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Research Paper

The local spillover effects of top-income inequality on innovation[1]

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ABSTRACT

The existing literature has widely explored the effects of technological change on income inequality. The reverse relationship – from income inequality to innovation – has received considerably less attention. This paper contributes to filling this gap by advancing and testing the hypothesis that higher levels of top-income inequality have local positive spillovers on entrepreneurship. Our empirical analysis confirms that top-income inequality increases the formation of new establishments and startups across USA cities for the period 2006–2018. Moreover, higher top-income inequality also has quality effects on business formation as it increases the proportion of new high-tech firms. To rationalise these findings, we propose a supply-side mechanism in which high-income households, facing lower marginal utility of income, save more and are more willing to undertake risky investments. Household-level evidence supports this channel, revealing that households in the top-tail of the income distribution display higher risk preferences and a stronger propensity to save.

1. Introduction

The relationship between income inequality and technological change has attracted considerable attention in recent decades, alongside the marked increase in income inequality within advanced countries (Aghion and Griffith, 2024; Auten and Splinter, 2024; Gomez, 2025; Guzzardi et al., 2024; Piketty and Saez, 2014; Saez and Zucman, 2020; Stiglitz, 2012), especially in the USA and other Anglo-Saxon countries. According to data from the World Inequality Database, the USA top 1% income share rose from 10.4% in 1980 to 20.7% in 2022, while the Gini index increased from 0.45 to 0.59.

Existing research has focused primarily on the effect of technological change on income inequality. The evidence is mixed, underscoring the complexity of the phenomenon and the need to investigate the various channels linking the multiple facets of technological change (rate, direction and bias) to economic inequality (e.g., income, wage and wealth).

Less emphasis has been placed on empirically exploring the reverse relationship, namely, the effect of income inequality on technological change, broadly defined. This paper contributes to filling this gap by studying the effects of top-income inequality on the rate of business formation and the emergence of high-tech businesses across USA cities.

We propose and mathematically illustrate a novel framework in which income inequality fosters innovative business formation at the local level. Acknowledging that, as income increases, the marginal propensity to save tends to rise and the willingness to engage in

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risky financial activities grows, we maintain that a greater portion of national income received by high-income earners can boost the local availability of private equity capital and increase opportunities to launch new and more innovative (riskier) entrepreneurial ventures.

Recent studies on entrepreneurial activity in the USA have emphasised the growing role of financial intermediaries and platforms in financing startups and new businesses (Ewens and Farre-Mensa, 2022; Kwon and Sorenson, 2023), and documented a strong local bias among investors in selecting firms to fund (Cumming and Dai, 2010; French and Poterba, 1991), particularly for venture capitalists (Kolympiris et al., 2018). Accordingly, the effect of income inequality on entrepreneurship via the supply of risky finance will be locally bounded.

Empirically, we first evaluate the proposed mechanisms using household-level data from the Survey of Consumer Finances (SCF). We construct measures of propensity to saving and risk tolerance at the household level and find that households in the top decile of the income distribution exhibit higher risk tolerance and display a greater propensity to save.

Subsequently, we exploit variation in top-income inequality and business formation across USA Metropolitan Core-Based Statistical Areas (CBSAs) from 2006 to 2018.[1] Business formation is an appropriate measure to test the supply-side effects of increases in top-income inequality, as the creation of new startups and businesses heavily relies on external financing and personal savings. Moreover, business formation reflects the exploitation and transformation of knowledge opportunities into marketable products and services (Audretsch and Belitski, 2017; Audretsch and Link, 2019; Audretsch et al., 2023) and is a determinant of business dynamism, which is one of the pivotal channels linking innovation and economic growth (Akcigit and Ates, 2021). Additionally, focusing on CBSAs enables us to compare similar locations in terms of labour force and institutional characteristics, thus mitigating concerns that omitted variables may confound our estimates (Brueckner and Lederman, 2018).

Given that income in survey data is top-censored, we construct a city-specific measure of top-income inequality based on the inverse Pareto coefficient rather than relying on income share measures (Armour, Burkhauser and Larrimore, 2016; Gottlieb et al., 2023). Controlling for state and year fixed effects and various city-specific covariates, our OLS estimates show that higher top-income inequality in a CBSA is associated with more business launches. Moreover, we find that this positive effect is driven by high-tech businesses, conveying the evidence that income inequality directly affects a key driver of economic growth by releasing new financial resources to select and finance ventures with higher growth potential and risk profiles. These results support the supply-side role played by financial investors, whose financing decisions are often directed toward technologically intensive startups (Kerr and Kerr, 2020).

Our OLS estimates do not rule out the possibility that entrepreneurship may be related to top-income inequality through omitted factors or that entrepreneurship itself causes income inequality (Aghion et al., 2019; Kwon and Sorenson, 2023; Marinoni and Voorheis, 2019). As a partial remedy, our baseline specifications include state fixed effects that may capture historical factors shaping income inequality across USA areas (Galor, 2022). Moreover, we show that the impact of unobservable variables is likely negligible relative to that of observables, based on the results of the Oster test (Diegert, Masten and Poirier, 2022; Oster, 2019). Finally, after ruling out other possible determinants of new business formation, we resort to an instrumental variable analysis.

Specifically, building on Galor, Klemp and Wainstock (2023), we instrument for local top-income inequality using a local adaptation of the ancestry-adjusted migratory distance from Africa, using the pre-sample distribution of ancestry shares within cities. The logic of the instrument is that ancestral groups that migrated and settled farther from Africa during the prehistoric migration of Homo Sapiens tend to exhibit today lower levels of diversity and, consequently, less heterogeneity in productive traits, implying less income dispersion (inequality) within those groups. The relationship between diversity and migratory distance from Africa is well documented in economic and cultural anthropology, where numerous studies show that more distant settlements experienced the "serial founder effect," a phenomenon where successive founder events – when a small group of individuals colonizes a new area, leading to a loss of genetic diversity compared to the original population – during range expansion lead to a stepwise reduction in genetic diversity (Atkinson, 2011; Ramachandran et al., 2005).

To support the instrument's exogeneity, we show that the most representative ancestry shares within a city are uncorrelated with pre-trends in entrepreneurship and are largely balanced across covariates measured at the beginning period. Moreover, we include the same rich set of time-varying city-level controls as in the OLS models (demographics, labour market and industrial structure, migration, religious composition, geography, and population dynamics), as well as additional controls for human capital and ancestry-weighted cultural traits. Furthermore, we introduce robustness specifications that control directly for bottom-tail income shares and top-wealth concentration meant to absorb the main observable channels through which ancestry composition might directly affect innovative entrepreneurship. Although we cannot exclude the existence of remaining alternative, unobserved channels, we are confident that their potential confounding effect is specific and narrow. Hence, we test whether our estimates are robust to small violations of the exclusion restriction and implement the plausibly exogenous IV approach of Conley, Hansen, and Rossi (2012), which confirms that our instrument remains valid even in the presence of substantial violations of the exclusion restriction. Finally, we show that the relationship between entrepreneurial entry and income inequality remains valid when we also account for city fixed effects and use an alternative instrumental variable strategy implementing a shift-share instrument.

Our empirical analysis contributes to the literature on the effects of income inequality on economic growth (Aghion and Griffith, 2024; Alesina and Rodrik, 1994; Banerjee and Duflo, 2003; Breunig and Majeed, 2020; Galor and Zeira, 1993; Marrero and Rodriguez, 2013; Panizza, 2002; Persson and Tabellini, 1994) by studying the relationship between top-income inequality and one of the main

[1] In this paper, we use the terms cities and Metropolitan Core-Based Statistical Areas intercheangeably.

engines of economic growth, namely innovation and high-tech entrepreneurship.

Overall, our findings carry important policy implications and highlight the need for further research to disentangle the nuanced and potentially opposing effects of different forms of inequality on business formation and innovation. We discuss policy implications in more detail in the conclusion section.

The rest of the paper is structured as follows. Section 2 outlines the theoretical background and discusses our proposed mechanisms. Section 3 presents the data and the econometric framework, while Section 4 discusses the results, robustness checks and extensions. Finally, Section 5 summarises the findings and concludes.

2. Theoretical framework

2.1. Related literature

The literature on inequality and technological change has primarily focused on the effect of technological change on income and wealth inequality.[2]

It is, however, equally important to explore the other side of the relationship, namely, whether income inequality affects technological change. We draw on the vast but inconclusive literature examining the effects of inequality on growth. Baselgia and Foellmi (2022) summarise the literature's achievements and inconsistencies according to two logics that describe the impact of inequality on growth and innovation: the demand-side and the savings channels. In both cases, empirical evidence is scarce. The demand-side channels, in particular, have yet to be tested empirically, as also highlighted by Baselgia and Foellmi (2022).

Previous studies that focused on the demand-side logic distinguished between market-size and price effects. Income inequality negatively affects innovation by reducing the market for new goods, as greater income concentration among a few individuals shrinks the pool of potential consumers. However, this negative market-size effect may be offset by a positive price effect when wealthy consumers are ready to pay higher prices for new goods. When the price effect outweighs the market-size effect, income inequality may stimulate the pace of innovations, as a greater willingness to pay high prices from high-income consumers provides more incentives to innovate (Bertola, 2000; Foellmi and Zweimüller, 2006; 2017; Zweimüller, 2000; 2006). The demand-side theoretical approach relies on homothetic consumer preferences plugged into standard innovation-led growth models, and on the binding assumption that innovative products occupy the position of luxury goods in consumption hierarchies (Foellmi and Zweimüller, 2006, 2017). Moreover, it has yet to find empirical support.

Focusing on the effect of high-income consumers' demand, the demand-side channel relates to the appropriation or value capture phase. Instead, we focus on supply-side channels that directly affect the likelihood of new firms' entry. The empirical literature on this facet is still scarce (Baselgia and Foellmi, 2022). Among the most recent contributions, Goel and Saunoris (2020) distinguish between greasing effects, in which income inequality motivates entrepreneurial activity to improve economic conditions, and sanding effects, in which income inequality constrains financial resources for low-income individuals and prevents them from starting a business. Sarkar, Rufín, and Haughton (2018) propose a positive feedback loop grounded in knowledge cumulability and revenue concentration: financial resources and human capital acquired by successful entrepreneurs support new ventures and further increase the share of regional income retained by a small social minority. From a behavioural perspective, Wei et al. (2025), similarly to Xie et al. (2023), suggest that income inequality promotes innovative entrepreneurship as a form of "deviant" behaviour triggered by social comparison and aimed at upward mobility and access to the elite's resources.

