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Industry Clusters and the Geography of Portfolio Choice

Jawad M. Addoum
Cornell University SC Johnson College of Business
jaddoum@cornell.edu (corresponding author)

Stefanos Delikouras
University of Miami Herbert Business School
sdelikouras@bus.miami.edu

Da Ke
University of South Carolina Darla Moore School of Business
da.ke@moore.sc.edu

George M. Korniotis
University of Miami Herbert Business School
gkorniotis@bus.miami.edu

Abstract

Using detailed data on U.S. households' locations, employment, and financial portfolios, we document that individuals employed in locally clustered industries are more likely to invest in risky assets. This pattern is strongest among individuals with high labor income, employed in skilled occupations, and with strong cognitive skills. Our overall evidence suggests the relation between industry clusters and investment decisions is best explained by clusters enhancing human capital among local industry workers, in turn amplifying their effective risk tolerance. Our findings highlight the important role of local labor market composition in generating household portfolio patterns within and across geographies.

I. Introduction

Households' financial portfolios exhibit immense heterogeneity, with some households placing oversized bets on a single stock while others do not participate in financial markets at all (Campbell (2006), Guiso and Sodini (2013)). Even among twins born and raised in the same family, there is considerable variation in

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portfolio allocations that remains unexplained (Barnea, Cronqvist, and Siegel (2010), Cesarini, Johannesson, Lichtenstein, Sandewall, and Wallace (2010)). Such heterogeneity has important implications for household welfare and the evolution of wealth inequality (Campbell (2016)). Despite many significant contributions in the literature (for recent reviews, see Beshears, Choi, Laibson, and Madrian (2018), Gomes, Haliassos, and Ramadorai (2021)), the substantial variation in household investment decisions is far from fully understood (Gomes (2020)).

In this article, we investigate geography as a potentially important source of the heterogeneity in household portfolios. Our investigation builds on recent work documenting the important role of geography in individuals' economic decisions and outcomes over the life cycle (e.g., Chetty, Hendren, Kline, and Saez (2014), Finkelstein, Gentzkow, and Williams (2016), Chetty and Hendren ((2018a), (2018b)), and Finkelstein, Gentzkow, and Williams (2021)). Distinct from the well-documented preference of individual investors for geographically proximate investments (e.g., Zhu (2002), Ivković and Weisbenner (2005)), our central focus is on the local labor market aspect of geography. This focus is motivated by the substantial spatial differences in labor market characteristics across the United States (Moretti (2011)). In locales with a dominant industry, households living in the same city may be exposed to vastly different labor market conditions, depending on their specific skills. From the perspective of an individual working in a locally dominant industry, the local labor market will tend to present a rich array of employment opportunities. In contrast, the local labor market will appear relatively thin from the standpoint of an individual whose skills are most suitable for an industry that is locally obscure. We investigate how such geographic variation in labor market conditions shapes household portfolio choice.

In particular, we focus on a concept dating back to Marshall (1890) – industry clusters, or local agglomeration economies. In such locations, economic activity is heavily skewed toward specific industries (e.g., tech firms in Silicon Valley, automotive industry in Detroit). To capture industry clusters, we measure the level of local agglomeration for each industry-location pair. Specifically, we adopt a measure commonly used in the literature on industrial localization (Hoover (1936)) – the labor supply share of an industry in a local labor market scaled by its nationwide labor supply share. We construct this measure for each industry-location pair during each decade from 1980 to 2018, using the 5% sample of the 1980–2000 U.S. decennial Census and the 2006–2010 American Community Survey. Our measure successfully captures well-known industry clusters, such as the entertainment and hotel industries in Las Vegas and Orlando, the automobile industry in Detroit, the electronics industry in Silicon Valley, the insurance industry in Hartford, and the asset management industry in New York and Boston.

With this measure, we perform our analysis at the household level using data from two U.S. household surveys: the Annual Social and Economic Supplement (ASEC) of the Current Population Survey and a confidential geocode version of the National Longitudinal Survey of Youth 1979 Cohort (NLSY79). To capture the level of local agglomeration experienced by each household head in their local labor market, we match their location of residence and industry of employment with our local agglomeration measure.

We document in both samples that individuals who work in locally agglomerated industries are significantly more likely to invest in risky assets, all else equal.

Our empirical specifications control for education, income, wealth, and other relevant demographic characteristics, as well as an exhaustive and varying set of location and time-fixed effects. In the NLSY79 sample, where we observe households repeatedly, the local agglomeration effect is even robust to the inclusion of household fixed effects, which difference out a wide array of confounding factors that are fixed within the household. In economic terms, we find that a 1-standard-deviation shift in local agglomeration increases the probability that a household invests in risky assets by 1.2–1.5 percentage points. Relative to the mean risky asset participation rates in our two samples, this effect represents an increase of 3%–5%. This is economically important and compares favorably to the magnitude of other factors affecting stock ownership recently identified in the household finance literature (e.g., Giannetti and Wang (2016)).

We also consider the intensive margin of household risky asset investment in the NLSY79 sample, and find an economically and statistically significant positive local agglomeration effect – that is, an increase in the level of local agglomeration is associated with a higher equity share. Furthermore, we demonstrate that the relation between local agglomeration and household portfolio decisions is robust to including important industry-specific local labor market controls such as local industry competitiveness and innovation. Our baseline result is also robust to excluding the largest cities (e.g., New York, Los Angeles, and Chicago) and the largest industries in the economy (e.g., construction, restaurants, and banking).

Given the strong positive relationship between local agglomeration economies and household investment in risky assets, we move on to evaluate a range of potential underlying mechanisms. We consider several alternative channels that might drive our main empirical findings. One channel of potential importance, emphasized by Branikas, Hong, and Xu (2020), is that households endogenously choose their geographic locations based on latent factors. Importantly, such latent factors may also drive household portfolio decisions. We start by considering risk preferences as one such factor. Under this interpretation, highly risk-tolerant individuals sort into highly agglomerated local economies and are more likely to invest in risky assets simply because of their higher risk appetites. Using a set of qualitative questions on respondents' willingness to take risks, we show in the NLSY79 sample that the impact of local agglomeration economies on household portfolio decisions remains largely unaffected after controlling for risk tolerance.

While this evidence suggests that risk preferences are unlikely to drive our results, there may be other important latent factors. In particular, Branikas et al. (2020) demonstrate that households sort into locations based on their positive views of local economic prospects, and that these views also drive their demand for stocks. Importantly, this mechanism may also drive households to self-select into highly agglomerated local economies. To address this selection concern, we focus on a subsample of individuals in the NLSY79 sample that have lived in the same commuting zone over the period from 1979 to 2014. Among these individuals, concerns about self-selection into local agglomeration economies are mitigated. Our baseline result is preserved among these nonmigrants, which suggests our findings are not driven by households sorting into local agglomeration economies based on latent factors.

An alternative interpretation of our findings is that the local agglomeration effect may be mechanically driven by employers' stock participation plans. Specifically, if firms in locally agglomerated industries grant more stock options to their employees (Kedia and Rajgopal (2009)), then this may mechanically generate the positive correlation between local agglomeration and household investment in risky assets. To evaluate this possibility, we focus on a subsample of households in the NLSY79 sample whose employers do not offer them stock options, and continue to find a large and statistically significant local agglomeration effect.

A related possibility is that firms in locally agglomerated industries may be more likely to provide, or may provide more generous, pension plans to their employees. Again, this could drive a mechanical link between local agglomeration and household investment in risky assets. To assess this possibility, we restrict the NLSY79 sample to the period between 1988 and 1993, when retirement accounts were lumped together with safe assets in the questionnaire design. As a result, reported investment in risky assets is nonretirement related during this period. Importantly, we find that the local agglomeration effect persists with strong economic and statistical significance. Overall, evidence from our two subsample analyses indicates that our findings are driven by neither mechanical effects related to employer stock participation schemes, nor by stockholdings related to employers' pension plan provision.

Next, we investigate the extent to which our findings simply reflect the fact that households have a tendency to overweight geographically proximate and professionally close stocks (e.g., Zhu (2002), Ivković and Weisbenner (2005), and Massa and Simonov (2006)) and that the total supply of local stocks affects household portfolio decisions (e.g., Hong, Kubik, and Stein (2008), Choi, Hong, Kubik, and Thompson (2016)). Specifically, locations with more locally agglomerated industries may feature more publicly traded firms. In turn, local households, many of whom work in the locally agglomerated industry, may be more likely to invest in local firms due to either information advantage or familiarity bias.

We construct a measure of local industry stock supply for each industry-location pair to evaluate the above potential mechanism. For each household, this measure is increasing in the book value of local stocks that are professionally close. We replace the local agglomeration measure in our baseline regressions with the local industry stock supply measure and find that individuals who work in industries with higher local stock supply are indeed more likely to invest in risky assets. However, the stock supply coefficient is rendered small and statistically insignificant in regressions where we also include our local agglomeration measure. In contrast, local agglomeration loads with strong statistical significance and economic magnitudes that even slightly exceed those in our baseline results. We find similar results when we focus on households with no local stocks in their industry of employment and on locations with a low aggregate supply of local stocks.

We also offer evidence distinguishing local agglomeration from geographic and professional proximity effects by examining investors' holdings in individual stocks. Using the Barber and Odean (2000) brokerage data, we follow the approach of Branikas et al. (2020) and proxy for each investor's industry of employment using the industry with the largest labor share in the account holder's zip code. We then compute the share of professionally distant stocks in each account holder's portfolio. In contrast to the professional-proximity-bias hypothesis, we find that investors in more locally agglomerated labor markets are more likely to invest in professionally distant stocks. Taken together, the evidence from our tests suggests that the strong relation between local agglomeration and household portfolio decisions is unlikely to be driven by investors' local and professional biases.

We conclude our analysis by offering evidence consistent with a human capital-based interpretation of our findings. Our tests follow the intuition developed in the literature on how human capital should affect portfolio decisions (e.g., Campbell and Viceira (2002), Cocco, Gomes, and Maenhout (2005), Calvet and Sodini (2014), and Betermier, Calvet, and Sodini (2017)). This literature suggests that human capital can affect portfolio decisions through its effects on lifetime income and total wealth that augment the household's effective risk tolerance. It can also affect such decisions through risk-based channels related to income volatility and the correlation between income growth and risky asset returns. While we find that income risk, both in terms of volatility and correlation with stock returns, does not appear to explain our findings, we do find that the agglomeration effect is strongest among workers with the highest average income. Thus, our findings suggest that the local agglomeration effect operates via the wealth effect of income on human capital, rather than through risk related to human capital returns.

