removing race indicators like photos. Gorbatai et al. (2023) further quantify how crowd-funding behavior changes in the immediate aftermath of salient events, such as police shootings exacerbating racial biases against Black creators on Kickstarter.[3] Additionally, several studies consider gender differences (Ewens and Townsend 2019). In a rare study of backers, Gafni et al. (2021) show taste-based discrimination along gender lines on Kickstarter. In an equity crowd-funding setting, Bapna and Ganco (2021) find that gender bias is strongest in low-stakes settings, with no bias uncovered in high-stakes settings.

We contribute by studying the ability of minority creators to successfully raise their funds during different social and political environments. Building on studies that quantify discrimination at points in time, we analyze quarterly variation in sentiment and minority campaign success. Our findings thus shed light on how biases can be exacerbated by the surrounding macro environment.[4] Moreover, our high-frequency identification complements studies that estimate race effects in financial settings and then seek to parse the role of biases and discrimination vs. other factors that might cause racial differences.

Migration Fear and Biases Towards Minorities

While immigrants account for over 14% of the U.S. population in 2022, public attitudes regarding migration have spiked in hostile sentiment throughout the nation's

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[2] Classic studies on localized spillovers include Jaffe et al. (1993) and Audretsch and Feldman (1996).

[3] This finding for crowd-funding contrasts with studies in the customer literature. Black-owned restaurants received sympathetic responses and greater traffic after George Floyd's murder and during Black Lives Matter movements, with digital signals of Black ownership deemed beneficial (Mitkina et al. 2023, Aneja et al. 2023, Agarwal et al. 2023). See also Balakrishnan et al. (2023). Castiglia and Ferraro (2024) also quantify how support for polarized positions respond when the underlying issue is salient and contested.

[4] Macro factors, such as policy choices, housing prices, and emerging industry opportunities, shape financial access and entrepreneurship. Recent examples include Adelino et al. (2015, 2017), Ehrlich and Kim (2015), Schmalz et al. (2017), Hombert et al. (2020), Bernstein et al. (2022), and Kerr et al. (2022). Our paper complements Engelberg et al.'s (2022) consideration of social and political influences.

history. Ending the relatively open border period during the Age of Mass Migration (Abramitzky and Boustan 2022), the Immigration Act of 1924 severely limited immigration to America from places outside of selected countries in northwestern Europe and was partly motivated by politicians as necessary to protect the nation's racial purity (e.g., Doran and Yoon 2019, Moser et al. 2019). While the Immigration and Nationality Act of 1965 later loosened policy and allowed for a more diverse set of origin countries, Goodman (2020) describes in *Deportation Machine* the many instances of local hostility spiking towards Chinese and Mexican immigrants as they became more prominent and the long history of politicians decrying immigration when rallying support to their campaigns.

The public often carries misperceptions about immigrants, and long-term acceptance and assimilation take time (e.g., Card et al. 2005, Clemens 2011, Weber 2019, Bursztyn et al. 2021, Alesina et al. 2022). While scholars note multiple causes for the formation of periodic hostile public attitudes towards immigration,[5] research consistently shows that public discourse and opinions on immigration are closely intertwined with attitudes toward racial and ethnic groups.[6] For example, Hartman et al. (2014) provide evidence that white Americans are significantly more offended by norm violations, such as entering the country illegally or working off the books, for Hispanics than for white Europeans. This work concludes hostility towards immigrants is largely social and psychological in nature, whereby prejudice, stereotyping, and group-based biases against minority ethnic groups often play an important role (Kinder and Kam 2010, Hainmueller and Hopkins 2014).

During the last decade, this academic work has held renewed importance. While the public rhetoric often focuses on immigration, such President Trump's effort to build the wall on the border with Mexico, hostile reactions can engulf a broader set of citizen minorities as well. The rise of white nationalist movements and their infusion into U.S. politics during the last decade came with immigration at the heart of political messaging, including concepts like "replacement theory" of a white majority through higher levels of immigration and the linking of immigrants to crime (Clark 2020). Several studies quantify the propagation of hostile attitudes evoked by President Trump towards minorities through social media (e.g.,

[5] For example, Tichenor (2002), Arzheimer (2009), Dancygier (2010), Lahav and Courtemanche (2012), and Hainmueller and Hopkins (2014).
[6] For example, Nelson and Kinder (1996), Citrin et al. (1997), King (2000), Kinder (2003), and Law and Zuo (2021). Recent research has further explored boundaries that develop between minority groups, like Fouka and Tabellini (2021), Fouka et al (2022), and Cikara et al. (2022). Borjas et al. (2006) consider competition in the labor market.

Edwards and Rushin 2019, Bursztyn et al. 2020, Newman et al. 2020, Müller and Schwarz 2022, Cao et al. 2022). Additional work identifies localized effects like higher racial profiling in police traffic stops in counties after a Trump political rally (Grosjean et al. 2023).

These hostile settings can impact economic outcomes. From a historical perspective, Cook (2014) documents how fear in the Jim Crow era reduced Black innovation. More recently, Fos et al. (2023) time a spike in partisanship in executive teams commencing around 2016. Kang (2020) documents that minority CEOs exhibit more pessimistic earnings forecasts after Trump's election. They also express more concerns about litigation and migration risk. Doleac and Stein (2013) measure lower trust for minorities in online settings — simply using a dark hand (vs. light-skinned hand) resulted in fewer online offers to sales of iPods and lower levels of trust by buyers. These biases could be exacerbated with hostile public opinion or uncertainty.

Our study contributes by providing econometric verification of the impact of spiking migration fears and attitudes towards minorities using high-frequency variation. The crowd-funding setting provides novel evidence in a setting that draws support from across the country. We also contribute to this literature by showing material consequences of hostile attitudes for minorities in a business and entrepreneurial setting.[7]

[7] While most minorities in our sample are native born, especially for Black creators, this paper also contributes to studies of immigrant entrepreneurship (e.g., Hunt 2011; Fairlie and Lofstrom 2015; Wang and Liu 2015; Gompers and Wang 2017; Kerr 2018; Kerr and Kerr 2016, 2020; Brown et al. 2020).

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