More precisely, our approach contributes to the recent literature on the effects of economic inequality on new business dynamics. The most closely related contribution on the income side is Doerr, Drechsel, and Lee (2024), who examine how rising top-income shares affect the financing and employment growth of small firms through changes in household portfolio composition and find that higher top-income inequality is associated with fewer jobs created by small firms across USA states over the period 1980–2015. Theoretically, they model the reallocation of credit between bank-dependent small firms and market-financed large firms when high-income households shift savings from deposits to market instruments. However, they do not explicitly model or measure innovative entrepreneurship. By contrast, our theoretical question concerns how the thickness of the local top-income tail affects the supply of risky equity capital and the risk-bearing capacity for the creation of innovative, high-tech entrepreneurship. Hence, we differ in

[2] According to the cross-country analysis of Antonelli and Gehringer (2017), the faster the rate of technological change, the lower the level of income inequality. Antonelli and Tubiana (2020, 2023) find that the creative destruction triggered by the introduction of radical innovations reduces income inequality, whereas the slow rates of incremental technological change reinforce it. Risso and Sánchez Carrera (2019) provide additional country-level evidence that R&D expenditures are associated with lower income inequality. At the sub-national level, Lee and Rodriguez-Pose (2013) find a positive relationship between technological change and income inequality in Europe, whereas they find only limited evidence in the USA. The results of the USA cross-state empirical investigations by Aghion et al. (2019) suggest that the faster the rate of innovation introduction, the higher the levels of income inequality. Other papers focus on the relationship between various proxies of entrepreneurship and income inequality, again yielding mixed evidence. For example, Atems and Shand (2018) estimate a positive relationship between the two variables across USA states. On the other hand, Al-Azzam (2025) estimates that entrepreneurship, as measured by the Global Entrepreneurship Monitor, decreases inequality across countries, and Liu and Qian (2023) reach the same conclusion for within-city disparities in the USA. Adopting a broader perspective, Gagliardi and Sorenson (2025) document that growth-oriented entrepreneurship in London produces good jobs but increases inequality through spatial sorting. Similarly, Kwon and Sorenson (2023), focusing specifically on Silicon Valley, argue that a high-tech sector boom driven by entrepreneurship might have the unintended consequence of crowding out business opportunities in co-located sectors, worsening the dispersion of the income distribution.

sample characteristics and the theoretical mechanisms under scrutiny.

Braggion, Dwarkasing, and Ongena (2021) emphasise the role of wealth, rather than income inequality, in local business dynamism and innovation. Their theoretical focus is on how highly concentrated financial and housing wealth can weaken financial development, public good provision, and local institutions, thereby discouraging firm entry, exit, and high-tech activity. Using data for USA metropolitan areas from 2004 to 2014, the authors construct measures of wealth inequality and relate them to business dynamics, venture capital, and high-tech outcomes. Interestingly, Braggion and coauthors find a positive correlation between entry and exit rates and income inequality (Gini coefficient), though they do not provide a detailed explanation for this result.

Our paper focuses on the effects of income inequality, captured by a Pareto-based measure of the upper tail of the income distribution, rather than wealth, on local business formation rates. Therefore, we explore the hypothesis that income inequality operates through multiple, partly offsetting channels that can grease the wheels of innovative, equity-financed entrepreneurship while sandpapering bank-dependent small firms' size growth.

2.2. Conceptual framework

We develop a conceptual framework that links, at the local level, top-income inequality, the availability of equity capital, and Schumpeterian entrepreneurial entry. We divide the framework into three interconnected parts: (i) a definition of equity rationing; (ii) the interaction between decreasing marginal utility of income, saving, and risk aversion; and, (iii) a staged finance model for innovative projects. Together, these mechanisms provide a micro-founded rationale for why regions with thicker top-income tails may have deeper equity markets and higher entrepreneurial activity, especially in knowledge-intensive, high-tech sectors.

2.2.1. Equity rationing and the local bias

Financial constraints are among the primary barriers to firm creation and development (Lee, Sameen, and Cowling, 2015). Debt financing of innovation suffers from information asymmetries, whereby bankers participate in the losses of failure without reaping the extra profits from successful ventures. An innovation system based solely on debt risks foregoing relevant opportunities due to banks' hyper-selective credit rationing (Stiglitz and Weiss, 1981). Similarly, an innovation system reliant exclusively on corporate investments risks overlooking technological opportunities that emerge beyond the incumbent's core competencies because of the so-called "not-invented-here syndrome" (Stiglitz and Weiss, 1981). Analogous to credit rationing, equity rationing occurs when financial markets do not provide equity to all the investors who seek it (Hellmann and Stiglitz, 2000). We posit that equity rationing directly affects the quantity and quality of new innovative businesses.

The supply of equity capital from financial intermediaries such as private equity, hedge funds and venture capitalists helps blend the positive aspects of debt and equity finance for innovation.[3] The "not-invented-here syndrome" does not afflict these financial intermediaries in the same way it does corporations: they rely, like banks, on networks of external experts to assess the viability of new undertakings. However, like corporations, they bear the losses of failing startups and reap the profits of successful ones (Gompers and Lerner, 2001). The abundance of private equity capital, especially if allocated through intermediaries, supports the financing of riskier projects, such as technologically innovative projects (Guiso, 1998; Lazonick and Mazzucato, 2013).

Evidence from the USA shows that the primary funding source for the initial stages of startup formation is private and family savings, followed by debt (Robb and Robinson, 2014; Stangler, Tareque and Morelix, 2016). Over the past two decades, the USA has witnessed significant growth in private equity capital, with a focus on late-stage startup development (Ewens and Farre-Mensa, 2022). Moreover, even though private equity financing, such as venture capital, backs a minority of startups, it disproportionately affects innovative startups' growth and, consequently, the economy (Kortum and Lerner, 2000).

We now introduce a simple representation of equity depth and rationing. Let ι denote the thickness of the top-income tail (a measure of top-income inequality, such as top income shares). Let $S(\iota)$ denote equity depth: the total euros of risky equity that the investor base is willing to hold at prevailing terms. Let r_e^* be the required gross return on equity that maximises investors' expected payoff under adverse selection, and let $D(r_e^*)$ be the total equity demand from projects that would like to raise equity at this price. Following the spirit of Hellmann and Stiglitz (2000), we represent rationing at the project level by assuming that each project that would like funding at r_e^* receives it with probability $\phi(\iota)$:

$$\phi(\iota) = \min\left\{1, \frac{S(\iota)}{D(r_e^*)}\right\} \in [0,1] \tag{1}$$

When equity is abundant (large ι), $\phi(\iota) = 1$ and rationing effectively disappears at the cap. When equity is scarce (small ι), $\phi(\iota) < 1$ and only a fraction of otherwise viable projects obtain funding, the remainder being rationed out solely because aggregate supply is insufficient at the chosen price.

A wide body of research shows that investors exhibit a *local bias* when selecting their investment opportunities; this local bias is

[3] Venture capital exemplifies how financial intermediaries efficiently support innovation (Antonelli and Teubal, 2008). Venture capital companies function as central agencies that operate as platforms managing a sequence of steps: i) they screen possible entrepreneurial undertakings and select those with higher potential; ii) they collect private equity raising risk capital owned primarily by wealthy households; iii) they fund new firms endowed with competent management; iv) they enable the eventual entry in the stock exchange of the successful ventures with an initial public offering (IPO); v) they facilitate the exit from the capital of the venture when the startup is finally acquired in the financial markets by larger firms.

particularly pronounced among venture capitalists (Cumming and Dai, 2010; French and Poterba, 1991; Hornuf, Schmitt and Stenzhorn, 2022; Manigart et al., 2002; Seasholes and Zhu, 2010; Shane and Cable, 2002; Wang and Prokop, 2025). The local bias is rooted in informational asymmetries and agency problems in imperfect markets (Stiglitz and Weiss, 1981). It is particularly relevant for innovative startups characterised by informational opacity and a large share of intangible assets (Hall and Lerner, 2010). Compared to publicly listed companies, innovative startups often lack detailed financial records, do not share information online, and are not scrutinised by financial analysts. Therefore, private equity investors tend to select their investments through personal and organisational networks, their own assessments of entrepreneurs' business plans, and local serendipitous encounters (Gompers and Lerner, 2001). Proximity helps build long-term relations between financial intermediaries and investors, enhancing investors' trust and confidence in financial intermediaries (Fritsch and Schilder, 2012).

Because investors exhibit local bias, both $S(\iota)$ and $\phi(\iota)$ are fundamentally local objects: differences in the wealth and risk-bearing capacity of local investors translate into differences in the probability that local projects are financed.

In the next subsection, we micro-found $S(\iota)$ by linking it to the distribution of wealth and risk preferences in the local investor base, and show how higher top-income inequality can increase equity depth and thus relax equity rationing.

2.2.2. *Marginal utility of income, marginal propensity to save and risk aversion*

The notion of decreasing marginal utility of income is an essential acquisition of economics (Einaudi, 1914; Sen, 1973). As is well known, the marginal utility of income declines with income. This appreciation has provided solid foundations for modern public finance and public economics; for example, progressive taxation is based on this logic (Layard, Mayraz and Nickell, 2008).

A convenient way to formalise decreasing marginal utility and risk-bearing is to assume that investors have constant relative risk aversion (CRRA) utility over a single-period payoff x (since we work in a single period, we can treat x as both wealth or consumption):

$$U(x) = \frac{x^{1-\gamma}}{1-\gamma}(\gamma > 0), U(x) = \ln x \, when \, \gamma = 1 \tag{2}$$

where γ is a relative risk-aversion index. Marginal utility and curvature are:

$$U'(x) = x^{-\gamma}, U''(x) = -\gamma x^{-\gamma-1} < 0(\gamma > 0) \tag{3}$$

so that U is strictly concave. It follows that absolute risk aversion $\mathrm{ARA}(x)$ is:

$$\mathrm{ARA}(x) \equiv -\frac{U''(x)}{U'(x)} = \frac{\gamma}{x} \tag{4}$$

which declines with wealth.

These properties capture the idea that richer households both save more and are more risk tolerant. The empirical literature confirms that the marginal propensity to save increases with income levels (Bourguignon, 1981; Dynan, Skinner and Zeldes, 2004; Fagereng et al., 2019), which means that high-income households commit an increasing share of their income to savings (Auclert and Rognlie, 2017) and can afford riskier undertakings because their savings are larger. In parallel, the literature shows that risk appetite increases with income levels due to the decreasing marginal utility of income. The lower the marginal utility of investors' income, the lower the average risk aversion of their financial investments (Mehra and Prescott, 2003). Affluent investors are more likely to participate in risky ventures, take a long-term approach to assessing their returns, and are better able to bear the consequences of financial losses. A large body of empirical evidence acknowledges that risk preference increases with individuals' income and wealth (Bach, Calvet and Sodini, 2020; Bucciol and Miniaci, 2011; Dohmen et al., 2011; Fossen, König and Schröder, 2023; Hemrajani et al., 2023; Pickard, Dohmen and Van Landeghem, 2024), also driven by the larger share of risky assets held by wealthy individuals in financial portfolios (Guiso, Haliassos and Jappelli, 2003).

To connect individual risk attitudes to the aggregate capacity to bear risk, let W_h denote the wealth of investor h and γ_h their CRRA parameter. From (4), the investor's absolute risk tolerance $\mathrm{ART_h}$ at W_h is equal to:

$$\mathrm{ART_h}(W_h) = \frac{W_h}{\gamma_h} \tag{5}$$

Let ι again denote (local) top-income inequality (a thicker top tail means larger ι). A natural measure of the local investor base's total risk-bearing capacity $\mathscr{T}(\iota)$ is the sum of the individual risk tolerances:

$$T(\iota) = \sum_h \frac{W_h}{\gamma_h} \tag{6}$$

An increase in top-income concentration brings a larger share of resources among individuals with higher risk attitudes and a greater propensity to save. Given decreasing absolute risk aversion, this reallocation raises $\mathscr{T}(\iota)$, that is, the aggregate risk tolerance of the local investor base.