We provide two additional tests supporting the notion that the local agglomeration effect operates through the level of human capital. First, we test the degree to which our findings are stronger among skilled workers in managerial, professional, and technical occupations. Agglomerated local labor markets are likely to hold enhanced prospects for promotions and career-enhancing job changes that are concentrated among such individuals (Moretti (2011)). In turn, we expect the local agglomeration effect to be strongest among this group. Consistent with this idea, we find that the local agglomeration effect is enhanced among skilled workers. Second, we draw on recent studies in labor economics demonstrating that both cognitive and social skills are important components of human capital (e.g., Deming (2017)). We find that the local agglomeration effect is enhanced among workers with high cognitive skills, rather than among those with strong social skills. This result suggests that the local agglomeration effect operates mainly through the cognitive, rather than the social, dimension of human capital.

Our article contributes to the household portfolio choice literature by highlighting the importance of place-based factors such as industry clusters. In contrast, the existing literature predominantly focuses on person-based factors, including, among others, standard and nonstandard preferences and beliefs (Haliassos and Bertaut (1995), Barberis, Huang, and Thaler (2006), and Guiso, Sapienza, and Zingales (2008)), education and financial knowledge (van Rooij, Lusardi, and Alessie (2011), Cole, Paulson, and Shastry (2014)), cognitive abilities and social skills (Hong, Kubik, and Stein (2004), Grinblatt, Keloharju, and Linnainmaa (2011)), personal experiences and identities (Malmendier and Nagel (2011), Knüpfer, Rantapuska, and Sarvimäki (2017), and Ke ((2021), (2022))), and physical attributes such as height and weight (Addoum, Korniotis, and Kumar (2017)). To our best knowledge, this article is the first to focus on local agglomerative patterns. Importantly, this geographic characteristic varies across households even within a local area, distinguishing our findings from the well-documented local bias of individual investors (e.g., Zhu (2002), Ivković and Weisbenner (2005)).

Closest to our article is the work of D'Acunto, Prokopczuk, and Weber (2019), who focus on the local cultural norm aspect of geography. In particular, they document that present-day households in German counties with higher anti-Jewish sentiment during the Nazi period are less likely to participate in the stock market. This article complements their work by underscoring the important role that the local labor market aspect of geography plays in shaping household portfolio choice.

Our article also relates to a recent wave of work that underscores the role of industry clusters in shaping financial outcomes. For example, agglomeration economies have been documented as an important determinant of local consumption growth (Davis, Fisher, and Whited (2014)), corporate investment (Dougal, Parsons, and Titman (2015)), acquisition opportunities (Almazan, Motta, Titman, and Uysal (2010)), and compensation policies (Kedia and Rajgopal (2009)). From a valuation perspective, Engelberg, Ozoguz, and Wang (2018) document that stock prices are more efficient among firms that are headquartered in industry clusters. Our article contributes to this growing literature by being the first to draw the link between industry clusters and household-level financial decisions.

The rest of the article proceeds as follows: Section II details the construction of our local agglomeration measure. Section III outlines our data sources and reports summary statistics. Section IV presents our main findings. Section V explores potential mechanisms. Section VI provides robustness checks and Section VII concludes.

II. Measuring Local Agglomeration

Labor markets in the United States are characterized by significant heterogeneity (Moretti (2011)). Even in the same city, for example, an equity analyst and a lawyer may be exposed to vastly different labor market thickness, depending on the respective numbers of investment companies and legal firms in the city. Hence, it is crucial for our purposes to quantify the *local* agglomeration of each industry to better understand the labor market conditions experienced by individuals living and working in a particular labor market.

A. Local Agglomeration Measure

For our local agglomeration measure, we adopt the location quotient statistic commonly used to quantify industrial localization (Hoover (1936)). Specifically, we define the local agglomeration of industry j in local labor market m as

$$\text{LOCAL\_AGGLOMERATION}_{jm} = s_{jm}/s_{jM}, \tag{1}$$

where s_{jm} is industry j's local labor supply in local labor market m scaled by total local labor supply across all industries in local labor market m (i.e., industry j's local labor supply *share* in labor market m). Similarly, s_{jM} is industry j's aggregate labor supply in the U.S. scaled by total aggregate labor supply across all industries in the U.S. We compute industry-level labor supply by aggregating individual labor

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supply in each industry, where individual labor supply is measured as the product of number of weeks worked in a year and usual number of hours worked per week. A local agglomeration measure that is significantly above 1 indicates that the industry is highly localized and much more important to the local labor market than to the overall U.S. economy.

B. Data on Local Industry Labor Supply

We calculate the level of local agglomeration for each industry-location pair during each decade between 1980 and 2018 using microdata from the 5% sample of the U.S. decennial Census (1980–2000) and the 2006–2010 American Community Survey. These data provide micro-level observations on a wide array of economic and demographic characteristics for more than 50 million individuals. We restrict the sample to workers aged between 16 and 64 who work more than 35 hours per week and 40 weeks per year. We use sampling weights when aggregating individual labor supply to the industry level. Following Autor, Dorn, and Hanson (2019), we use a balanced panel of 222 industries across decades based on the 1990 Census industry codes.

We use two geographic classifications to define labor markets, depending on the household location identifiers in the two households surveys described in Sections III.A and III.B. Specifically, depending on the sample, we define local labor markets as either metropolitan statistical areas (MSAs) or commuting zones (CZs). Our sample includes 238 MSAs and 741 CZs, which are geographic areas meant to capture both urban and rural labor markets (Tolbert and Sizer (1996)).[1] Each decade, we calculate the level of local agglomeration for each industry-MSA pair and industry-CZ pair. Both MSA-based and CZ-based local agglomeration measures are winsorized at 99.5% to mitigate the influence of extreme values.

C. Examples of Highly Agglomerated Local Economies

To derive some intuition related to our local agglomeration measure, we list the 25 most locally agglomerated MSA-industry pairs in 2000 in Table 1. We focus on the 50 largest MSAs based on population and the 50 largest industries based on aggregate labor supply. Several notable industry-MSA pairs show up on the list. For example, Las Vegas, naturally associated with casinos and resorts, claims the top two spots for its local entertainment and hotel industries. These two industries have respective local agglomeration levels of 14.16 and 12.60 in Las Vegas, highlighting their extreme importance to the local economy. In addition, Detroit, known as the "motor city," and San Jose, the MSA containing Silicon Valley, both show up with local agglomeration levels above 10. Hartford, commonly known as the "insurance capital of the world," and New York, the heart of the financial industry, also make the list. Finally, several military bases (e.g., Washington DC, Oklahoma City, San Antonio, and San Diego) rank highly due to their extremely localized nature.

[1]Commuting zones were first developed by Tolbert and Sizer (1996), who analyzed journey-to-work data in the 1990 Census. Rather than relying on arbitrary geographic features (e.g., county lines), CZs capture local labor markets defined by relationships between buyers and suppliers of labor. CZs also have the advantage of capturing nonmetro labor markets.

TABLE 1

Top 25 Local Agglomeration Economies

Table 1 lists the 25 most locally agglomerated MSA-industry pairs in 2000 based on our local agglomeration measure described in Section II.A. We focus on the 50 largest MSAs based on population and the 50 largest industries based on aggregate labor supply. We use the industry classification from the 1990 Census and the MSA delineation from the 1999 Office of Management and Budget.

Rank	MSA	Industry	Local Agglomeration
1	Las Vegas, NV	Miscellaneous entertainment and recreation services	14.16
2	Las Vegas, NV	Hotels and motels	12.60
3	Detroit, MI	Motor vehicles and motor vehicle equipment	11.08
4	San Jose, CA	Electrical machinery, equipment, and supplies	10.81
5	Norfolk-VA Beach-Newport News, VA	National security and international affairs	6.75
6	Washington, DC/MD/VA	National security and international affairs	6.63
7	Orlando, FL	Miscellaneous entertainment and recreation services	6.26
8	Oklahoma City, OK	National security and international affairs	6.04
9	San Antonio, TX	National security and international affairs	5.30
10	San Jose, CA	Computer and data processing services	5.02
11	Austin, TX	Electrical machinery, equipment, and supplies	4.94
12	Hartford-Bristol-Middletown-New Britain, CT	Insurance	4.71
13	Washington, DC/MD/VA	Membership organizations	4.48
14	Orlando, FL	Hotels and motels	4.28
15	Miami-Hialeah, FL	Services incidental to transportation	4.25
16	Baltimore, MD	National security and international affairs	3.98
17	San Diego, CA	National security and international affairs	3.83
18	Washington, DC/MD/VA	Management and public relations services	3.80
19	New York-Northeastern NJ	Security, commodity brokerage, and investment companies	3.75
20	Sacramento, CA	General government	3.46
21	Salt Lake City-Ogden, UT	National security and international affairs	3.40
22	Baltimore, MD	Administration of human resources programs	3.40
23	Memphis, TN/AR/MS	Trucking service	3.36
24	Portland, OR-WA	Electrical machinery, equipment, and supplies	3.29
25	Boston, MA-NH	Security, commodity brokerage, and investment companies	3.19

III. Household Data and Summary Statistics

Apart from the U.S. Census and American Community Survey microdata used to construct our local agglomeration measure, we use two U.S. household surveys as our primary data sources for household portfolio decisions. The first sample is the ASEC of the Current Population Survey and the second is the National Longitudinal Survey of Youth 1979 Cohort (NLSY79). Additionally, we use the Barber and Odean (2000) brokerage data to examine investors' direct stockholdings. We also extract accounting variables and information on industry classifications for publicly traded firms from Standard and Poor's Compustat database. Further, where available, we identify firm headquarter locations using Loughran and McDonald's Augmented 10-X Header Data. In other cases, we obtain headquarter location information from Compustat. We use these measures to construct industry-specific local labor market characteristics such as local industry competitiveness, innovation, and stock supply.

A. ASEC Sample

The ASEC sample is a sequence of annual cross-sectional samples representative of the U.S. population. The ASEC includes an extensive income questionnaire, as well as demographic and socioeconomic characteristics. Following Ke (2021), we exploit the question on whether the household owns any stocks or mutual funds to measure household investment in risky assets. Over our sample period from 1988 to 2018, the ASEC includes over 2 million households. The large sample size allows us to control for household heterogeneity along multiple dimensions and to obtain precise estimates of any local agglomeration effect. Additionally, the ASEC covers multiple cohorts over a 30-year sample period, allowing us to show that our findings from the cohort-specific NLSY79 can be generalized.

B. NLSY79 Sample

To complement the ASEC sample, we also use a confidential geocode version of the NLSY79 survey. The NLSY79 sample follows a nationally representative sample of 12,686 individuals aged between 14 and 22 in 1979. Our sample period starts in 1988, when the NLSY79 collects information about respondents' financial assets for the first time.

Following Angerer and Lam (2009), we classify risky assets as holdings in common stocks, preferred stocks, stock options, government or corporate bonds, and mutual funds.[2] Starting in 1994, individual retirement accounts and tax-deferred accounts are also included in risky assets. Safe assets include savings and checking accounts, money market funds, certificates of deposit, U.S. savings bonds, and personal loans to others. We define the risky asset share of each household's portfolio as the value of risky assets scaled by total liquid wealth, which is the total value of both risky and safe assets.

Although much smaller in size than the ASEC sample, the NLSY79 sample plays an important role in our analysis for several reasons. First, the NLSY79 reports information on household wealth, which is not reported in the ASEC sample but is known to be a key determinant of household portfolio choice (Calvet, Campbell, and Sodini (2007)). Second, the panel structure of the NLSY79 allows us to follow households over time so that we are able to identify a subsample of nonmigrants and address selection concerns.

In addition, the NLSY79 allows for the calculation of household income risk measures and collects information on risk aversion, cognitive ability, and social skill, all of which are crucial for investigating potential mechanisms underlying our findings.

C. Sample Design and Summary Statistics

We restrict both samples to employed household heads aged between 24 and 64 with positive family income. In the ASEC sample, household location is identified at the MSA level, and we therefore match households with MSA-level local

[2]Inclusion of bonds in the definition of risky assets is driven by the NLSY's questionnaire design, which lumped these holdings together with stocks and mutual funds before 2004. We verify that this potential misclassification is not critical for our findings, in that our results are robust to excluding bondholders from the sample.

TABLE 2

Summary Statistics

Table 2 reports summary statistics for the two samples in this article: the Annual Social and Economic Supplement (ASEC) of the Current Population Survey and the National Longitudinal Survey of Youth 1979 Cohort (NLSY79). RISKY_ASSET_INVEST for the ASEC sample is an indicator equal to 1 if the household owns any stocks or mutual funds. RISKY_ASSET_INVEST for the NLSY79 sample is an indicator equal to 1 if the household owns any stocks, government/corporate bonds, or mutual funds. RISKY_ASSET_SHARE is the ratio of the value of risky assets to total liquid wealth, defined as the total value of risky and safe assets. Risky assets include stocks, government/corporate bonds, and mutual funds. Safe assets include savings and checking accounts, money market funds, certificates of deposit, U.S. savings bonds, and personal loans to others. Both samples are restricted to employed household heads aged 24–64 with positive family income. The local agglomeration measure is described in Section II.A. Income and wealth variables are in thousands and deflated to 2012 dollars by the price index for personal consumption expenditures.

	ASEC (N = 671,456)		NLSY79 (N = 71,119)	
	Mean	Std. Dev.	Mean	Std. Dev.
RISKY_ASSET_INVEST	29.81%	45.74%	36.97%	48.27%
RISKY_ASSET_SHARE			24.66%	37.35%
LOCAL_AGGLOMERATION	1.50	1.63	1.52	1.89
MALE	62.09%	48.52%	51.43%	49.98%
WHITE	67.58%	46.81%	56.76%	49.54%
AGE	42.76	10.14	34.84	7.52
COLLEGE	66.38%	47.24%	46.58%	49.88%
MARRIED	65.91%	47.40%	56.16%	49.62%
NUMBER_OF_CHILDREN	1.16	1.20	1.16	1.21
RENT	31.59%	46.49%	47.64%	49.94%
FAMILY_INCOME	90.87	84.52	72.72	122.43
NET_WORTH			134.25	353.52

agglomeration measures based on the MSA of residence and the head's industry of employment. For the NLSY79 sample, where geocodes allow us to match households to CZs, we assign CZ-level local agglomeration measures based on the CZ of residence and the head's industry of employment.

Table 2 reports the summary statistics for both samples. In the ASEC sample, close to 30% of the households invest in stocks or mutual funds and the average level of local agglomeration for heads' industry of employment is 1.50. In the NLSY79 sample, 37% of the households invest in risky assets and the average risky asset share is 25%. The average level of local agglomeration is 1.52.

IV. Main Tests and Results

A. Empirical Methodology

We quantify the impact of local agglomeration economies on household investment in risky assets by estimating multivariate regressions. Specifically, we estimate the following empirical model:

$$y_{ijmt} = \beta \times \text{LOCAL\_AGGLOMERATION}_{jmt} + \gamma' \mathbf{X}_{ijmt} + \delta_{mt} + \varepsilon_{ijmt}, \tag{2}$$

where y is the portfolio choice outcome of interest for household i, working in industry j, and residing in local labor market m in year t. $\mathbf{X}$ is a vector of controls that are important for household investment in risky assets (Campbell (2006), Guiso and Sodini (2013)), including the sex, race, age, education, and marital status of the respondent, the number of children in the household, a homeownership indicator, and family income. We also include local labor market-by-year fixed effects (denoted by δ_{mt}, representing MSA-year (CZ-year) indicators in the ASEC

(NLSY79) sample).[3] In the NLSY79 sample, we further include household wealth as a standard control. In robustness tests, we also take advantage of the longitudinal nature of the NLSY79 by verifying that the effect associated with local agglomeration is robust to the inclusion of household fixed effects.

Our coefficient of interest, β, measures the effect of local agglomeration economies on household investment in risky assets. We run ordinary least squares regressions because of the inclusion of a large number of fixed effects. Standard errors are clustered at the state level in the ASEC sample and at the household level in the NLSY79 sample.

B. Baseline Estimates

Our first set of baseline results is estimated using the ASEC sample and reported in column 1 of Table 3. These estimates document a statistically significant relation between local agglomeration and household investment in risky assets. The coefficient of interest implies that a 1-standard-deviation rise in local agglomeration increases the probability that a household invests in risky assets by 1.5 percentage points. Since less than 30% of the households in the ASEC sample invest in risky assets, this represents an increase of more than 5%. This effect is comparable in magnitude to those reported by recent studies in the literature. For example, Giannetti and Wang (2016) investigate the impact of corporate scandals on household stock market participation and the economic significance of their baseline effect is close to 4%.

In columns 2 and 3 of Table 3, we provide estimates using the NLSY79 sample. We find evidence that echoes our baseline result from the ASEC sample. Specifically, in column 2, we find that local agglomeration is associated with a statistically significant increase in the probability that a household invests in risky assets. This effect is also economically significant. A 1-standard-deviation increase in local agglomeration is associated with a 1.2 percentage point increase in the probability that a household invests in risky assets. Given that 37% of the households in the NLSY79 sample invest in risky assets, the 1.2 percentage points imply an increase of 3% relative to the mean.

In column 3, we consider the intensive margin of household investment in risky assets, and find a statistically significant relation between local agglomeration and household risky asset share. The coefficient of interest suggests that with a 1-standard-deviation rise in local agglomeration, households allocate 0.9% more of their liquid wealth to risky assets. Since households in the NLSY79 sample have an average risky asset share of 25%, this implies an increase of almost 4% relative to the baseline.

[3]Our use of within-location-time variation effectively rules out many competing explanations for the local agglomeration effect we document. In particular, known determinants of household investment decisions that vary across (but are fixed within) geographies cannot be the mechanisms underlying our baseline results (e.g., economic growth stagnation documented by Glaeser, Kallal, Scheinkman, and Shleifer (1992) and Glaeser, Scheinkman, and Shleifer (1995), and wealth effects of local housing growth documented by Chetty, Sándor, and Szeidl (2017). Instead, the underlying mechanism must vary across households within a given geographic location. See Section IV.C and Table 4 for details.

TABLE 3

Baseline Regressions

Table 3 reports OLS estimates of the impact of local agglomeration economies on household investment in risky assets. RISKY_ASSET_INVEST for the ASEC sample is an indicator equal to 1 if the household owns any stocks or mutual funds. RISKY_ASSET_INVEST for the NLSY79 sample is an indicator equal to 1 if the household owns any stocks, government/corporate bonds, or mutual funds. RISKY_ASSET_SHARE is the ratio of the value of risky assets to total liquid wealth, defined as the total value of risky and safe assets. Risky assets include stocks, government/corporate bonds, and mutual funds. Safe assets include savings and checking accounts, money market funds, certificates of deposit, U.S. savings bonds, and personal loans to others. The local agglomeration measure is described in Section II.A. Standard errors in parentheses are clustered at the state level for the ASEC sample and at the household level for the NLSY79 sample. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	ASEC	NLSY79	
	RISKY_ASSET_INVEST	RISKY_ASSET_INVEST	RISKY_ASSET_SHARE
	1	2	3
LOCAL_AGGLOMERATION	0.009***	0.006***	0.005***
	(0.001)	(0.001)	(0.001)
MALE	0.021***	−0.003	−0.002
	(0.001)	(0.005)	(0.003)
WHITE	0.098***	0.061***	0.030***
	(0.006)	(0.006)	(0.004)
AGE	0.002***	−0.001	−0.002**
	(0.000)	(0.001)	(0.001)
COLLEGE	0.114***	0.106***	0.058***
	(0.002)	(0.005)	(0.004)
MARRIED	−0.014***	0.020***	0.016***
	(0.002)	(0.005)	(0.004)
NUMBER_OF_CHILDREN	−0.013***	−0.014***	−0.003**
	(0.001)	(0.002)	(0.001)
RENT	−0.070***	−0.111***	−0.065***
	(0.002)	(0.005)	(0.004)
LOG_FAMILY_INCOME	0.146***	0.098***	0.058***
	(0.003)	(0.003)	(0.002)
NET_WORTH		0.128***	0.100***
		(0.007)	(0.006)
MSA/Czone × year FE	Yes	Yes	Yes
No. of obs.	671,451	69,626	69,626
Adj. R^2	0.197	0.358	0.376

Overall, our main tests in Table 3 demonstrate that local agglomeration is positively associated with household investment in risky assets, both on the extensive and intensive margins. In the following sections, we test the robustness of our baseline results and, more importantly, examine the underlying mechanisms.