We can now link this aggregate risk-bearing capacity to local equity depth. Consider a diversified risky portfolio with expected gross return μ, variance σ^2, and a risk-free gross return r_f. Under CRRA preferences, the optimal share of wealth that investor h allocates to this risky portfolio is approximately:

$$\alpha_h^* \approx \frac{\mu - r_f}{\gamma_h \sigma^2} \tag{7}$$

so the level of risky wealth is:

$$\alpha_h^* W_h = \left(\frac{\mu - r_f}{\sigma^2}\right) \frac{W_h}{\gamma_h} \tag{8}$$

Interpreting this portfolio as entrepreneurial equity, local equity depth is:

$$S(\iota) = \sum_h \alpha_h^* W_h = \left(\frac{\mu - r_f}{\sigma^2}\right) \sum_h \frac{W_h}{\gamma_h} = \lambda\, T(\iota) \tag{9}$$

where $\lambda \equiv (\mu - r_f)/\sigma^2 > 0$ is a constant. Thus, higher top-income inequality ι increases $\mathscr{T}(\iota)$ and, through (9), raises local equity depth $S(\iota)$.

A standard Arrow-Pratt mean–variance approximation under CRRA preferences further implies that, for a risky payoff with variance σ^2, the required excess return on equity is approximately proportional to aggregate risk aversion, hence inversely proportional to aggregate risk tolerance. Denoting by $r_e(\iota)$ the required gross return on equity and by r_f the risk-free gross return, we can write heuristically that:

$$r_e(\iota) - r_f \ \approx\ \frac{\sigma^2}{\mathscr{T}(\iota)} \tag{10}$$

Higher top-income inequality, by raising $\mathscr{T}(\iota)$, tends to reduce the required risk premium $r_e(\iota) - r_f$.

Combining (9), (1) and (10), a rise in top-income inequality increases the quantity of risky equity supplied locally, raises the probability that otherwise viable projects obtain external equity, and reduces the cost of that equity:

$$\iota \uparrow \Rightarrow \mathscr{T}(\iota)\uparrow, S(\iota)\uparrow, \phi(\iota)\uparrow, r_e(\iota)\downarrow$$

2.2.3. Innovation, staged finance, and composition of entry

A convenient way to introduce innovative entrepreneurship in the model is through a staged model typical of venture capital contracts (Bergemann and Hege, 2005; Dixit and Pindyck, 1994; Gompers, 1996; Kerr, Nanda and Rhodes-Kropf, 2014; McDonald and Siegel, 1986; Nanda and Rhodes-Kropf, 2017). Indeed, innovative projects are rarely one-shot: founders usually invest modest resources upfront to learn about the project's potential (a prototype or pilot), and only proceed to large-scale investment if: (i) the pilot looks promising; and, (ii) follow-on financing is actually available.

We capture this in a simple two-stage structure:

- Pilot stage (now): the entrepreneur invests K_0 to develop a prototype or run a pilot. With probability q, the pilot yields "good news" about the technology or market; with probability $(1-q)$ the news is bad.
- Scale-up stage (if good): conditional on good news, the entrepreneur seeks K_1 in outside equity to scale up production. Conditional on scaling up, the venture succeeds with probability p_G and yields payoff R to the founder before paying outside investors.
- Stopping rule: if the pilot yields bad news, the entrepreneur stops, and the project's value is zero beyond the sunk cost K_0. This "right but not obligation" to scale is the hallmark of a real option.

Under risk-neutral evaluation, the expected net value of starting the project at local inequality ι can be written as:

$$V(\iota) = -K_0 + \phi(\iota)\, q\, [p_G R - r_e(\iota) K_1]_+ \tag{11}$$

where $[x]_+ \equiv \max\{x, 0\}$ captures the option to abandon if scaling up is not profitable. The entrepreneur starts if $V(\iota) \geq 0$ (or if $V(\iota)$ exceeds the value of the best outside option, such as wage employment).

Eq. (11) makes explicit how local equity conditions affect innovative entry:

- *A quantity margin*: deeper local equity (higher $S(\iota)$) relaxes rationing and raises $\phi(\iota)$, the probability that follow-on funds are available when the pilot is successful.
- *A price margin*: higher aggregate risk tolerance $\mathscr{T}(\iota)$ reduces the required risk premium by (10), lowering $r_e(\iota)$ and thus the cost of scaling up.
- *An option value effect*: the continuation payoff $[p_G R - r_e(\iota)K_1]_+$ is convex, with a floor at zero (option to abandon) and unbounded upside. This convexity is central to the value of real options under uncertainty (Dixit and Pindyck, 1994; McDonald and Siegel, 1986).

Innovative projects are not all alike. Empirically, more radical or exploratory technological search tends to generate more failures and more breakthroughs, that is, more dispersed outcomes (Fleming, 2001). We define an "innovative spread" in success probabilities between good and bad pilots:

$$\Delta \equiv p_G - p_B \tag{12}$$

where p_B is the success probability obtained after a bad pilot. Holding the average success likelihood and payoff scale fixed, a larger Δ implies more dispersed outcomes: very good prospects when the pilot is favourable, and clearly poor prospects otherwise.

In our two-stage structure, the entrepreneur only continues after good news, so increasing Δ (raising p_G and lowering p_B) increases the chance that the good-news path clears the continuation bar $[p_G R - r_e(\imath)K_1]_+$, while the bad-news path remains at zero. Therefore, the expected option value $V(\imath)$ in (11) is increasing in Δ: more innovative projects benefit disproportionately from the option to expand only when the pilot is promising.

Crucially, this interacts with equity depth. When local equity is deeper (higher $S(\imath)$), follow-on funding is more likely to be available (higher $\phi(\imath)$), and the cost of equity is lower (lower $r_e(\imath)$). Both forces raise $V(\imath)$, but they do so more strongly for high-Δ projects, whose continuation payoff is more sensitive to improvements in financing conditions. As a result, increases in top-income inequality that deepen local equity markets not only raise overall entry, but also tilt the composition of entry toward more innovative, high-variance projects (Kerr, Nanda and Rhodes-Kropf, 2014; Nanda and Rhodes-Kropf, 2017).

Putting together the mechanisms in Sections 2.2.1–2.2.3, we hypothesise that higher top-income inequality, by concentrating savings and risk-bearing capacity among affluent households, increases local equity depth $S(\imath)$, relaxes equity rationing (raises $\phi(\imath)$), lowers the cost of equity $r_e(\imath)$ and disproportionately favours the formation of innovative knowledge-intensive, high-tech establishments that are financed through staged equity contracts and derive the greatest value from real options.

3. Empirical framework

This section presents the data and econometric strategy to study the relationship between top-income inequality and innovation.

3.1. Unit of analysis

To examine the relationship between top-income inequality and entrepreneurship in the USA, we build a dataset by collecting data from various sources and conduct the analysis at the scale of the Metropolitan CBSAs, which are delineated by the Office of Management and Budget (OMB) as clusters of contiguous counties with a combined population of at least 50,000 people and a high degree of economic and social interactions. Therefore, these areas represent independent and functionally distinct internally integrated labour markets (Osman and Kemeny, 2022). In our main analysis, we construct a measure of top-income inequality at the city level using the 2005–2007 waves of the American Community Survey (ACS). Then, we relate it to various city outcome variables proxying for business formation and entrepreneurship observed for the period 2006–2018. Therefore, our baseline estimation links a time-invariant measure of income inequality to a time-varying measure of entrepreneurship. This choice is dictated by the need to use a large sample size to compute our measure of inequality, i.e., the inverse Pareto coefficient. Nonetheless, we will also show that our main results are robust to using the full panel structure of the data by computing an alternative measure of top-income inequality. In this last case, we also control for CBSA-specific fixed effects.

3.2. Business formation and entrepreneurship

Following the related literature, we define and measure entrepreneurship as the entry of new businesses (Glaeser, Kerr and Kerr, 2015; Kerr and Nanda, 2009). Therefore, our primary dependent variable is the number of new business launches. To construct our primary dependent variable, we use data on establishments' entry from the Business Dynamics Statistics (BDS), a database maintained by the USA Census that provides annual data on the number of establishments aggregated at various geographical scales. The BDS describes an establishment as a "fixed physical location where economic activity occurs" (Haltiwanger, Jarmin and Miranda, 2009). Establishments are then part of a firm, which can have either a single establishment (single-unit firm) or multiple establishments (multi-unit firm). Each firm is defined at the enterprise level, such that all establishments are considered under the firm's operational control. Moreover, BDS data exclude self-employed workers and domestic service workers, thus not considering economic subjects that do not necessarily engage in entrepreneurial activities.

Our primary dependent variable is the yearly number of new establishment entries per capita in each Metropolitan CBSA from 2006 to 2018. Moreover, we will also disentangle the establishments based on their industry. Specifically, we will look at the effect of top-income inequality on the entry of new establishments belonging to the high-tech sector. In line with the theoretical mechanisms articulated in Section 2, we expect that the effect of top-income inequality should be concentrated on knowledge-intensive establishments, which are more reliant on external financing sources, one of the main channels in our proposed relationship. We will present these additional specifications in Section 4.2.5.

We complement our baseline results with additional analyses exploiting data on for-profit business registrations from the Startup Cartography Project (SCP, Andrews et al., 2022).[4] The SCP contains data on the number of new business registrations extracted from state-level business registration records created when a firm is registered as a corporation, Limited Liability Company (LLC), or partnership, for 1988–2016. All corporations, LLCs or partnerships face strong incentives to register into a local jurisdiction. For example, corporations take advantage of tax benefits, limited liability, and the possibility of trading and issuing ownership shares. The

[4] Available at: https://www.startupcartography.com.

SCP focuses on for-profit firms in local jurisdictions or for-profit firms whose jurisdiction is in Delaware but that operate in a different state. Therefore, non-profit businesses and companies whose operations are not in the state where they are registered are excluded.

We extract information on the Startup Formation Rate (SFR), which is the count of new businesses created within a given population. We then aggregate county data on the number of startups at the 2013 CBSA level, using a crosswalk from the Census Bureau of Economic Analysis, and use the yearly number of new startups divided by the Metropolitan CBSA population for the period 2006–2016 as an additional dependent variable.

3.3. Top-income inequality

To construct measures of top-income inequality at the city level, we use the American Community Survey (ACS) data for the years 2005, 2006 and 2007, aggregated to form the 2006 period.[5] The data are obtained through IPUMS (Ruggles et al., 2021).[6] We restrict the sample to respondents between the ages of 16 and 64. Moreover, we exclude residents in group quarters (e.g., individuals in prisons or mental health institutions), unpaid family workers, self-employed and armed forces. We focus on full-time and full-year workers (i.e., individuals working at least 40 weeks per year and 30 h per week).[7] An essential limitation of the publicly available ACS data is that income is top-censored. Computing measures of top-income inequality without considering the top-coding issue might introduce a measurement bias. To overcome this limitation, we follow prior literature and assume that larger incomes follow a Pareto distribution (Aghion et al., 2019; Armour, Burkhauser and Larrimore, 2016; Gottlieb et al., 2023). As a result, we measure top-income inequality by the inverse of the Pareto parameter, the so-called Pareto's α. A Pareto distribution can be described by the following cumulative density function:

$$\Pr(X < x) = 1 - \left(\frac{x_{min}}{x}\right)^{\alpha} \tag{13}$$

where x is some value drawn from the random variable X greater than x_{min}, while x_{min} is the cutoff parameter and α is the scale parameter. The degree of inequality within the top-tail increases with the inverse of the scale parameter α. Based on the modified Hill estimator, which is a widely used estimator for the shape parameter of the Pareto distribution (Hill, 1975), the maximum likelihood estimation for the Pareto parameter is:

$$\widehat{\alpha}^{-1} = \frac{1}{N}\sum_{i\in\Delta} ln\left(\frac{x_i}{x_{min}}\right) \tag{14}$$

where $\widehat{\alpha}^{-1}$ is the inverse of the Pareto parameter, Δ is the set of observations, and x_i is the income of the i^{th} observation drawn from a Pareto distribution. Following Aghion et al. (2019) and Gottlieb et al. (2023), we adjust Eq. (14) for the limited number of observations among the censored ones. The details of this procedure and a more detailed discussion on how we construct our measure of top-income inequality are provided in section A1 of the Online Appendix.[8] The raw correlation between the inverse of the Pareto parameter and the top 10% income share constructed including top-censored observations is very high (~86%).