C. Alternative Specifications

To understand the stability of our baseline results when accounting for heterogeneity across households and local labor markets, we examine how the local agglomeration effect varies when imposing more stringent fixed effects than in our baseline specification.

In our first alternative specification, reported in column 2 of Table 4, we replace the MSA-by-year fixed effects in our baseline ASEC regression with a set of MSA-sector-occupation-year fixed effects. For comparison, we reestimate our baseline specification with MSA-by-year fixed effects in column 1 using the restricted sample where sector and occupation information is available. In this test, we effectively compare the portfolio choices made by individuals within the same broad industry and occupation group in an MSA in a given year. The broad industry

TABLE 4

Alternative Specifications

Table 4 tests the robustness of the baseline results in Table 3 using alternative specifications. RISKY_ASSET_INVEST for the ASEC sample is an indicator equal to 1 if the household owns any stocks or mutual funds. RISKY_ASSET_INVEST for the NLSY79 sample is an indicator equal to 1 if the household owns any stocks, government/corporate bonds, or mutual funds. The local agglomeration measure is described in Section II.A. The controls from Table 3 are also included. Sectors are classified into the following 10 broad categories: agriculture, forestry, and fishing; mining; construction; manufacturing; transportation, communications, electric, gas, and sanitary services; wholesale trade; retail trade; finance, insurance, and real estate; services; and public administration. Occupations are classified into the following 11 groups: agriculture; food preparation, buildings and grounds, and cleaning; managers; office and administration; operators, fabricators, and laborers; personal care and services; production, craft, and repair; professionals; protective service; sales; and technicians. Standard errors in parentheses are clustered at the MSA level for the ASEC sample and at the household level for the NLSY79 sample. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	ASEC		NLSY79	
	RISKY_ASSET_INVEST		RISKY_ASSET_INVEST	RISKY_ASSET_SHARE
	1	2	3	4
LOCAL_AGGLOMERATION	0.010***	0.009***	0.003**	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes
MSA × year FE	Yes			
MSA × sector × occupation		Yes		
Year FE		Yes		
Czone FE			Yes	Yes
Year FE			Yes	Yes
Household FE			Yes	Yes
No. of obs.	588,522	588,522	70,396	70,396
Adj. R^2	0.200	0.213	0.484	0.464

groups correspond to the 10 SIC divisions and the 11 occupation groups are defined as in Acemoglu and Autor (2011).[4] Importantly, the MSA-sector-occupation-year fixed effects account both for time-specific (e.g., wage volatility) and time-varying (e.g., dynamic hedging motives) differences across broad sector-occupation groups that could affect household investment in risky assets (e.g., Merton (1971), Viceira (2001), and Betermier, Jansson, Parlour, and Walden (2012)).[5]

When we impose the MSA-sector-occupation-year fixed effects in column 2, we continue to find a positive and significant local agglomeration effect on risky asset investment. Comparing the estimates in the first two columns, we find that the effect of local agglomeration is only mildly attenuated by the inclusion of MSA-sector-occupation-year fixed effects.

Next, in columns 3 and 4 of Table 4, we make use of the longitudinal nature of the NLSY79 sample by replacing the CZ-by-year fixed effects in the baseline

[4]Specifically, industries are classified into the following broad sector categories: agriculture, forestry, and fishing; mining; construction; manufacturing; transportation, communications, electric, gas, and sanitary services; wholesale trade; retail trade; finance, insurance, and real estate; services; and public administration. Occupations are classified into the following groups: agriculture; food preparation, buildings and grounds, and cleaning; managers; office and administration; operators, fabricators, and laborers; personal care and services; production, craft, and repair; professionals; protective service; sales; and technicians.

[5]To build intuition, consider two individuals living in the same MSA. One is a materials engineer who works for a medical device manufacturer and the other is a mechanical engineer who works for an automobile parts supplier. According to our broad sector-occupation classifications, both would be in the manufacturing-professional sector-occupation category. However, their local agglomeration measures would still differ on the basis of the relative labor supply shares of medical device versus automobile parts firms in the local economy.

specification with household fixed effects. We also include CZ- and year-level fixed effects. In this specification, we identify the effect of local agglomeration using variation induced by households who either move from one location to another or change industries within a local labor market (or, in a limited set of cases, both). Even when controlling for all observable and unobservable time-invariant household characteristics affecting portfolio decisions, we continue to find a positive local agglomeration effect that is statistically significant at the 5% level. It is worth noting that this within-household analysis differences out confounding factors that are relatively stable within the household, including, among others, sociability (Hong et al. (2004)), trust (Guiso et al. (2008)), cognitive and noncognitive skills (Grinblatt et al. (2011), Kuhnen and Melzer (2018)), and financial sophistication (van Rooij et al. (2011)).

The stability of our estimates across specifications with increasingly restrictive sets of fixed effects rules out a host of potential explanations for our baseline results. In particular, the local agglomeration effect cannot be explained by simple mechanisms that vary over time within states or local labor markets. Even within broad sectors and occupations in a given local labor market, we find that exposure to industry clusters is a quantitatively important driver of portfolio decisions.

V. Mechanisms

Our evidence demonstrates that households employed in locally agglomerated industries exhibit a strong incremental propensity to invest in risky assets. In this section, we investigate potential mechanisms underlying this relation. We begin by examining several potential channels, including the effects of selection, employers' stock participation plans, and local stock supply. We continue by showing that our findings are consistent with a human capital-based interpretation, wherein local agglomeration enhances industry workers' human capital and increases their effective risk tolerance (Bodie, Merton, and Samuelson (1992)).

A. Selection Effects

We acknowledge that our analysis is not immune to endogeneity concerns. One important concern is the sorting of households into local agglomeration economies based on latent factors, which may be correlated with household portfolio decisions (Branikas et al. (2020)). In this section, we consider such potential confounding factors.

1. Risk Preferences

We start by considering risk preferences, which have been shown to impact both household portfolios and career choices (e.g., Vissing-Jørgensen and Attanasio (2003), Bonin, Dohmen, Falk, Huffman, and Sunde (2007)). In particular, one might argue that highly risk-tolerant individuals simply tend to sort into local agglomeration economies. As a result, their observed portfolio decisions may not be driven by agglomerative patterns, but could instead simply be the result of their stronger risk appetites.

TABLE 5

Sorting of Households into Local Agglomeration Economies: The Role of Risk Preference

Table 5 uses the NLSY79 sample to analyze the role of risk preference in explaining the impact of local agglomeration economies on household investment in risky assets. RISKY_ASSET_INVEST is an indicator equal to 1 if the household owns any stocks, government/corporate bonds, or mutual funds. RISKY_ASSET_SHARE is the ratio of the value of risky assets to total liquid wealth, defined as the total value of risky and safe assets. Risky assets include stocks, government/corporate bonds, and mutual funds. Safe assets include savings and checking accounts, money market funds, certificates of deposit, U.S. savings bonds, and personal loans to others. The local agglomeration measure is described in Section II.A. For each of the three self-assessed risk tolerance (RT) measures, the ratings range from 0 to 10, where 0 means "unwilling to take any risk" and 10 means "fully prepared to take risks." We also include the controls from Table 3. Standard errors in parentheses are clustered at the household level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	RISKY_ASSET_INVEST			RISKY_ASSET_SHARE		
	1	2	3	4	5	6
LOCAL_AGGLOMERATION	0.007***	0.007***	0.007***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RT_IN_GENERAL	0.002**			0.001		
	(0.001)			(0.001)		
RT_IN_FINANCIAL_MATTERS		0.007***			0.003***	
		(0.001)			(0.001)	
RT_IN_OCCUPATION			0.004***			0.001**
			(0.001)			(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Czone × year FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	58,074	58,074	58,074	58,074	58,074	58,074
Adj. R^2	0.360	0.361	0.360	0.373	0.374	0.373

To evaluate this possibility, we exploit three questions on willingness to take risks from the 2010–2014 waves of the NLSY79.[6] The first question of the NLSY79 questionnaire used in this analysis asks: "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?" The second question asks: "People can behave differently in different situations. How would you rate your willingness to take risks in financial matters?" The third question asks: "How would you rate your willingness to take risks in your occupation?" For each question, respondents rate themselves from 0 to 10, where 0 means "unwilling to take any risks" and 10 means "fully prepared to take risks."

We include the above three measures of risk tolerance in our baseline regressions as additional controls and report the results in Table 5. According to these results, the risk tolerance measures are positive and statistically significant determinants of the household's decision to invest in risky assets. More importantly, across all specifications, the impact of local agglomeration economies on household investment in risky assets remains statistically and economically significant after we explicitly control for risk tolerance. For example, the estimate of local agglomeration in column 2 of Table 5 implies that with a 1-standard-deviation increase in local agglomeration, households are still 1.3 percentage points more likely to invest in risky assets, even after controlling for risk tolerance in financial matters. Similarly, in column 5, we find that with a 1-standard-deviation shift in local agglomeration, households allocate 1.0% more of their liquid wealth to risky

[6]Dohmen, Falk, Huffman, Sunde, Schupp, and Wagner (2011) find that general qualitative questions on risk preference have better predictive power than experimental evidence and quantitative measures of risk aversion. The data source used in their study is the German Socio-Economic Panel, which has identical general qualitative questions to those in the NLSY79.

assets, holding risk tolerance in financial matters constant. These estimates are even slightly larger than those in the baseline regressions where risk tolerance is not explicitly controlled for. Overall, the results in Table 5 indicate that risk preferences are unlikely to explain our findings.

2. Location Choice and Nonmigrant Households

Next, we consider another important latent factor that may codetermine households' location and portfolio choices. Specifically, Branikas et al. (2020) demonstrate that households sort into locations based on their positive views of local economic prospects and that these views also drive their demand for stocks. Importantly, this mechanism may also drive households to self-select into local agglomeration economies.

To address this selection concern, we examine the impact of local agglomeration on the portfolios of nonmigrant households, a subsample for whom concerns about self-selection into local agglomeration economies are mitigated. We conduct this nonmigrant household analysis in both the ASEC and NLSY79 samples. The results are reported in Table 6.

For the ASEC sample, we consider progressively stricter definitions of nonmigration. In column 1, we restrict the ASEC sample to households living in the same house as 1 year ago and still find a statistically significant relation between local agglomeration and household investment in risky assets. In column 2, we restrict the ASEC sample to households living in the same house as 5 years ago and the local agglomeration effect remains statistically significant. In both cases, the economic significance of the local agglomeration coefficient is about the same as in our baseline result.