3.4. Main econometric strategy

We now turn to the econometric strategy used to estimate the impact of top-income inequality on business entry. The computation of a city-specific Pareto parameter in Eq. (2) requires a reasonably large sample of individuals above a certain cutoff, x_{min}, and with top-coded income levels. However, the annual ACS covers only 1% of the USA population, and the percentage of individuals with top-coded income is 0.8% nationally for the 2005–2007 ACS sample. Hence, computing a city-specific Pareto parameter based on a single ACS wave sample would introduce substantial noise.

To address this, we aggregate three single-year ACS waves, which increase the overall sample size, to construct a measure of top-income inequality for the initial period and relate it to subsequent entrepreneurial entry. Our estimation strategy is thus similar to Braggion, Dwarkasing and Ongena (2021), who link a time-varying measure of entrepreneurship to a time-invariant measure of income inequality. However, we also show that our results are robust when using the panel structure and include area-level fixed effects. The estimates of this additional specification are presented in Section 4.2.4.

We thus estimate the following baseline model:

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[5] We aggregate three waves of the ACS data to improve coverage, as in Winters (2014) and Connor, Kemeny and Storper (2023), among others.

[6] Specifically, we extracted data from the annual ACS survey for the years 2005, 2006 and 2007. After 2000, the most representative survey available to us is the ACS, which covers 1% of the US population (Acemoglu and Autor, 2011).

[7] Restricting the analysis to individuals between 16 and 64 years old working full-time is a standard assumption used by the literature (Aeppli and Wilmers, 2022; Hoffman, Lee and Lemieux, 2020).

[8] The use of eq. (14) to compute our measure of top-income inequality might generate a "generated regressor" problem. We thus implement a boostrap procedure with 500 replications that re-estimates $\widehat{\alpha}^{-1}$ in each replication, merges the bootstrapped $\widehat{\alpha}^{-1}$ into the second-stage dataset, and re-runs the baseline regression. The standard deviation of the resulting distribution of second-stage coefficients provides bootstrap standard errors that account for first-step estimation bias. The results are robust: conclusions and statistical significance for the inverse Pareto coefficient are unchanged. We thank an anonymous reviewer for suggesting us this test. Results are available from the authors upon request.

$$\log\left(y_{cst}\right) = \beta_0 + \beta_1 \log\left(\alpha_{cs}^{-1}\right) + \boldsymbol{X}'_{cst}\beta_2 + \mu_{st} + e_{cst} \tag{15}$$

where $\log\left(y_{cst}\right)$ is the log of the yearly number of new establishments per capita in city c, state s, at year t. Our explanatory variable of interest is $\log(\alpha_{cs}^{-1})$, the log of the inverse Pareto parameter, our proxy for top-income inequality, in city c, state s. The vector $\boldsymbol{X}'_{cst}$ denotes a set of time-varying, city-level control variables. This allows us to account for time-varying city characteristics that could confound the relationship between innovation and top-income inequality. Specifically, we include demographic and economic controls such as the share of individuals between 16 and 24 years, the share of female individuals, the share of white individuals, the share of foreign-born individuals, the share of individuals employed in the manufacturing sector, the share of unemployed individuals, the population growth rate, and the city land size, as well as a proxy for city-level degree of risk aversion, measured as the Catholic-to-Protestant ratio (Abakah and Li, 2023; Braggion, Dwarkasing and Ongena, 2021). Table A2 in section A2 of the Online Appendix provides detailed descriptions and sources for all variables used in the empirical analysis.

We augment Eq. (15) with state-by-year fixed effects, indicated by the term μ_{st}. Year fixed effects control for macroeconomic shocks affecting all cities simultaneously, while state fixed effects capture, among others, the role of the deep determinants of inequality, such as legal and historical institutions (Acemoglu, Gallego and Robinson, 2014; Galor, Moav and Wollrath, 2009). Moreover, the interaction between year and state fixed effects enables us to account for state-specific year shocks. We run several alternative specifications of Eq. (15), as documented in the results section. We cluster standard errors at the city level, the unit of our treatment variable, to allow for within-city and over-time error correlations.[9]

3.5. Instrumental variable

Our instrumental variable builds on the hypothesis proposed by Ashraf and Galor (2013) and applied to the study of income inequality by Galor, Klemp and Wainstock (2023). Precisely, the hypothesis posits that a substantial fraction of contemporary income inequality in market economies reflects interpersonal diversity shaped by the prehistoric migration of Homo Sapiens out of East Africa. The out-of-Africa migration was one of the most critical events in human history. According to the prevailing "serial founder effect" hypothesis (Atkinson, 2011; Ramachandran et al., 2005), the migration out of Africa toward more distant areas occurred in successive, stepwise waves: migrating groups moved first to nearby locations and, over time, to increasingly distant ones. Hence, distance is a function of migration time in such a framework. Each migration involved a loss of diversity, as each group leaving Africa was a subgroup of the initial population; hence, by definition, less representative of the original population's diversity. The new settlements were characterized by a higher probability of intergenerational dominance by a single character, thereby reducing the diversity of the subgroup. Indeed, empirical evidence shows that populations migrating farther from East Africa exhibit lower contemporary cultural, demographic, and behavioural diversity (Ashraf and Galor, 2013). Given that interpersonal diversity within a population is associated with more considerable differences in productive traits and, hence, economic disparities (Alesina, Harnoss and Rapoport, 2016; Gorodnichenko and Roland, 2017), we expect that populations descended from more distant migratory groups exhibit lower levels of interpersonal diversity and, hence, income inequality.

To implement this strategy, we use data from the 2000 wave of the USA Census, which samples 5% of the USA total population. We use Census data from 2000 to increase our sample size and introduce a 6-year lag to reduce concerns about simultaneity between entrepreneurship and the distribution of ethnic groups within a city. Following the logic of the epidemiological approach (Fernandez, 2011; Fernandez and Fogli, 2009), we restrict the sample to USA-born individuals.[10] Following Galor, Klemp and Wainstock (2023), we match each ancestral ethnic group to its modern country homeland and compute the prehistoric migratory distance from Africa at the country level as the distance between Addis Ababa (Ethiopia) and the capital city of the modern country homeland, as in Ashraf and Galor (2013).[11] Our instrument is thus defined as:

$$Instrument_c = \sum_{k=1}^{K} \mu_{kc} \times MigratoryDistanceFromAfrica_k \tag{16}$$

where μ_{kc} is the share of individuals in city c with ancestors coming from country k, while $MigratoryDistanceFromAfrica_k$ is the prehistoric migratory distance from Africa to country k, given by the distance from Addis Ababa to the modern capital city of country k, taken from Ashraf and Galor (2013).

We believe that our instrument is plausibly exogenous. By focusing only on USA-born individuals, we ensure that we focus on individuals who have been exposed to the same institutional background and differ, beyond their personal characteristics and other cultural values, in their ancestry group's migratory distance from Africa, an event that occurred a thousand years ago. Moreover, Galor, Klemp and Wainstock (2023) have shown that other potential confounders at the ancestry-group level do not bias the effect of migratory distance from Africa on income inequality.

The exclusion restriction requires that the migratory distance from Africa affects current levels of entrepreneurship only through channels related to top-income inequality. To support this, we include a broad set of city-level controls, such as the unemployment

[9] Our results are robust to estimating eq. (15) with standard errors clustered at the state level. See Table A7 in the Online Appendix.

[10] We use the variable *ancestr1d* in IPUMS, which contains the self-reported primary ancestry group of the individuals, reflecting both their country of origin or the parents' country of origin.

[11] We precisely follow the procedure detailed in section A.1.1 of Galor, Klemp and Wainstock (2023).

rate, the share of the white population, and the Catholic-to-Protestant ratio, as well as state fixed effects, which capture differences in institutional characteristics across states. However, we cannot rule out empirically that, in principle, the distribution of ancestry shares within a city might affect entrepreneurship through other channels than income inequality. For example, it might be that some ancestral groups might inherently be more innovative than others (Fairlie and Meyer, 1996; Kerr and Kerr, 2020).

Nonetheless, we run additional tests to reinforce the validity of our approach. First, we show that including alternative channels potentially shaped by migratory distance from Africa, such as the share of college-educated individuals, individualism/collectivism orientation, risk-taking and income per capita, does not alter our IV estimates drastically. Second, following the logic of the Bartik instrument (Borusyak, Hull and Jaravel, 2025), we conduct balance and falsification tests to confirm that the composition of ancestral groups within a city is not systematically correlated with pre-treatment city characteristics or pre-treatment trends in business formation, where the treatment timing is the year we measure the IV (2000). Third, we demonstrate that our IV results are robust to violations of the exclusion restriction by applying the method of Conley, Hansen and Rossi (2012), who provide a framework for causal inference in IV models when the instruments' exclusion restriction may not be fully satisfied. Fourth, we also show that our results hold when we include city fixed effects along with a shift-share instrumental variable strategy.

3.6. Descriptive evidence

This section reports preliminary descriptive statistics. Table 1 reports the descriptive statistics of the variables used in our baseline econometric model.[12]

Fig. 1 shows the distribution of the number of establishment entries per capita, scaled by population in thousands, averaged over 2006–2018. Cities are coloured according to the sextile rank of the respective distribution. A more intense business formation rate characterises regions in darker blue. The number of new establishment entries per capita is exceptionally high in Florida, the Western Region, and the Northeast.

On the other hand, Fig. 2 displays the geographical distribution of top-income inequality across cities. We observe that the most significant levels of inequality characterise cities in California, Texas, Florida, and parts of the Atlantic Coast.

Finally, Fig. 3 shows a preliminary insight into our main result. It plots the number of new establishments per 1000 inhabitants (on the y-axis), averaged over 2006–2018, against top-income inequality (on the x-axis) at the city level. The graph suggests a positive cross-sectional relationship between establishment entries and top-income inequality.

4. Results

4.1. Income distribution and theoretical channels

We start by presenting evidence on the mechanisms underlying the relationship between top-income inequality and entrepreneurship described in Section 2.

We extract household balance sheet data from the Survey of Consumer Finances (SCF), a triennial cross-sectional survey containing information on household wealth, income, asset composition, and demographic characteristics. The SCF provides one of the most accurate sources of microdata on USA households' wealth. We collect information from the 2007, 2010, 2013, and 2016 waves for our analysis, which coincide with our sample period.

We start by examining the allocation of risky assets across the income distribution among USA households.[13] This variable is intended to capture the households' risk propensity. Fig. 4 shows the share of risky assets over the total financial wealth held by USA households across six income groups, revealing that the share of wealth allocated to risky assets increases as income rises. Specifically, while risky assets represent 3% of the total financial wealth for the bottom 20% of the income distribution, the share of risky assets equals 24% for the top 10%. Therefore, top earners invest much more in risky activities than low-income households.

However, we acknowledge that this proxy might imperfectly measure the households' risk propensity to invest in startups and newly born firms. For example, risky assets also include investments in public companies or hedge funds, which do not relate to the emergence of startups. Therefore, we provide empirical support for our theoretical channels by presenting additional results using an

[12] For a sake of interpretation, Table 1 offers descriptive statistics of the number of establishment entries per capita and the inverse of the Pareto parameter (α^{-1}) in levels. However, all the estimation models are carried out by taking the log of both the variables.

[13] We measure risky assets by adopting the definition used by the Board of Governors of the Federal Reserve System, available at their macro bulletin: https://www.federalreserve.gov/econres/files/bulletin.macro.txt. Risky assets equal the sum of the total value of financial assets held by households that are invested in equity and bonds. Equity includes publicly traded stocks, stock mutual funds, combination funds, IRAs/Keoghs invested in stocks, other managed assets w/equity interest (e.g. annuities, trusts, MIAs), thrift-type retirement accounts invested in stocks, savings accounts classified as 529 (educational savings accounts). Bonds includes government saving bonds, corporate bonds, commercial paper, state or municipal non-saving bonds, foreign bonds and other non-saving bonds, debentures, mortgage-backed securities, negotiable certificates of deposit, treasury bills (T-bills), treasury certificates (T-certificates), treasury bonds (Tbonds), zero-coupon bonds, and similar instruments normally traded in financial markets.

Table 1
Descriptive statistics.

Variables	Obs.	Mean	Std. Dev.	Min	Max	p1	p99
Establishment entries per capita	3138	2.037	0.683	0.729	7.858	1.022	4.181
α^{-1}	3138	0.224	0.038	0.159	0.54	0.165	0.319
Age1624	3138	0.145	0.03	0.064	0.348	0.099	0.254
Female	3138	0.501	0.016	0.439	0.611	0.463	0.547
White	3138	0.821	0.103	0.432	0.987	0.542	0.975
Manufacturing	3138	0.111	0.053	0.014	0.397	0.026	0.262
Unemployed	3138	0.054	0.021	0.009	0.14	0.02	0.119
Foreign-born	3138	0.117	0.093	0.006	0.498	0.014	0.439
Catholic-to-Protestant ratio	3138	2.101	2.905	0.037	17.816	0.047	16.355
Land size	3138	7.581	0.91	5.414	10.213	5.807	9.832
Population growth	3138	0.008	0.012	−0.28	0.114	−0.012	0.042

Notes: This table reports the number of observations (Obs.), the mean (Mean), the standard deviation (Std. Dev.), the minimum value (Min), the maximum value (Max), the 1st percentile (p1) and the 99th percentile (p99) of the main variables included in the empirical analysis. Variables are defined in Table A2, section A2, of the Online Appendix.

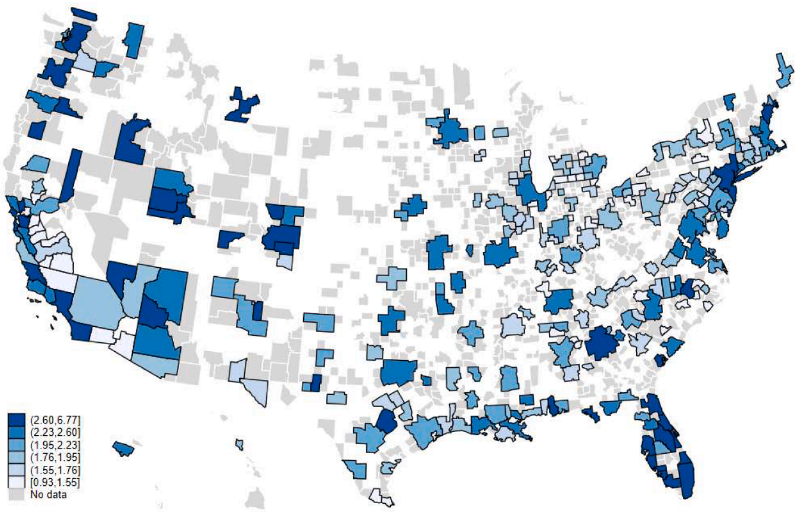

Fig. 1. Geographic distribution of the number of establishment entries per capita across Metropolitan CBSAs between 2006 and 2018
Notes: The graph plots the average number of new establishments per 1000 inhabitants across Metropolitan CBSAs for 2006–2018. Data on establishments are from the Business Dynamics Statistics (BDS).

alternative measure of risk preference, which we show in Fig. 5.

Indeed, Fig. 5 plots the share of individuals willing to take risks to receive a financial return for each income group.[14] Fig. 5 indicates that the percentage of individuals willing to take risks is highest for the top 10% of the income distribution. About 8% of individuals within the top 10% of the income distribution show a positive risk attitude. In contrast, on average, only 3.5% of the individuals between the 20th and the 90th percentiles show a positive risk attitude.

Finally, we present the percentage of households who saved part of their income in the previous year by income group.[15] Fig. 6 highlights that the propensity to save increases linearly with income. On average, only 33% of households report having saved the year before in the bottom 20% of the income distribution. On the contrary, 87% of the respondents within the top 10% of the income distribution have saved. Therefore, we conclude that the propensity to save was much higher among the top earners.

Figure A1 in the Appendix also presents binned scatterplots of the relationship between the aforementioned asset variables and log income. All the graphs show a positive relationship between asset composition and income.

To further support these descriptive statistics, we turn to an individual regression analysis, which links each of the three outcome

[14] We measure risk attitude by using information from question X3014 of the SCF. Specifically, the respondent is asked to answer on a scale from 1 to 4 to the following question: "Which of the statements on this page comes closest to the amount of financial risk that you are willing to take when you save or make investments?". We measure risk attitude with an indicator variable that takes a value equal to one if the respondent answers: "Take substantial financial risks expecting to earn substantial returns." This response corresponds to the maximum score, 4.

[15] We measure the propensity to save by using information from question X7508 of the SCF: "Over the past year, would you say that your (family's) spending exceeded your (family's) income, that it was about the same as your income, or that you spent less than your income?". Our measure of propensity to save is an indicator variable equal to one if the respondent has declared that spending was less than income.

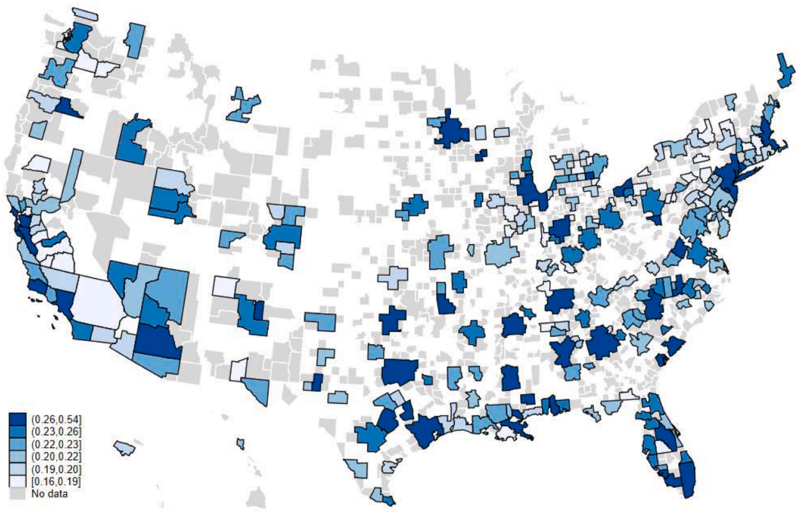

Fig. 2. Geographic distribution of top-income inequality across Metropolitan CBSAs.
Notes: The graph plots the inverse of the Pareto parameter ($\hat{\alpha}^{-1}$), our proxy of top-income inequality, across Metropolitan CBSAs for 2006. The inverse of the Pareto parameter is built using data from the ACS 2005–2007.

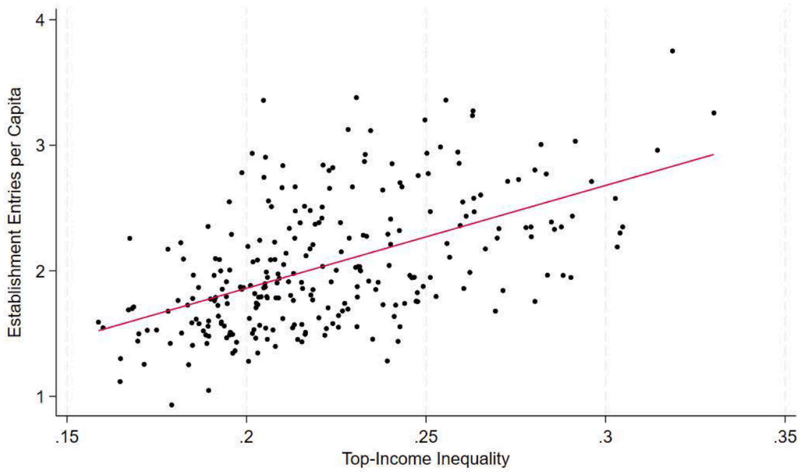

Fig. 3. New establishments per capita and top-income inequality.
Notes: The graph displays the scatterplot between the number of new establishments per 1000 inhabitants against top-income inequality measured by the inverse of the Pareto parameter.

variables described above to whether the household is within the top 10% of the income distribution. Hence, we estimate the following set of regressions:

$$y_i = \alpha + \beta_1 Top10_i + X'_i \beta_2 + e_i \tag{17}$$

where y_i is either the share of risky assets, the risk attitude, or the propensity to save, as described in Figs. 4, 5 and 6, respectively; $Top10_i$ is a dummy variable that takes a value equal to one if the household is in the top 10% of the income distribution and $\boldsymbol{X}'_i$ is a vector of control variables, which includes a series of information about the head of household: the log of the age, a dummy for whether is a male, has a college degree and is married; the log of the number of kids in the household, and categorical dummies for race, macro-occupation and macro-industry.[16] Eq. (17) also includes survey wave fixed effects.

Table 2 shows the results of these specifications. The dependent variables are the share of risky assets held by the individual in

[16] Race: white non-Hispanic, black, Hispanic and others; macro-occupation: managerial/professional occupations, technical/sales/services occupations, other occupations and not working; macro-industry: mining + construction + manufacturing, transportation + communications + utilities and sanitary services + wholesale trade + finance, insurance and real estate, agriculture + retail trade + services + public administration.