TABLE 6

Selection Effects: Evidence from Nonmigrants

Table 6 reports the impact of local agglomeration economies on household investment in risky assets among nonmigrants. In column 1, the ASEC sample is restricted to households living in the same house as 1 year ago. In column 2, the ASEC sample is restricted to households living in the same house as 5 years ago in 1995, 2005, and 2015. The NLSY79 sample is restricted to households that have lived in the same commuting zone from 1979 to 2014. RISKY_ASSET_INVEST for the ASEC sample is an indicator equal to 1 if the household owns any stocks or mutual funds. RISKY_ASSET_INVEST for the NLSY79 sample is an indicator equal to 1 if the household owns any stocks, government/corporate bonds, or mutual funds. RISKY_ASSET_SHARE is the ratio of the value of risky assets to total liquid wealth, defined as the total value of risky and safe assets. Risky assets include stocks, government/corporate bonds, and mutual funds. Safe assets include savings and checking accounts, money market funds, certificates of deposit, U.S. savings bonds, and personal loans to others. The local agglomeration measure is described in Section II.A. We also include the controls from Table 2. Standard errors in parentheses are clustered at the state level for the ASEC sample and at the household level for the NLSY79 sample. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	ASEC		NLSY79	
	Same House as 1 Year Ago	Same House as 5 Years Ago	Same CZ from 1979 to 2014	
	RISKY_ASSET_INVEST	RISKY_ASSET_INVEST	RISKY_ASSET_INVEST	RISKY_ASSET_SHARE
	1	2	3	4
LOCAL_AGGLOMERATION	0.009***	0.007***	0.005***	0.004**
	(0.001)	(0.002)	(0.002)	(0.001)
Controls	Yes	Yes	Yes	Yes
MSA/Czone × year FE	Yes	Yes	Yes	Yes
No. of obs.	572,967	38,939	28,301	28,301
Adj. R^2	0.197	0.185	0.364	0.370

In columns 3 and 4, we exploit the panel nature of the NLSY79 sample and focus on a subset of households that have continuously lived in the same commuting zone over the period from 1979 to 2014. Among these households, the head spent almost 4 decades following their teenage years in the same location. As a result, the local agglomeration effect should be free of other location-related confounders. Among these nonmigrants, we find a statistically and economically significant positive correlation between local agglomeration and household investment in risky assets, both on the extensive and intensive margins.

Collectively, the evidence in Table 6 suggests that our findings do not appear to be driven by the sorting of households into local agglomeration economies based on latent factors. We microfound this result by examining subsamples of households that exhibit restricted (in the ASEC sample) or zero (in the NLSY79 sample) mobility across geographical units.

B. Employer Effects

An alternative interpretation of our findings is that firms in locally agglomerated industries may drive the location effects in companies' stock option policies (Kedia and Rajgopal (2009)). In turn, the positive correlation between local agglomeration and household investment in risky assets would be generated mechanically. To evaluate this possibility, we exploit two questions on stock options from the 2010–2014 waves of the NLSY79. The first question asks: "Were you offered any stock options by your employer?" The second question asks: "Do you expect to be offered a stock option by your current employer in the future?" We restrict the NLSY79 sample to individuals who respond "No" to both questions and rerun our baseline regressions.

The first two columns of Table 7 report the subsample results. In column 1, we find a statistically significant relation between local agglomeration and household risky asset participation among individuals who are not offered any stock options by their employer. Among this subset, a 1-standard-deviation increase in local agglomeration is associated with a 1.3 percentage point increase in the probability that a household invests in risky assets. In column 2, we consider the intensive margin of household investment in risky assets and find that the local agglomeration effect remains statistically and economically significant among these households. Given the evidence that the local agglomeration effect persists even among individuals who are not granted any stock options, our findings are unlikely to be driven by a mechanical link between local agglomeration and stockholdings through stock option grants.

Another possibility is that firms in locally agglomerated industries are more likely to provide (or provide more generous) pension plans to their employees, which can again mechanically lead to the higher stockholdings we document. To assess this possibility, we rerun our baseline regressions restricting our NLSY79 sample to the period from 1988 to 1993. During this period, retirement accounts were lumped with safe assets due to the NLSY79 questionnaire design. As a result, observed investment in risky assets is nonretirement related prior to 1994.

Columns 3 and 4 of Table 7 report these results. In column 3, we find a statistically significant relation between local agglomeration and household

TABLE 7

The Employer Channel: Stock Options and Retirement Accounts

Table 7 focuses on the NLSY79 sample to assess the employer channel potentially underlying the impact of local agglomeration economies on household investment in risky assets. RISKY_ASSET_INVEST is an indicator equal to 1 if the household owns any stocks, government/corporate bonds, or mutual funds. RISKY_ASSET_SHARE is the ratio of the value of risky assets to total liquid wealth, defined as the total value of risky and safe assets. Risky assets include stocks, government/corporate bonds, and mutual funds. Safe assets include savings and checking accounts, money market funds, certificates of deposit, U.S. savings bonds, and personal loans to others. In columns 1 and 2, the NLSY79 sample is restricted to respondents from the 2010–2014 waves who are not offered any stock options by their employer and do not expect to be offered stock options in the future. The analysis period in columns 3 and 4 is between 1988 and 1993, a period when individual retirement accounts are lumped with safe assets and therefore risky asset investment is by definition nonretirement investment. The local agglomeration measure is described in Section II.A. We also include the controls from Table 3. Standard errors in parentheses are clustered at the household level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	No Stock Option		Nonretirement Investment	
	RISKY_ASSET_ INVEST	RISKY_ASSET_ SHARE	RISKY_ASSET_ INVEST	RISKY_ASSET_ SHARE
	1	2	3	4
LOCAL_AGGLOMERATION	0.007***	0.006***	0.006***	0.002**
	(0.002)	(0.001)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes
Czone × year FE	Yes	Yes	Yes	Yes
No. of obs.	40,212	40,212	32,603	32,603
Adj. R^2	0.358	0.375	0.132	0.067

investment in nonretirement risky assets. In column 4, we find that the local agglomeration effect also remains statistically and economically significant on the intensive margin of investment in nonretirement risky assets. Overall, our evidence suggests that the local agglomeration effect is driven by neither mechanical effects related to employer stock participation schemes, nor by stockholdings related to employers' pension plans.

C. Local Bias and Local Stock Supply

A well-documented phenomenon in the individual investor literature is that households tend to overweight geographically proximate stocks in their portfolios (e.g., Zhu (2002), Ivković and Weisbenner (2005)). The literature also provides evidence that households tend to overweight professionally close stocks (e.g., Massa and Simonov (2006), Døskeland and Hvide (2011)) and that the total supply of local stocks affects household portfolios (e.g., Hong et al. (2008), Choi et al. (2016)).

Given these findings, one might be concerned that our results simply reflect these established empirical regularities. In particular, locations with more locally agglomerated industries may feature more publicly traded firms. In turn, local households, many of whom work in the locally agglomerated industry, may be more likely to invest in these local firms because of either information advantage or familiarity bias. To evaluate this interpretation, we construct a measure of local industry stock supply. We define the stock supply of industry j in local labor market m as

$$\text{LOCAL\_INDUSTRY\_STOCK\_SUPPLY}_{jm} = s_{jm}^{b} / s_{jM}^{b}, \quad (3)$$

TABLE 8

Local Agglomeration Versus Local Industry Stock Supply

Table 8 analyzes the role of local industry stock supply in explaining the impact of local agglomeration economies on household investment in risky assets. RISKY_ASSET_INVEST for the ASEC sample is an indicator equal to 1 if the household owns any stocks or mutual funds. RISKY_ASSET_INVEST for the NLSY79 sample is an indicator equal to 1 if the household owns any stocks, government/corporate bonds, or mutual funds. RISKY_ASSET_SHARE is the ratio of the value of risky assets to total liquid wealth, defined as the total value of risky and safe assets. Risky assets include stocks, government/corporate bonds, and mutual funds. Safe assets include savings and checking accounts, money market funds, certificates of deposit, U.S. savings bonds, and personal loans to others. LOCAL_INDUSTRY_STOCK_SUPPLY is an index constructed the same way as the local agglomeration measure described in Section II.A, except that individual labor supply is replaced by firms' book equity. We also include the controls from Table 3. Standard errors in parentheses are clustered at the state level for the ASEC sample and at the household level for the NLSY79 sample. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	ASEC		NLSY79			
	RISKY_ASSET_INVEST		RISKY_ASSET_INVEST		RISKY_ASSET_SHARE	
	1	2	3	4	5	6
LOCAL_INDUSTRY_STOCK_SUPPLY	0.003***	0.001***	0.002**	0.000	0.002**	0.001
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
LOCAL_AGGLOMERATION		0.009***		0.007***		0.005***
		(0.001)		(0.001)		(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
MSA/Czone × year FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	501,044	501,044	53,681	53,681	53,681	53,681
Adj. R^2	0.202	0.203	0.363	0.364	0.379	0.379

where s^b_{jm} is industry j's local stock supply in local labor market m scaled by total local stock supply across all industries in the local labor market. s^b_{jM} is industry j's aggregate stock supply in the U.S. scaled by total aggregate stock supply across all industries in the U.S. We compute industry-level stock supply by aggregating the book equity of all firms in each industry. We include the local industry stock supply measure as an additional control in our regressions and report the results in Table 8.[7]

In column 1, we focus on the ASEC sample and replace the local agglomeration measure in our baseline specification with the local industry stock supply measure. We find a statistically significant relation between local industry stock supply and household investment in risky assets, with comparable magnitude to the local agglomeration effect. In particular, a 1-standard-deviation shift in local industry stock supply implies that the probability of a household investing in risky assets changes by 1.0 percentage points.

Next, in column 2, we include both the local agglomeration and local industry stock supply measures. We find that the economic magnitude of the local industry stock supply coefficient drops by more than one-half (though it remains statistically significant). Importantly, our local agglomeration measure loads significantly, with a large economic magnitude that matches our baseline results.

Columns 3 to 6 of Table 8 document a similar pattern for the NLSY79 sample. In particular, the local industry stock supply effect is positive and significant when included as an isolated regressor. However, the stock supply coefficient is rendered small and statistically insignificant in specifications where we include our local

[7]The correlation between the local agglomeration measure and the local industry stock supply measure is 0.43 for the ASEC sample and 0.37 for the NLSY79 sample.