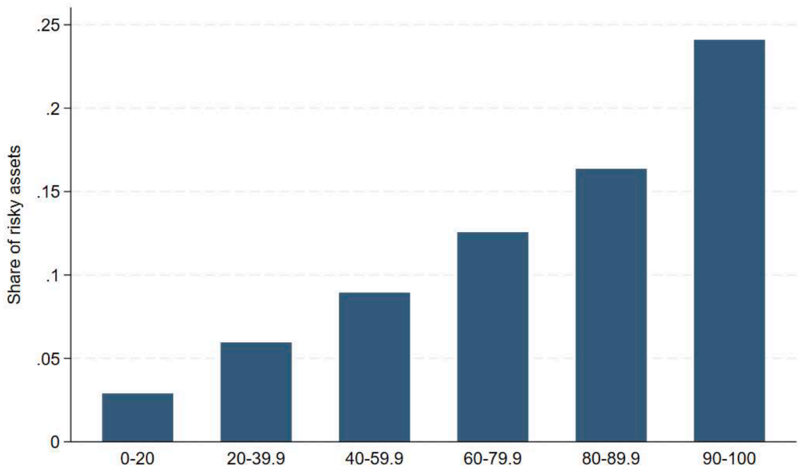

Fig. 4. Share of risky assets across income percentiles.
Notes: The graph shows the share of risky assets (defined in footnote 13) over total financial wealth among USA households across six income groups (0–20%, 20–39.9, 40–59.9, 60–79.9, 80–89.9 and 90–100). Data are from the SCF's 2007, 2010, 2013 and 2016 waves.

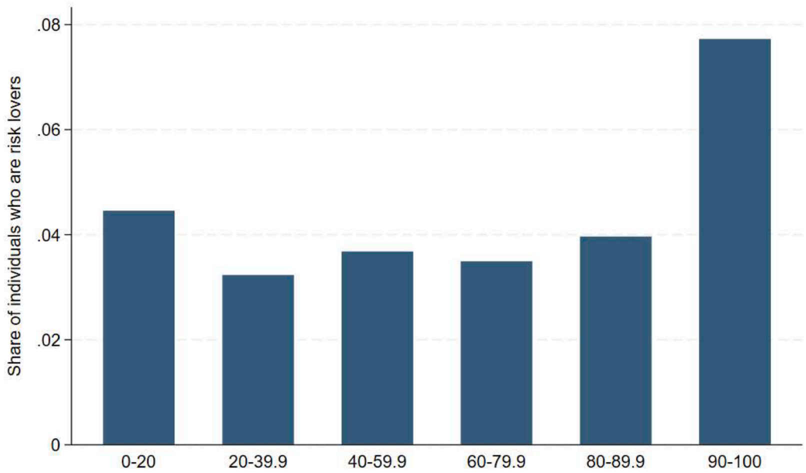

Fig. 5. Risk attitude assets across income percentiles. *Notes:* The graph shows the share of individuals willing to take substantial financial risks (as defined in footnote 14) among USA households across six income groups (0–20%, 20–39.9, 40–59.9, 60–79.9, 80–89.9 and 90–100). Data are from the SCF's 2007, 2010, 2013 and 2016 waves.

column (1), the risk attitude indicator in column (2) and the propensity to save in column (3). All the specifications in Table 2 are estimated by OLS. Since the dependent variables in columns (2) and (3) are categorical, we implement a linear probability model. Table 2 shows that the dummy indicating whether the household's income belongs to the top 10% of the income distribution is positive and statistically significant across all specifications of Table 2. Being in the top 10% increases the probability of having risky assets in the total financial wealth by 9.2%, risk attitude by 3.7% and propensity to save by 23.1%, holding other factors constant.

Table A3 in the Online Appendix, section A2, confirms the results when we include a dummy for each income percentile category. Specifically, the coefficient for being in the top-income percentile is the largest among the income groups across all the specifications.

4.2. Top-income inequality and entrepreneurship

4.2.1. OLS specification

We first present the relationship between the log of the yearly number of establishment entries per capita and top-income inequality, measured by the time-invariant inverse Pareto parameter. Table 3 shows the results.

In column (1), we examine the bivariate relationship between the two variables without fixed effects, while column (2) adds state and year fixed effects to the estimation model. Control (3) shows the results of the bivariate relationship using interacted state-by-year fixed effects. Finally, column (4) adds city control variables. Across all the specifications in columns (1)-(4), we observe a positive correlation between top-income inequality and the number of new establishment entries. Moreover, the estimated coefficient of top-

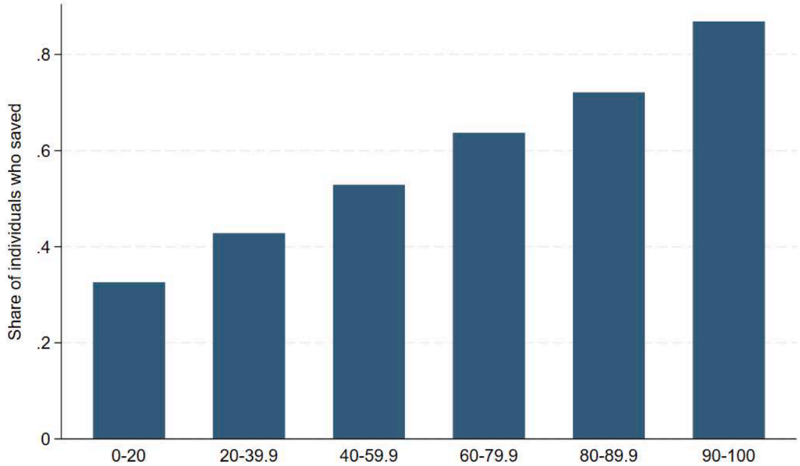

Fig. 6. Propensity to save across income percentiles.
Notes: The graph shows the share of households who have saved in the previous year (as defined in footnote 15) among USA households across six income groups (0–20%, 20–39.9, 40–59.9, 60–79.9, 80–89.9 and 90–100). Data are from the SCF's 2007, 2010, 2013 and 2016 waves.

Table 2
Individual financial outcomes and top-income share.

	(1) Risky assets	(2) Risk attitude	(3) Propensity to save
Top10	0.092***	0.037***	0.231***
	(0.002)	(0.002)	(0.004)
Controls	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes
Observations	113,885	115,810	115,810
R^2	0.177	0.013	0.140

Notes: The table reports the results from estimating different Eq. (17) specifications with OLS. The dependent variables are shown in the column header and explained in the text. Robust standard errors are shown in parentheses. ***p < 0.01.

Table 3
Establishments' entry and top-income inequality.

	(1)	(2)	(3)	(4)
$\log(\alpha^{-1})$	0.929***	0.919***	0.920***	0.704***
	(0.121)	(0.098)	(0.106)	(0.092)
State FE	-	Yes	-	-
Year FE	-	Yes	-	-
State × Year FE	-	-	Yes	Yes
City controls	-	-	-	Yes
Observations	3235	3235	3125	3041
R^2	0.231	0.663	0.671	0.728

Notes: The dependent variable is the log of the yearly number of new establishment entries per capita between 2006 and 2018. All models are estimated with the OLS estimator. City controls include the share of individuals between 16 and 24 years, the share of females, the share of white individuals, the share of foreign-born individuals, the share of individuals employed in the manufacturing sector, the share of unemployed individuals, the Catholic to Protestant ratio, city population growth and city land area. Standard errors clustered at the city level are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

income inequality is statistically significant at the 1% level.[17] Our results are also economically relevant. Looking at the estimates in column (4), a 1% increase in top-income inequality increases establishment entries per capita by 0.7%. The coefficient of top-income inequality is relatively stable as we add controls to the regression model. The coefficient of the inverse Pareto parameter is 0.929 in column (1) when no controls are included and the R-squared equals 0.231. On the contrary, the coefficient becomes 0.704 in column

[17] Table A4, section A2, of the Online Appendix, provides the estimates of Equation (15) with the coefficients for the control variables displayed.

(4) when we add region-by-year fixed effects and city-specific control variables, while the R-squared becomes 0.728.

To properly test the likelihood that omitted variables affect our estimates, we present the results of the Oster test (2019), which enables us to assess how large the unobservables must be, relative to the observables, to cancel out our estimated effect. The Oster test for the estimates obtained in column (4) is 1.79, above the suggested cutoff of 1.[18] The Oster test assumes that the unobservables are uncorrelated with the included control variables. Hence, the omitted variables are assumed to be exogenous to the observables. Consequently, we also implement the approach indicated by Diegert, Masten and Poirier (2022), which relaxes such an assumption. The use of this approach points out that unobservables must be greater by 64% than observables to eliminate the effect we find. However, this seems implausible given the high R-squared we obtain in our full specification. Similar conclusions are reached by Eshaghnia, Heckman and Razavi (2023).

Our evidence suggests that higher top-income inequality substantially affects the formation of new local businesses, as we conjectured. To corroborate the supply-side mechanism we propose, it is helpful to look at the correlation between top-income inequality and a local proxy of venture capitalism. For this reason, we extract information on the number of venture capital deals between USA venture capital companies and USA companies receiving funds in all venture capital stages. We obtain this information from PitchBook, an extensive database on global capital markets. PitchBook aggregates data at the USA state level on the number of venture capital deals per year. We use this information and relate it to the top 1% income share at the state level, sourced from Frank (2009). Figure A2 in the Online Appendix plots the average number of venture capital deals between 2006 and 2018 against the average top 1% income share across USA states. The graph shows a clear positive relationship between the two variables, indicating a spatial correlation between the strength of the venture capitalism industry and top-income inequality. In further specifications presented in Table A9, we obtain that the effect of top-income inequality on entrepreneurial entry is stronger in areas with a greater concentration of venture capital.

4.2.2. Instrumental variable results

The results presented in the previous section capture the correlation between top-income inequality and establishment entry. However, even though we control for several city-level confounding factors and state fixed effects, we cannot completely rule out endogeneity concerns. To address this, we use the weighted ancestral distance from Africa as an instrument for top-income inequality. As discussed in Section 3.5, our instrument combines the predetermined (as of the 2000 Census) city-level distribution of individuals' ancestral countries with the distance between each country's modern capital and Addis Ababa. Accordingly, following the logic of Bartik-type instruments, the exogeneity of the instrument relies on the absence of correlation between the pre-treatment distribution of individuals' ancestries within a city and unobservable determinants of long-term business formation (Borusyak, Hull and Jaravel, 2025). In such settings, one can interpret the exogeneity of the ancestral shares as a set of parallel trend assumptions analogous to those in a difference-in-differences framework. In other words, share exogeneity implies that a researcher must be confident in using each share as an instrument and that each share must satisfy the assumption of parallel trends (Goldsmith-Pinkham, Sorkin and Swift, 2020).

In light of these considerations, we follow Borusyak, Hull and Jaravel (2025) and implement a series of tests to support the validity of our IV. First, since our instrument uses a sample of USA-born individuals, we include the city-level share of the USA-born population in 2000 in all IV specifications. It ensures that our instrument leverages the variation in the composition of individuals' ancestries within the US-born population. Second, we verify whether ancestry shares correlate with pre-trends in the outcome variable. A statistically significant correlation between the outcome variable measured before 2000 (the instrument's year) and the ancestry shares would suggest the presence of unobserved trends that jointly influence both the instrument and the dependent variable. To test this, we regress past levels of establishment entries per capita on the shares of the five most common ancestry groups in the 2000 Census (i.e., United Kingdom, Germany, Mexico, Italy and Ireland), interacted with a linear time trend, while controlling for observable covariates. Table A5 in the Online Appendix reports the results of this test for various pre-treatment windows, to show that our results are robust to different pre-trends of the outcome variables (i.e., 1985–1995, 1980–1995, 1980–1990). Reassuringly, none of the share-specific time trends are statistically significant. Third, we check whether ancestry shares correlate with pre-treatment observable city characteristics measured in 2000. Precisely, we want to exclude cities with specific characteristics that might be correlated with the outcome variable, as these may introduce systematic differences in ancestry shares, jeopardising the exclusion restriction. Table A6 presents the results. Although some shares are weakly correlated with covariates included as controls in our empirical models, they appear to be satisfactorily balanced.

Table 4 presents the results of the IV models. First, the first-stage coefficients confirm that the weighted migratory distance from Africa has a negative and statistically significant effect on top-income inequality. Such a result is in line with the conjecture of Galor, Klemp and Wainstock (2023) that ethnic groups located farther from Africa are associated with lower levels of diversity and, in turn, income inequality. The first-stage F-statistics of the Kleibergen-Paap test are consistently above the accepted threshold of 10 in every specification of Table 4, suggesting that the instrument is powerful. Regarding the second stage, column (1) reports the bivariate relationship between business formation and top-income inequality, including state and year fixed effects, while column (2) includes

[18] The Oster test computes how large the effect of the unobservable must be to cancel out the effect of the observables. Therefore, it may indicate whether an omitted variable bias is present in the analysis. Larger values of the test (δ) are associated with a lower probability that omitted variables influence the results. Instead, when δ=1, the observables are as important as the unobservables. In implementing the Oster test, we set an $R_{max}=\overline{R}\times1.3$, following Oster (2019), who suggests setting it equal to the R^2 obtained by including all the controls multiplied by 1.3. We obtain smaller values for the test when we set larger values of R_{max}, but still above the suggested cutoff.

Table 4
Establishments' entry and top-income inequality – IV estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log (α^{-1})	2.416***	2.429***	1.653***	1.643***	2.117***	0.848***	1.515***
	(0.546)	(0.591)	(0.296)	(0.518)	(0.797)	(0.298)	(0.266)
Log(Consumption pc)				0.124			
				(0.096)			
%College					−0.900		
					(1.036)		
Individualism						0.010	
						(0.008)	
Power distance						0.000	
						(0.012)	
Uncertainty Avoidance						−0.010	
						(0.010)	
Long-term orientation						0.001	
						(0.006)	
Risk-taking							2.172***
							(0.735)
State FE	Yes	-	-	Yes	-	-	-
Year FE	Yes	-	-	Yes	-	-	-
State × Year FE	-	Yes	Yes	-	Yes	Yes	Yes
City controls	-	-	Yes	Yes	Yes	Yes	Yes
First stage coefficient	−0.024***	−0.024***	−0.051***	−0.030***	−0.024***	−0.064***	−0.053***
First stage (K-P) F-stat	15.79	13.57	44.39	15.78	12.48	16.11	39.93
Observations	3158	3021	2937	2937	2937	2937	2937

Notes: The dependent variable is the log of the yearly number of new establishment entries per capita between 2006 and 2018. All models are estimated with the 2SLS estimator. City controls include the share of individuals between 16 and 24 years, the share of females, the share of white individuals, the share of foreign-born individuals, the share of individuals employed in the manufacturing sector, the share of unemployed individuals, the Catholic to Protestant ratio, city population growth and city land area. Standard errors clustered at the city level are presented in parentheses. * $p < 0.10$,** $p < 0.05$,*** $p < 0.01$.

the interaction between state and year fixed effects. We add city-specific control variables since column (3) onwards. In every specification of columns (1)-(3), top-income inequality exerts a positive and statistically significant effect on establishment entries when instrumented, confirming the results of the baseline OLS results. According to the results of the complete specification in column (3), a 1% increase in top income inequality leads to a 1.6% increase in establishments per capita.

Additionally, we test the robustness of our results against different assumptions on standard errors. First, we re-estimate the baseline OLS model and the IV in its full specification (Table 4, column 3), but we use standard errors clustered at the state level. Table A7 shows the results of this alternative specification, which fully confirms the main findings, even though the standard errors are larger in magnitude. Then, we also control for possible spatial autocorrelation in the residuals by using Conley standard errors in place of clustered standard errors. Table A8 shows the results of the OLS and IV estimates with alternative distance cutoffs (i.e., 50 km, 100 km, 200 km). Even if we allow for spatial autocorrelation in the residuals, our main findings remain unchanged.

We also control for other potential confounders to reduce the concern that our instrument affects entrepreneurship through alternative channels other than top-income inequality. First, we directly test the demand-side channel with a proxy of per capita consumption expenditure in durable goods, entering the specification in log form.[19] Results from column (4) of Table 4 show that this demand-side proxy is neither statistically significant nor alters the magnitude of top-income inequality substantially. Second, we also control for the share of individuals with a college degree in column (5): the coefficient of top-income inequality increases and remains highly statistically significant.

Other cultural characteristics of the ancestral country are portable and can be transmitted through generations. For example, cultural traits such as individualism or uncertainty avoidance could foster entrepreneurial entry and be related to higher levels of inequality among USA-born descendants of ancestral populations (Assmann and Ehrl, 2021; Gorodnichenko and Roland, 2017; Nikolaev, Boudreaux and Salahodjaev, 2017). Analogously to the construction of our instrumental variable, we impute, at the city level, measures of Individualism, Power Distance, Uncertainty Avoidance and Long-Term Orientation, using information on the ancestries of USA-born individuals. We source country-level data on these cultural values from Hofstede et al. (2010). Column (6) shows the results of this additional test. As shown in column (6), the estimate of top-income inequality reduces in magnitude but remains highly statistically significant. Additionally, none of the cultural values considered were statistically significant. In column (7), we also account for a measure of country-level risk-taking from Falk et al. (2018). Culturally transmitted values of risk-taking are proven to affect entrepreneurial propensity among second-generation Americans (Chanda and Unel, 2021). In line with the theoretical

[19] Data on per capita consumption expenditure of durable goods are from the Bureau of Economic Analysis. However, these data are only available at the state level. Therefore, the regression specification of column (4) of Table 4 includes only state and year fixed effects in place of state times year fixed effects.

expectations, risk-taking increases business formation in USA cities. Nonetheless, top-income inequality continues to exert a positive and statistically significant effect on the number of new establishments.

Even though top-income inequality remains highly statistically significant when we add further control variables, the change in its magnitude across specifications might signal a potential violation of the exclusion restriction. Therefore, we implement Conley, Hansen and Rossi (2012)'s approach to assess the robustness of our results to violations of the exclusion restriction. As shown in Section A3 of the Online Appendix, even allowing for extensive violations, we still find a positive effect of top-income inequality on establishment entry, supporting the validity of our instrument. Therefore, these results support the intuition that our instrument is only weakly affected by omitted variables.

4.2.3. Confounding factors

Table 5 addresses other potential confounding factors in the income inequality-innovation relationship. First, we explore whether our results are driven by the amount of income going to the bottom 10%. For example, areas with greater top-income inequality may also be poorer and qualify with lower entrepreneurial activity (Lee and Rodriguez-Pose, 2021). Although we control for the share of the white population and the share of foreign-born individuals, which are considered factors associated with greater levels of poverty and inequality, we also add the share of income belonging to the bottom 10% of the income distribution. Columns (1) and (2) show that top-income inequality still exerts a positive and statistically significant effect on new establishments' entry ($p < 0.01$) when the bottom 10% share is included.

Second, we directly compare our results with those of Braggion, Dwarkasing and Ongena (2021) in columns (3) and (4). We construct a measure of wealth inequality in 2006 using data from the Internal Revenue Service (IRS), which provides income dividends at the ZIP code level. Precisely, we add to the estimation model the share of income going to the top 10% of the wealth distribution.[20] Even though wealth inequality exerts a negative and statistically significant effect on business formation, in line with Braggion, Dwarkasing and Ongena (2021)'s conclusions, the coefficient of top-income inequality is not affected and remains positive and statistically significant.

The opposite effects of wealth and income inequality should not surprise. Even though capital rents contribute to shaping income, the wealth and income distributions differ sharply, with wealth being more concentrated than income (Saez, 2017). Indeed, we may encounter high-wealth and low-income as well as high-income and low-wealth individuals. Unlike income, wealth accumulation is tightly linked to power. In line with Braggion, Dwarkasing and Ongena (2021)'s explanation, wealth inequality might deter individuals from starting a new firm if a portion of the wealthy elite harms the provision of local public goods or human capital formation, for example, by hampering redistribution to poor households or public schools to protect its status (Galor and Zeira, 1993; Galor, Moav and Vollrath, 2009), discouraging the entry of new competitors (Cingano, 2014), reducing social mobility (Schechtl, 2024) or influencing political campaign through a disproportionate political power (Bonica and Rosenthal, 2015).

In addition, when wealth is highly concentrated, financial markets tend to become less inclusive: access to credit may be restricted to a narrow elite, making it more difficult for individuals without substantial assets to secure funding. This can lead to an economic environment in which entrepreneurship becomes the preserve of the already wealthy, stifling broader participation and reducing the diversity of ideas and ventures. Contrary to wealth inequality, which tends to grow through asset price inflation and capital gains, income inequality is more responsive to human capital disparities, the strength and pervasiveness of labour market institutions, and appropriation mechanisms of the returns to innovation. Higher income inequality, therefore, may reflect a more socially acceptable economic environment in which the rewards for innovation and risk-taking are high, incentivising entrepreneurial entry among individuals who perceive upward mobility as desirable and attainable.

Third, we explore whether our results are affected by the two most innovative states in the USA, namely California and Massachusetts. Looking at the results implemented in columns (5) and (6), we find that excluding these states does not alter the results.

Fourth, in columns (7) and (8), we investigate whether the effects of the financial crisis drive our results, estimating our relationship over the period 2009–2018. Focusing on the post-2008 period, we find that our results still hold.

4.2.4. Alternative instrumental variable strategy and city fixed effects

In previous sections, we have shown that top-income inequality, when measured by the inverse Pareto coefficient, exerts a positive and statistically significant effect on the entry of new establishments. We also showed that our instrumental variable strategy is robust to the inclusion of several confounding factors and potential violations of the exclusion restriction. However, our baseline estimation model does not fully exploit the panel structure of our data because, for sample size reasons, the measure of income inequality adopted is time-invariant. Hence, our baseline estimation does not include city-specific fixed effects, leaving room for the potential effect of omitted time-invariant characteristics. Additionally, our instrument might be susceptible to correlation with local time-invariant factors, especially if individuals with a certain ancestry sort into specific areas because of deep-rooted factors.

Therefore, to provide even more robust evidence of the relationship between top-income inequality and entrepreneurship, we implement an alternative specification using our entire panel structure. Specifically, we construct the share of income going to the top 10% of the income distribution in each city-year and then estimate a panel model with a two-way fixed effects estimator, including both CBSA (city) and year fixed effects. We follow the same logic in estimating the inverse Pareto coefficient and replace the top-coded income values in our sample with the figures imputed by assuming a Pareto distribution, analogously to Aghion et al. (2019). The

[20] We follow the procedure implemented by Braggion, Dwarkasing and Ongena (2021) to construct the share of financial wealth owned by the top 10%. We invite the reader to refer to their Appendix A.1 for the construction of this variable.