TABLE 9

Evidence from Local Markets with Low Stock Supply

Table 9 reestimates the baseline regressions in Table 3 restricting the sample to i) households without local industry stock supply in Panel A and to ii) local labor markets with aggregate stock supply below the sample median in Panel B. Standard errors in parentheses are clustered at the MSA level for the ASEC sample and at the household level for the NLSY79 sample. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	ASEC	NLSY79	
	RISKY_ASSET_INVEST	RISKY_ASSET_INVEST	RISKY_ASSET_SHARE
	1	2	3
Panel A. Households Without Local Industry Stock Supply			
LOCAL_AGGLOMERATION	0.007***	0.006***	0.004***
	(0.001)	(0.002)	(0.001)
Controls	Yes	Yes	Yes
MSA/Czone × year FE	Yes	Yes	Yes
No. of obs.	323,776	37,469	37,469
Adj. R^2	0.189	0.369	0.376
Panel B. Areas with Low Aggregate Stock Supply			
LOCAL_AGGLOMERATION	0.006***	0.005***	0.004***
	(0.001)	(0.002)	(0.001)
Controls	Yes	Yes	Yes
MSA/Czone × year FE	Yes	Yes	Yes
No. of obs.	285,543	31,784	31,784
Adj. R^2	0.183	0.360	0.378

agglomeration measure. In contrast, local agglomeration loads with strong statistical significance and economic magnitudes that even slightly exceed those in our baseline results. This evidence suggests that the strong relation between local agglomeration and household portfolio decisions is unlikely to be driven by the local biases of individual investors.

Because of potential nonlinearities in the effect of local industry stock supply, we conduct two additional tests. In Panel A of Table 9, we examine the local agglomeration effect in locations with a low supply of local stocks. In particular, we restrict the sample to households with zero local industry stock supply. Further, in Panel B, we restrict the sample to local labor markets with low (i.e., below median) aggregate stock supply. In both cases, we find that our results continue to hold with strong economic and statistical significance. Overall, the results from these tests suggest that households in locally agglomerated industries invest more in stocks even when these companies are likely to be headquartered far away.

In our final set of tests aimed at distinguishing the local agglomeration effect from economic stories surrounding investors' local and professional stockholding biases, we examine direct stockholdings of investors in the Barber and Odean (2000) brokerage data. Specifically, we test whether investors working in locally agglomerated industries invest more in professionally distant stocks. Following the approach of Branikas et al. (2020), we proxy for each account holder's industry of employment using the industry with the largest labor share in the account holder's zip code. We measure the professionally distant stock share as the ratio of the total value of portfolio stocks not in the account holder's inferred industry of employment to the total portfolio value. In Table 10, we regress the professionally distant stock share on the local agglomeration measure, a standard set of controls including

TABLE 10

Local Agglomeration and Professionally Distant Stock Share

Table 10 analyzes the impact of local agglomeration economies on household portfolio tilt toward professionally distant stocks. The data set used in this analysis includes the month-end account statements of about 78,000 households at a large discount brokerage house from 1991 to 1996 (Barber and Odean (2000)). Professionally distant stock share is measured as the ratio of the total value of stocks that do not match the account holder's sector of employment to the total portfolio value. The account holder's sector of employment is proxied by the largest sector in the account holder's zip code based on labor share. Sectors are based on the SIC divisions and the local agglomeration measure is described in Section II.A. Controls include gender, age, marital status, income level, and home ownership status. Standard errors in parentheses are clustered at the account level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	PROFESSIONALLY_DISTANT_STOCK_SHARE	
	1	2
LOCAL_AGGLOMERATION	0.012**	0.011***
	(0.005)	(0.005)
Controls	Yes	Yes
Sector × year-month FE	Yes	Yes
No. of obs.	1,865,743	1,865,636
Adj. R^2	0.011	0.013

gender, age, marital status, income level, and home ownership status, and sector-by-year-month fixed effects. Contrary to the professional-proximity-bias hypothesis but consistent with our overall economic story and other tests above, we find that investors in more locally agglomerated labor markets are more likely to invest in professionally distant stocks.

D. Human Capital Channel: Local Agglomeration and Income

A potential explanation for our baseline results is that local agglomeration economies enhance workers' human capital. Working in locally agglomerated industries may have several effects on workers' human capital and associated labor income streams. First, economies of scale (Marshall (1890)), improvements in the worker-employer matching process (Helsley and Strange (1990)), and learning spillovers (Glaeser (1999)) can all lead to higher wages among workers in locally agglomerated industries. At the same time, thicker labor markets for workers in such industries can implicitly provide insurance to workers, leading to shorter unemployment spells and lower income volatility (Krugman (1991)). Both effects would lead to higher human capital and, from a portfolio choice perspective, imply a higher optimal weight in risky assets as households exhibit lower effective risk aversion (e.g., Merton (1971), Angerer and Lam (2009)).

A related potential implication of local agglomeration on labor income comes in the form of correlation risk, whereby locally agglomerated industry workers' income growth could be more correlated with stock market returns. For example, if locally agglomerated industries also tend to be the largest industries nationally, then these industries' risks would be systematic. In turn, the income growth of workers in these locally agglomerated industries would be highly correlated with stock market returns. All else equal, portfolio choice theory implies that such workers would want to hedge this income risk through lower stock allocations (Viceira (2001), Campbell and Viceira (2002)).

We test each of these channels in Table 11, where we compute measures of the level, volatility, and correlation risk of workers' income processes, and examine the

TABLE 11

The Human Capital Channel: Income Level, Risk, and Correlation with the Stock Market

Table 11 uses the NLSY79 sample to analyze the interaction effects of local agglomeration with income level, risk, and correlation with the stock market on household investment in risky assets. RISKY_ASSET_INVEST is an indicator equal to 1 if the household owns any stocks, government/corporate bonds, or mutual funds. RISKY_ASSET_SHARE is the ratio of the value of risky assets to total liquid wealth, defined as the total value of risky and safe assets. Risky assets include stocks, government/corporate bonds, and mutual funds. Safe assets include savings and checking accounts, money market funds, certificates of deposit, U.S. savings bonds, and personal loans to others. The local agglomeration measure is described in Section II.A. $\overline{\ln(y)}$ is the average log labor income, $\text{sd}(dy)$ is the standard deviation of labor income growth rate, and $\text{corr}(R_m, dy)$ is the correlation between the value-weighted U.S. stock market return and labor income growth rate. To compute the labor income growth rate and its correlation with the market return, the sample is restricted to respondents with at least 4 years of data. All three income statistics are demeaned. We also include the controls from Table 3. Standard errors in parentheses are clustered at the household level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	RISKY_ASSET_INVEST			RISKY_ASSET_SHARE		
	1	2	3	4	5	6
LOCAL_AGGLOMERATION × $\overline{\ln(y)}$			0.005**			0.004**
			(0.002)			(0.002)
LOCAL_AGGLOMERATION × $\text{sd}(dy)$			0.002			0.002
			(0.007)			(0.005)
LOCAL_AGGLOMERATION × $\text{corr}(R_m, dy)$			0.000			0.000
			(0.004)			(0.003)
LOCAL_AGGLOMERATION	0.006***	0.004***	0.003***	0.005***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\overline{\ln(y)}$		0.066***	0.059***		0.033***	0.028***
		(0.005)	(0.006)		(0.003)	(0.004)
$\text{sd}(dy)$		−0.065***	−0.068***		−0.086***	−0.089***
		(0.013)	(0.018)		(0.010)	(0.013)
$\text{corr}(R_m, dy)$		−0.015**	−0.016**		−0.010**	−0.011*
		(0.006)	(0.008)		(0.005)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Czone × year FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	65,800	65,800	65,800	65,800	65,800	65,800
Adj. R^2	0.356	0.365	0.365	0.372	0.379	0.379

ability of each to mediate the relation between local agglomeration and risky asset investment decisions. Because calculating these measures requires a time series of income observations, we focus this analysis on the sample of NLSY79 households with at least four annual data points. For later comparison, columns 1 and 4 present the baseline local agglomeration coefficient estimates for the population of NLSY79 households who satisfy this condition. The economic magnitudes and statistical significance for both participation and allocation decisions are identical to those estimated using the slightly larger sample in our baseline regressions in Table 3.

In columns 2 and 5, we include measures of the level, volatility, and correlation risk of workers' income as additional controls. Specifically, for NLSY79 households with at least four annual observations, we compute the average log labor income, standard deviation of labor income growth, and correlation between the value-weighted U.S. stock market return and the household's labor income growth rate. For ease of interpretation when we interact these statistics with local agglomeration, we demean each of the income measures.

Including all three measures as additional controls, we find the expected relations. In particular, average labor income is associated with a higher propensity to invest in risky assets as well as higher risky allocations. In contrast, higher income volatility and correlation with stock returns are both negatively associated with these portfolio decisions, consistent with theory and related empirical evidence (Viceira (2001), Campbell and Viceira (2002), and Angerer and Lam (2009)). The strength of the local agglomeration coefficients in columns 2 and 5 indicate that our measure is not simply a proxy for measures of income (both in terms of levels and risk).

We next investigate the extent to which the local agglomeration effect covaries with the income measures. In columns 3 and 6, we further add interactions between local agglomeration and the income measures to our portfolio regressions. We find that the two income risk interactions do not load significantly. In contrast, the interaction between local agglomeration and average log labor income is positive and significant. Together, these results indicate that the local agglomeration effect does not operate through an income risk channel. Instead, the effect is concentrated among workers with the highest average labor income and, in turn, the highest human capital. Furthermore, comparing the remaining local agglomeration coefficients in columns 3 and 6 with our baseline estimates in Table 3 indicates that the human capital channel accounts for about half of the local agglomeration effect.

E. Skilled Labor and the Human Capital Channel

As a further test of the human capital channel, we examine whether the effects of local agglomeration are stronger among skilled workers (e.g., software developers vs. manual laborers). Agglomerated local labor markets are likely to hold enhanced prospects for promotions and career-enhancing job changes that are concentrated among such individuals. In turn, we expect the local agglomeration effect to be strongest among this group. We test this implication by examining the interaction between local agglomeration and skilled labor in our regressions, expecting a positive coefficient for this interaction term. Following Acemoglu and Autor (2011), we classify workers as skilled if their occupation is managerial, professional, or technical. Table 12 reports the results for the ASEC (column 1) and the NLSY79 (columns 2 and 3) samples.