Table 5
Establishments' entry and top-income inequality - Confounding factors and sample selections.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bottom 10%		Top 10% wealth		Excluding CA and MA		Post-2008	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
log (α^{-1})	0.594***	1.894***	0.648***	1.530***	0.609***	1.491***	0.749***	1.750***
	(0.100)	(0.386)	(0.078)	(0.283)	(0.103)	(0.325)	(0.101)	(0.321)
Share Bottom 10%	−16.732**	30.021						
	(6.470)	(17.116)						
Top 10% wealth			−0.637***	−0.459*				
			(0.127)	(0.277)				
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First stage IV coefficient	-	−0.039***	-	−0.056***	-	−0.048***	-	−0.051***
First stage (K-P) F-stat	-	39.69	-	22.78	-	31.03	-	40.07
Observations	3041	2937	2976	2872	2664	2560	2294	2214

Notes: The dependent variable is the log of the yearly number of new establishment entries per capita between 2006 and 2018. The estimation model is indicated in the column head. City controls include the share of individuals between 16 and 24 years, the share of females, the share of white individuals, the share of foreign-born individuals, the share of individuals employed in the manufacturing sector, the share of unemployed individuals, the Catholic to Protestant ratio, city population growth and city land area. Standard errors clustered at the city level are presented in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

instrument adopted in the previous model was time-invariant. Therefore, since we now exploit the within-city variation by accounting for city fixed effects, we employ a shift-share instrument that combines the initial level of the top 10% income share with the leave-one-out 1-year change in the top 10% income share in all other CBSAs except the one considered, analogously to similar strategies adopted by Doerr, Drechsel and Lee (2024) and Pickard, Dohmen and Van Landeghem (2024). We present the results from this alternative specification in Table 6.

Columns (1)-(4) show the results from the OLS specification of the relationship between establishment entry and the top 10% income share. Column (1) presents the results of a bivariate relationship with state and year fixed effects. Column (2) adds the interaction between state and year fixed effects, while column (3) uses city and year fixed effects, hence controlling for both time-invariant city characteristics and macroeconomic shocks common to all areas. Finally, column (4) adds demographic and socio-economic controls, as well as state-by-year fixed effects.

Across all the columns (1)-(4), the coefficient of top-income share turns out to be positive and statistically significant. Columns (5)-(8), on the other hand, implement the instrumental variable strategy with the alternative shift-share instrument for the top 10% income share. The coefficient of the 10% top income share remains positive and statistically significant, providing further support to our hypothesised relationship.

4.2.5. Alternative outcome variables

Finally, we explore alternative outcome variables. Table A9 in the Online Appendix presents the OLS and IV results of these tests.

First, we test our hypothesis using a different measure of business formation, namely, startup creation. Columns (1) and (2) use the SCP measure to study the impact of top-income inequality on the Inverse Hyperbolic Sine transformation of the number of new startups per capita. We find a positive and statistically significant effect ($p < 0.01$) with OLS and IV estimates, proving the robustness of our model to an alternative measure of business formation. Our effect might be driven only by the creation of new establishments by already existing older firms. To rule out this possibility, Columns (3) and (4) look at the number of establishments per capita created by firms younger than 5 years old.[21] However, the estimated coefficient of top-income inequality is still positive and statistically significant.

Then, consistently with our theoretical proposition, we move to test whether top-income inequality relaxes equity constraints and releases new resources to select and finance undertakings with better growth opportunities but high-risk profiles. Extensive research distinguishes between entrepreneurial quantity (the rate of new establishments or startups) and quality (whether new ventures are high-growth, productive, and substantially impact the environment in which they are established). This distinction is salient because low-quality entrepreneurship has less potential for supporting economic growth. Hence, territories facing the introduction of more high-quality entrepreneurship experience better performances (Chowdhury, Audretsch and Belitzki, 2019; Haltiwanger, 2022). Columns (5) and (6) show the effects of top-income inequality on the proportion of new high-tech establishments over the total number of establishments in a city. We extract data on the number of new establishments by industry from the USA County Business Patterns. We rely upon the classification provided by Heckler (2005) and consider high-tech establishments with a NAICS code belonging to the level 1 definition of high-tech industry (Decker et al., 2020).[22] The OLS and IV estimates show a positive and statistically significant

[21] The BDS data report the number of establishment entries at the city level across age categories (0, 1 to 5, 6 to 10 and 11+). To preserve the confidentiality of the respondents, a more detailed disaggregation at this geographical level is not provided.
[22] The reader is invited to refer to the level 1 of Table 1 in Heckler (2005) for the list of industries classified as high-tech.

Table 6
Alternative econometric model – Top 10% income share and alternative IV.

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) IV	(7) IV	(8) IV
Top 10% Income Share	2.235***	2.440***	0.093**	0.095**	6.677***	5.510***	0.371*	0.413**
	(0.170)	(0.193)	(0.044)	(0.044)	(1.239)	(0.848)	(0.199)	(0.194)
State FE	Yes	Yes	Yes	-	Yes	Yes	Yes	-
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	-	Yes	-	Yes	-	Yes	-	Yes
City FE	-	-	Yes	Yes	-	-	Yes	Yes
City controls	-	-	-	Yes	-	-	-	Yes
First stage (K-P) F-stat	-	-	-	-	26.95	52.17	41.29	42.41
Observations	2947	2846	2846	2846	2947	2846	2846	2846

Notes: The dependent variable is the log of the yearly number of new establishment entries per capita between 2006 and 2018. The estimation model is indicated in the column head. City controls include the share of individuals between 16 and 24 years, the share of females, the share of white individuals, the share of foreign-born individuals, the share of individuals employed in the manufacturing sector, the share of unemployed individuals and city population growth. Standard errors clustered at the city level are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

impact (p < 0.01). Such a result confirms our theoretical prediction and strengthens the channel linking inequality to economic growth, as high-quality (technologically intensive and productive) new establishments drive the aggregate effect.

Finally, we evaluate whether our estimates are stronger in areas with a higher concentration of venture capital. Columns (7) and (8) thus present OLS and IV specification of a model where we interact our measure of top-income inequality with the local concentration of venture capital deals at the state level. The results shown in columns (7) and (8) confirm that the effect of top-income inequality on the entry of new establishments is stronger in areas with more venture capital deals.

Finally, columns (9) and (10) present the results of the impact of top-income inequality on the log of the city's GDP per capita, taken as an encompassing measure of economic development, which is positive and statistically significant.

5. Conclusions

This paper examines the relationship between income inequality and innovation, exploring how the increasing supply of equity capital and declining risk aversion, triggered by high income levels, support new business formation at the local level. Our work shows that, despite the variety of forces at play in entrepreneurial decisions, income inequality reduces and actually compensates for the negative effects of equity rationing on the local entry of innovative new firms by increasing the local supply of private equity capital and mitigating the adverse consequences of rationing.

However, whether income inequality is socially problematic largely depends on its causes. If income inequality is the outcome of political inequality, in which political power centralisation favours the uneven collocation of income to the politically connected, it is undesirable. Still, if it stems from the inherent development of economic forces, such as innovative entrepreneurship, public decision-makers should carefully consider the consequences of redistributive interventions (Packard and Bylund, 2018).

Agarwal and Holmes (2019)'s discussion on inequality-correcting interventions is instrumental here. The authors claim that public intervention to reduce income or wealth inequality might generate economic distortions blatantly at odds with procedural justice, which holds that unequal outcomes (read income) are the product of heterogeneous distributions of motivation and ability, and rewards commensurate to value creation.[23] Rather than equality of outcomes, what should matter most is equality of opportunity, which is highly correlated with (upward) mobility in income and status (Chetty et al., 2014).

With the same spirit but adopting a different theoretical perspective, Packard and Bylund (2018) propose moving away from income-inequality-reducing public interventions because of their potential to distort entrepreneurial incentives and judgment. Such a distortion is problematic, as entrepreneurial efforts fuel economic prosperity, as we also maintain in the paper. Most importantly, absolute well-being, rather than income, should attract our attention.[24] The authors claim that highly entrepreneurial societies shall display high income inequality, as an output of disruptive entrepreneurial success leading to monopoly profits, but low(er) disparity in well-being levels across the income distribution because wider and better technological solutions diffuse over society through entrepreneurial competition.

Interestingly, such considerations speak to the equity-efficiency trade-off first formalised in Mirrlees's theory of optimal taxation. That inequality fuels innovative entrepreneurship via high-income individuals resonates with Mirrlees's idea that redistribution comes at an efficiency cost (Mirrlees, 1971) – in our framework, the cost is the reduced risk capital for high-variance, high-return activities like innovation. In other words, inequality creates at the local level a class of agents more willing and able to bear the downside risk of innovation, something that redistribution might inadvertently downsize. However, redistributive taxes answer a societal need for

[23] The authors also discuss distortions coming from an incentive to lobby and use political power to influence public decisions, which, in the absence of perfect oversight of public institutions, can lead to the undesired outcome of public policies reinforcing inequality rather than subverting it. For a similar argument, see the discussion of "kleptocracy" and weak institutions initiated by Acemoglu and Robinson (2015).

[24] The authors adopt a classical economics view and treat well-being as fulfilment from consumption. Although income and well-being are correlated, this correlation is ambiguous and not linear in income due to diminishing marginal utility.

justice and equity that cannot be dismissed. A redistributive equity-innovation trade-off is set, which may be influential for policy drafting.

Hence, distributional policy should be entrepreneurship-neutral, whereas innovation policy should be opportunity-enhancing and pursue extended access to capital, particularly in regions or social groups where inequality constrains the capacity to take entrepreneurial risks (Doerr et al., 2024). It includes strengthening public and mission-oriented financing instruments, inclusive venture capital mechanisms, and funding models that broaden the participation of diverse groups in innovation financing. Consequently, policy frameworks should better coordinate innovation policy with distributional/redistributive tools. While innovation policy should target capital access, opportunity development, and entrepreneurial support, tax and redistribution systems must ensure that the benefits of innovation do not remain concentrated, although procedurally just. Distributional objectives should be addressed through complementary mechanisms that align technological dynamism with broader societal welfare.

Our results suggest an important avenue for research on how the regional distribution of financial intermediaries shapes entrepreneurial entry. In regions with limited sophisticated financial activity, screening new ventures is difficult, and risk assessment is quite preliminary. Only affluent investors can personally and directly assess the chances of success of local undertakings. When financial activities are missing, proximity and personal interactions help with the screening and assessment of new ventures, the access to local tacit knowledge about their quality, and the provision of local finance by affluent investors. On the contrary, when financial intermediaries are present and active, they can improve matching between investors and entrepreneurs.

Our evidence suggests that these intermediation capacities may amplify rather than offset the extent to which a thicker local top tail translates into entrepreneurial entry, consistent with the finding that the inequality–entry relationship is stronger in areas with greater venture capital presence. Hence, our results might suggest that the positive relationship between top-income inequality and business entry is a pathological response to the system's pathological structure, in which risk-bearing resources at the top are most effectively mobilized in places where financial activity is concentrated. Our analysis stirs a new policy area of interventions that broaden access to high-quality intermediation, reducing geographic barriers to finance, expanding the reach of seed and early-stage investors, and facilitating screening and assessment in underserved regions so that entrepreneurial opportunities are less dependent on the presence of a large local top-income group.

6. Data access statement

The authors do not have permission to share all the data underlying the empirical results.

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Declaration of competing interest

The authors do not have any conflicts of interest to declare that are relevant to the content of this article.

Supplementary materials

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Data availability

The authors do not have permission to share data.

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