In column 1, we find that the interaction between local agglomeration and skilled labor has a positive and statistically significant effect on risky asset investment. Combined, the estimates of the local agglomeration and interaction terms imply that a 1-standard-deviation increase in local agglomeration in the ASEC sample increases the probability of a skilled worker investing in risky assets by 2.5 percentage points. In contrast, unskilled workers are more likely to invest in risky assets by only 0.7 percentage points for the same shift in local agglomeration. Thus, the statistically significant differential effect of local agglomeration among skilled versus unskilled workers amounts to 1.8 percentage points on average. Given that only 21% of the unskilled workers in the ASEC sample invest in stocks or mutual funds, this differential is also economically important.

In column 2 of Table 12, we find similar results for the households in the NLSY79 sample. Specifically, the estimate for the interaction term between local agglomeration and skilled labor implies that, all else equal, skilled workers in the NLSY79 sample experiencing a 1-standard-deviation increase in local agglomeration are more likely to invest in risky assets by 2.2 percentage points. In contrast, the magnitude of the effect is only 0.9 percentage points among unskilled workers. In column 3, we consider the intensive margin of household investment in risky

TABLE 12

The Human Capital Channel: Evidence from Skilled Labor

Table 12 reports the interaction effects of local agglomeration with skilled labor on household investment in risky assets. RISKY_ASSET_INVEST for the ASEC sample is an indicator equal to 1 if the household owns any stocks or mutual funds. RISKY_ASSET_INVEST for the NLSY79 sample is an indicator equal to 1 if the household owns any stocks, government/corporate bonds, or mutual funds. RISKY_ASSET_SHARE is the ratio of the value of risky assets to total liquid wealth, defined as the total value of risky and safe assets. Risky assets include stocks, government/corporate bonds, and mutual funds. Safe assets include savings and checking accounts, money market funds, certificates of deposit, U.S. savings bonds, and personal loans to others. The local agglomeration measure is described in Section II.A. SKILLED_LABOR is an indicator equal to 1 if the head of household has a professional, managerial, or technical occupation. We also include the controls from Table 3. Standard errors in parentheses are clustered at the state level for the ASEC sample and at the household level for the NLSY79 sample. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	ASEC	NLSY79	
	RISKY_ASSET_INVEST	RISKY_ASSET_INVEST	RISKY_ASSET_SHARE
	1	2	3
LOCAL_AGGLOMERATION × SKILLED_LABOR	0.011***	0.007***	0.005**
	(0.001)	(0.003)	(0.002)
LOCAL_AGGLOMERATION	0.004***	0.005***	0.004***
	(0.001)	(0.001)	(0.001)
SKILLED_LABOR	0.047***	0.043***	0.023***
	(0.002)	(0.006)	(0.004)
Controls	Yes	Yes	Yes
MSA/Czone × year FE	Yes	Yes	Yes
No. of obs.	671,451	69,626	69,626
Adj. R^2	0.201	0.361	0.377

assets. Based on the estimates for the local agglomeration and its interaction with the skilled labor indicator, we find that a 1-standard-deviation increase in local agglomeration implies that skilled workers allocate 1.6% more of their liquid wealth to risky assets, compared with only 0.7% for unskilled workers. Importantly, the differential effects between skilled and unskilled workers are significant at the 5% level or better in both cases.

F. Human Capital Channel: Cognitive Versus Social Skills

In our next test, we analyze the type of skills through which local agglomeration enhances human capital. In particular, we draw on recent studies in labor economics demonstrating that both cognitive and social skills are important components of human capital (e.g., Deming (2017)). Accordingly, we examine the interaction effect between local agglomeration economies and measures of both cognitive and social skills. Because the ASEC survey does not report information on cognitive or social skills, we conduct this analysis in only the NLSY79 sample. Following the labor economics literature (e.g., Neal and Johnson (1996)), we use respondents' standardized scores on the Armed Forces Qualifying Test to proxy for cognitive skill. To measure social skill, we use the standardized measure constructed by Deming (2017), which relies on respondents' self-reported sociability in childhood and adulthood, as well as their participation in high school clubs and team sports.

Table 13 reports the results. Before analyzing any interaction effects, we find that cognitive skill is itself an important determinant of household investment in risky assets, consistent with the findings of Grinblatt et al. (2011). In particular, as shown in columns 1 and 3, a 1-standard-deviation increase in cognitive skill is associated with a 6.1 percentage point increase in the probability that a household

TABLE 13

The Human Capital Channel: Cognitive Versus Social Skills

Table 13 focuses on the NLSY79 sample to analyze the interaction effects of local agglomeration with cognitive and social skills on household investment in risky assets. RISKY_ASSET_INVEST is an indicator equal to 1 if the household owns any stocks, government/corporate bonds, or mutual funds. RISKY_ASSET_SHARE is the ratio of the value of risky assets to total liquid wealth, defined as the total value of risky and safe assets. Risky assets include stocks, government/corporate bonds, and mutual funds. Safe assets include savings and checking accounts, money market funds, certificates of deposit, U.S. savings bonds, and personal loans to others. The local agglomeration measure is described in Section II.A. COGNITIVE_SKILL is measured by respondents' scores on the Armed Forces Qualifying Test, normalized to have a mean of 0 and a standard deviation of 1. SOCIAL_SKILL is measured by respondents' sociability in childhood and adulthood, as well as their participation in high school clubs and team sports, normalized to have a mean of 0 and a standard deviation of 1. We also include the controls from Table 3. Standard errors in parentheses are clustered at the household level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	RISKY_ASSET_INVEST		RISKY_ASSET_SHARE	
	1	2	3	4
LOCAL_AGGLOMERATION × COGNITIVE_SKILL	0.002*	0.003**	0.001	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
LOCAL_AGGLOMERATION × SOCIAL_SKILL		−0.002		−0.002*
		(0.001)		(0.001)
LOCAL_AGGLOMERATION	0.006***	0.006***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
COGNITIVE_SKILL	0.061***	0.057***	0.033***	0.031***
	(0.004)	(0.004)	(0.003)	(0.003)
SOCIAL_SKILL		0.022***		0.011***
		(0.003)		(0.002)
Controls	Yes	Yes	Yes	Yes
Czone × year FE	Yes	Yes	Yes	Yes
No. of obs.	67,102	67,102	67,102	67,102
Adj. R^2	0.368	0.369	0.381	0.382

invests in risky assets and a 3.3 percentage point increase in risky asset allocation. Meanwhile, we find that social skill is also itself an important determinant of household investment in risky assets, which is consistent with the results of Hong et al. (2004). Specifically, as shown in columns 2 and 4, a 1-standard-deviation increase in social skill is associated with a 2.2 percentage point increase in the probability that a household invests in risky assets and a 1.1 percentage point increase in risky asset share.

More importantly, we find in column 1 that cognitive skill also exhibits a statistically significant interaction effect with local agglomeration economies on household investment in risky assets. This interaction effect implies that a 1-standard-deviation increase in cognitive skill enhances the impact of a 1-standard-deviation increase in local agglomeration on the probability that a household invests in risky assets by 0.4 percentage points. In contrast, the results in column 2 show that the interaction effect of local agglomeration economies with social skill is, if anything, negative. Columns 3 and 4 show a similar pattern for the intensive margin of household investment in risky assets. Taken together, these results suggest that local agglomeration impacts household investment in risky assets primarily through the cognitive rather than the social dimension of human capital.

VI. Additional Robustness Checks

We close our empirical analysis with several robustness tests. Results are presented in the Appendix.

A. Local Agglomeration and Local Market Conditions

In our first set of robustness tests, we account for the potential concern that our local agglomeration measure might pick up important industry-level labor market characteristics that vary across geographies, but are not related to the human capital channel we document. For example, workers in locally agglomerated industries may have especially positive views on job growth prospects when working in a location where firms in their industry of employment are innovative. In contrast, workers may feel less job security when working in an industry-location pair where their employer is a local monopolist, even if their industry of employment is relatively agglomerated. To address these confounding factors, we consider two important industry-specific local labor market characteristics as additional regression controls: local industry concentration and innovation.

To measure local industry concentration, we follow Hou and Robinson (2006) and use the Herfindahl–Hirschman Index (HHI) defined as

$$\text{HHI}_{jm} = \sum_i s_{ijm}^2, \tag{4}$$

where s_{ijm} is the book equity share of firm i in industry j in local labor market m. Similar to our local agglomeration measure, we calculate HHI each decade from 1980 to 2018 for each industry-location pair. Small values of the HHI imply that the local market of industry j is shared by many competing firms, whereas large values imply that the local market is concentrated among a few large firms in industry j.

To measure local industry innovation, we calculate the aggregate R&D expenses over the past 5 years of all firms headquartered in a local labor market within an industry, scaled by the total assets of industry firms in the local labor market. We again perform the calculations each decade from 1980 to 2018 for each industry-location pair. Table A1 reports the results of including these additional controls.

Starting with the ASEC sample in column 1, we find a negative and statistically significant relation between local industry concentration and household investment in risky assets. In economic terms, a 1-standard-deviation decrease in industry concentration is associated with a 1.9 percentage point increase in the probability that a household invests in risky assets. Meanwhile, we observe a statistically significant positive correlation between local industry innovation and household investment in risky assets. This result has smaller economic magnitude, with a 1-standard-deviation increase in local industry innovation implying that households are 1.0 percentage points more likely to invest in stocks or mutual funds.

More importantly, in column 1 we show that the impact of local agglomeration economies on household investment in risky assets remains large and statistically significant after we include the industry-specific local labor market controls. In particular, a 1-standard-deviation increase in local agglomeration is associated with a 1.2 percentage point increase in the probability that a household invests in risky assets, with statistical significance remaining at the 1% level.

Turning our attention to the NLSY79 sample, the results in columns 2 and 3 of Table A1 document similar findings for the risky asset participation and allocation decisions. Specifically, consistent with the evidence from the ASEC sample, we find that the effect of local industry concentration on risky asset investment and portfolio allocation is negative. In contrast, the effects of local industry innovation on household portfolio decisions are positive. Last but equally important, columns 2 and 3 indicate that the impact of local agglomeration economies on household investment and asset allocation decisions remains large and statistically significant after we include the industry-specific local labor market controls. Overall, we conclude that our baseline result is robust to including industry-specific local labor market characteristics as additional controls.

B. Size Extremes in Local Agglomeration Economies

In our next set of robustness tests, we address the potential concern that our findings may be driven by a few particularly large metropolitan areas and may therefore not be readily generalizable to smaller cities. One might also be concerned about the effect of particularly small local labor markets, since a small number of industry firms could potentially bias our local agglomeration measure upward in such small markets. An analogous set of concerns applies to industries that are either particularly large or extremely small in terms of nationwide labor supply share. To address these concerns, we exclude extremely small and large local labor markets and industries from our samples and rerun our baseline regressions.

Table A2 reports the results of these tests. In columns 1–3, we exclude the top as well as the bottom 10% of MSAs (CZs) in the ASEC (NLSY79) sample based on aggregate labor supply each decade. To illustrate, the largest MSAs in 2000 include, among others, New York NY, Detroit MI, San Diego CA, and Indianapolis IN. The smallest MSAs in 2000 include, among others, Sumter SC, Yuba City CA, Anniston AL, and Wichita Falls TX. In columns 4–6, we exclude the top as well as the bottom 10% of industries based on aggregate labor supply each decade. For example, in 2000, the largest industries in the sample include, among others, construction, insurance, and motor vehicles, whereas the smallest include shoe repair shops, bowling centers, and tobacco manufacturers.

According to the estimates in column 1, when we exclude the top and bottom 10% of the MSAs in the ASEC sample, the relation between local agglomeration economies and household investment in risky assets remains positive and statistically significant. Furthermore, the economic magnitude of the relation is preserved, with a 1-standard-deviation increase in local agglomeration associated with a 1.1 percentage point increase in the probability that a household invests in risky assets. Columns 2 and 3 of Table A2 show a similar pattern for the NLSY79 sample. Specifically, after excluding the top as well as the bottom 10% of CZs, we continue to find a statistically and economically significant impact of local agglomeration economies on household investment in risky assets, both on the extensive and intensive margins.

Turning our attention to industry size, the estimates in column 4 indicate that the local agglomeration effect remains economically and statistically significant after the top and bottom industries are excluded from the ASEC sample. Similarly,

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in columns 5 and 6, we find that the local agglomeration coefficient in the NLSY79 sample remains largely unchanged despite the exclusion of the largest and smallest industries. Overall, these findings show that our baseline results are robust to excluding the largest and smallest localities and industries.

C. Within-Industry Variation

An alternative approach to examining the local agglomeration effect is to account for heterogeneity across industries by including industry-fixed effects. However, the addition of these fixed effects complicates interpretation of our coefficient of interest, since the local agglomeration measure is already scaled by national labor shares for each industry. As a result, industry effects are implicitly accounted for and the inclusion of industry-fixed effects could result in over-differencing. Nevertheless, in Table A3, we show that the local agglomeration effect in fact becomes much stronger when we add industry-year fixed effects to our baseline specification.

D. Standard Errors

In the NLSY79 sample, we cluster standard errors at the household level because of the panel nature of the data. Even with a comprehensive set of time-varying controls, the repeated household observations could generate a within-household correlation structure in the panel. In Table A4, we consider the impact of reestimating our baseline NLSY79 regressions with standard errors clustered by commuting zone. Further, in Table A5, we reestimate our main results in both the ASEC and NLSY79 samples with standard errors clustered at the industry level as an alternative robustness check. In all cases, we find that our results continue to hold with statistical significance at the 1% level.

VII. Conclusion

In this article, we investigate the role of geography in shaping household portfolio decisions. Analyzing data from two U.S. household surveys, we document a strong positive relation between local agglomeration and household investment in risky assets, both on the extensive and intensive margins. We show that this pattern, previously undocumented in the household finance literature, is economically important and robust across many different regression specifications and subsamples. Additionally, our evidence suggests that the local agglomeration effect mainly operates through the cognitive dimension of human capital.

Our findings underscore the importance of geography in financial decisions, and focus on the effects of local labor markets on household investments. In this context, we show that our results are distinct from investors' local biases that have been well-documented in the literature. Given the substantial welfare implications of heterogeneity in household portfolio allocations, an important line of future research would be to study whether the local agglomeration effect on portfolio choice contributes to the wealth inequality across cities.

Appendix

TABLE A1
Local Industry Concentration and Innovation

Table A1 tests the robustness of the baseline results in Table 3 by including local industry concentration and innovation as controls. LOCAL_INDUSRY_HHI is the Herfindahl–Hirschman Index (HHI) of the book equity of firms headquartered in a local labor market within an industry. LOCAL_INDUSRY_R&D is the aggregate R&D expenses of all the firms headquartered in a local labor market within an industry scaled by the total assets of the industry in the local labor market. RISKY_ASSET_INVEST for the ASEC sample is an indicator equal to 1 if the household owns any stocks or mutual funds. RISKY_ASSET_INVEST for the NLSY79 sample is an indicator equal to 1 if the household owns any stocks, government/corporate bonds, or mutual funds. RISKY_ASSET_SHARE is the ratio of the value of risky assets to total liquid wealth, defined as the total value of risky and safe assets. Risky assets include stocks, government/corporate bonds, and mutual funds. Safe assets include savings and checking accounts, money market funds, certificates of deposit, U.S. savings bonds, and personal loans to others. The local agglomeration measure is described in Section II.A. The controls from Table 3 are also included. Standard errors in parentheses are clustered at the state level for the ASEC sample and at the household level for the NLSY79 sample. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	ASEC	NLSY79	
	RISKY_ASSET_INVEST	RISKY_ASSET_INVEST	RISKY_ASSET_SHARE
	1	2	3
LOCAL_AGGLOMERATION	0.006***	0.006***	0.005**
	(0.002)	(0.003)	(0.002)
LOCAL_INDUSRY_HHI	−0.061***	−0.042***	−0.028**
	(0.0095	(0.016)	(0.012)
LOCAL_INDUSRY_R&D	0.240***	0.302**	0.152
	(0.049)	(0.140)	(0.100)
Controls	Yes	Yes	Yes
MSA/Czone × year FE	Yes	Yes	Yes
No. of obs.	176,712	15,879	15,879
Adj. R^2	0.225	0.353	0.390

TABLE A2
Excluding the Largest and the Smallest Local Labor Markets and Industries

Table A2 tests the robustness of the baseline results in Table 3 by excluding the top and the bottom 10% of local labor markets and industries based on aggregate labor supply. RISKY_ASSET_INVEST for the ASEC sample is an indicator equal to 1 if the household owns any stocks or mutual funds. RISKY_ASSET_INVEST for the NLSY79 sample is an indicator equal to 1 if the household owns any stocks, government/corporate bonds, or mutual funds. RISKY_ASSET_SHARE is the ratio of the value of risky assets to total liquid wealth, defined as the total value of risky and safe assets. Risky assets include stocks, government/corporate bonds, and mutual funds. Safe assets include savings and checking accounts, money market funds, certificates of deposit, U.S. savings bonds, and personal loans to others. The local agglomeration measure is described in Section II.A. The controls from Table 3 are also included. Standard errors in parentheses are clustered at the state level for the ASEC sample and at the household level for the NLSY79 sample. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Excluding Top and Bottom 10% Local Labor Markets			Excluding Top and Bottom 10% Industries		
	ASEC	NLSY79	NLSY79	ASEC	NLSY79	NLSY79
	RISKY_ASSET_INVEST		RISKY_ASSET_SHARE	RISKY_ASSET_INVEST		RISKY_ASSET_SHARE
	1	2	3	4	5	6
LOCAL_AGGLOMERATION	0.006***	0.003**	0.003**	0.008***	0.006**	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
MSA/Czone × year FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	329,709	25,411	25,411	563,178	37,277	37,277
Adj. R^2	0.186	0.375	0.374	0.201	0.361	0.382

TABLE A3
Local Labor Supply Share and Household Portfolio Choice

Table A3 reports OLS estimates of the impact of local agglomeration economies on household invest in risky assets. RISKY_ASSET_INVEST for the ASEC sample is an indicator equal to 1 if the household owns any stocks or mutual funds. RISKY_ASSET_INVEST for the NLSY79 sample is an indicator equal to 1 if the household owns any stocks, government/corporate bonds, or mutual funds. RISKY_ASSET_SHARE is the ratio of the value of risky assets to total liquid wealth, defined as the total value of risky and safe assets. Risky assets include stocks, government/corporate bonds, and mutual funds. Safe assets include savings and checking accounts, money market funds, certificates of deposit, U.S. savings bonds, and personal loans to others. LOCAL_LABOR_SUPPLY_SHARE is measured as an industry's local labor supply in a local labor market scaled by total local labor supply across all industries in that local labor market. Standard errors in parentheses are clustered at the MSA level for the ASEC sample and at the household level for the NLSY79 sample. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	ASEC	NLSY79	
	RISKY_ASSET_INVEST	RISKY_ASSET_INVEST	RISKY_ASSET_SHARE
	1	2	3
LOCAL_LABOR_SUPPLY_SHARE	0.642***	0.506***	0.466***
	(0.107)	(0.216)	(0.159)
Controls	Yes	Yes	Yes
MSA/Czone × year FE	Yes	Yes	Yes
Industry × year FE	Yes	Yes	Yes
No. of obs.	671,380	69,486	69,486
Adj. R^2	0.211	0.377	0.398

TABLE A4
Clustering Standard Errors at the Community Zone Level

Table A4 uses the NLSY79 sample and reestimates the baseline regressions in Table 3 with standard errors clustered at the commuting zone level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	RISKY_ASSET_INVEST	RISKY_ASSET_SHARE
	1	2
LOCAL_AGGLOMERATION	0.006***	0.005***
	(0.001)	(0.001)
Controls	Yes	Yes
Czone × year FE	Yes	Yes
No. of obs.	69,626	69,626
Adj. R^2	0.358	0.376

TABLE A5
Clustering Standard Errors at the Industry Level

Table A5 clusters standard errors at the industry level and reestimates the baseline regressions in Table 3. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	ASEC	NLSY79	
	RISKY_ASSET_INVEST	RISKY_ASSET_INVEST	RISKY_ASSET_SHARE
	1	2	3
LOCAL_AGGLOMERATION	0.009***	0.006***	0.005***
	(0.002)	(0.002)	(0.001)
Controls	Yes	Yes	Yes
MSA/Czone × year FE	Yes	Yes	Yes
No. of obs.	671,451	69,626	69,626
Adj. R^2	0.197	0.358	0.376

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