Psychological Distance and Subjective Prior Beliefs*

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We develop a theoretical framework to explain how households form subjective prior beliefs about expected excess stock returns. Using a novel mathematical definition of familiarity and the Principle of Maximum Entropy, we derive an exponential law linking beliefs to the psychological distance between a household and a firm. The model, estimated using Finnish household portfolio and firm location data, finds that subjective expected returns decrease by a quarter every 71 miles (115 km). Our framework significantly outperforms rational belief models in predicting firm-level stock return variations and highlights how belief distortions create welfare inequality, offering new insights about belief formation.

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In light of the substantial evidence against rational expectations, a central question in economics is how agents form their subjective beliefs.[1] This process is typically divided into two steps: forming prior beliefs and updating priors upon receiving new information. The current literature has focused on how prior beliefs are updated. For instance, the diagnostic expectations framework proposed by Bordalo, Gennaioli, and Shleifer (2018), suggests that individuals overweight salient information, leading to overreaction, while Malmendier and Nagel (2015) emphasize the influence of personal experiences, such as periods of high inflation, on belief formation. However, these theories do not study the formation of initial priors. Our paper aims to address this gap in the literature by developing a novel theory of subjective prior beliefs.[2] Our theory provides a mathematical definition of *familiarity*, a concept developed in Huberman (2001), and uses the *Principle of Maximum Entropy* to show that familiarity follows an exponential law akin to the Universal Law of Generalization in psychology (Shepard, 1987) and power laws in economics and finance (Gabaix, 2009). We then provide empirical support for our theory.

In our theory, the level of household h's familiarity with data about firm n, f_{hn}, distorts objective data. For example, a measured expected excess return of, say, μ_n is distorted to obtain a subjective prior $f_{hn} \times \mu_n$.[3] Existing theory in financial economics, e.g., Bhamra and Uppal (2019), treats familiarity as an exogenous parameter, similar to risk aversion. Thus, exogenously specified heterogeneity in familiarity is used generate heterogeneity in subjective expected excess returns, facilitating the exercise of matching observed features of the data. Unfortunately, when applying such a theory to a data set with many households and firms, the number of familiarity parameters f_{hn} becomes excessively large: in a model with H households and N firms, one would have $H \times N$ free parameters. Our theoretical framework breaks with the idea that familiarity is a free parameter. Instead, we develop a theory in which familiarity depends on measurable quantities, thereby reducing the number of free parameters from $H \times N$ to just two. One can thus discipline the process of generating heterogeneity in prior beliefs, which is essential when interrogating the data.

[1] Evidence that beliefs deviate from rational expectations is available from surveys (Greenwood and Shleifer, 2014, Gennaioli and Shleifer, 2018, Bhandari, Borovička, and Ho, 2019, Adam, Matveev, and Nagel, 2021), empirical studies (Malmendier and Nagel, 2011, 2015, Weber, 2022), and experiments (Afrouzi, Kwon, Landier, Ma, and Thesmar, 2023). For reviews of the literature on modeling beliefs that deviate from rational beliefs, see Camerer (1995, 1998), and Manski (2004, 2018). For the literature that discusses how information rigidities affect expectations, see, for instance, Coibion and Gorodnichenko (2012, 2015).

[2] Our dataset, which is about portfolio holdings of Finnish households, is particularly well-suited for this study because of the high persistence in portfolio holdings over time. This persistence allows us to focus on cross-sectional heterogeneity in prior beliefs rather than the updating of beliefs.

[3] Therefore, when there is complete familiarity, i.e., $f_{hn} = 1$, there is no distortion of μ_n. For the polar case of zero familiarity, the subjective expected excess return becomes zero. For the intermediate case of familiarity between zero and one, the subjective expected excess return lies between μ_n and zero.

We endogenize the familiarity parameters f_{hn} by building on two key ideas: the psychological distance between household h and firm n and the Principle of Maximum Entropy. We assume each household has a mental model of the world, with itself at the center and with firms located relative to itself. The *psychological distance*, D_{hn}, between household h and firm n equals the geographical distance, d_{hn}, between them,[4] if the geographical distance is less than a threshold $\overline{d}$, which we shall determine empirically. However, if the geographical distance exceeds $\overline{d}$, then the psychological distance between this household and the firm is infinite. In this manner, we capture the idea that for households, it is of little importance whether a firm is located 100 miles or 1000 miles beyond the threshold distance—both distances are very large.

To model how psychological distance influences the formation of subjective priors, we introduce the concept of a *familiarity region*, representing the mental boundary within which households perceive data about firms or their assets as familiar. For firms that lie inside the familiarity region, the household trusts the measurement of their expected excess returns; for firms that lie outside the familiarity region, the household sets their expected excess returns to zero. We assume that household h has a familiarity region $\mathcal{F}_h(S)$ of random radius (size) S, which is centered on itself. The mean radius of a household's familiarity region is known to be a constant r, but the distribution of S is unknown. Instead of assuming a particular distribution, we apply the Principle of Maximum Entropy (Jaynes, 1957, 1986) to identify the probability distribution for the radius of the familiarity region and show that it has an exponential distribution.[5]

We define the *familiarity level* household h has with measurements about firm n, f_{hn}, as the *probability* that firm n lies within the household's familiarity region, i.e., $f_{hn} = \Pr\big(\text{firm } n \in \mathcal{F}_h(S)\big)$. We then show that $f_{hn} = \exp\left(\frac{-D_{hn}}{r}\right)$, where D_{hn} is the psychological distance between h and n. Recall that psychological distance equals geographical distance below some threshold distance $\overline{d}$. Therefore, our theory makes it possible to determine $H \times N$ familiarity parameters from just two parameters: $\overline{d}$ and r, along with directly measurable geographical distances.

The familiarity level of a household with a firm determines its subjective prior beliefs about the firm's expected excess returns. Having defined household h's familiarity with firm n as the probability the firm lies within household h's familiarity region, it then follows that the

[4] While in our empirical work psychological distance depends on geographical distance, the theory we develop applies more generally to multidimensional measures of distance that account for, in addition to spatial distance, linguistic, cultural, social, and temporal distances, as we show below (c.f. equation (2)).

[5] The Principle of Maximum Entropy (Jaynes, 1957, 1986) is a method used in various fields such as statistics, physics, and information theory to derive the most unbiased probability distributions possible given a set of known constraints.

household's subjective prior belief is given by the probability-weighted mean of the measured expected excess return, μ_n, and zero, i.e., $\mu_{hn} = f_{hn}\mu_n + (1 - f_{hn})0 = f_{hn}\mu_n$.

We now explain how we estimate the two parameters, $\overline{d}$ and r. Subjective prior beliefs are not observable. However, the portfolio choices of each household reflect its beliefs about firm-level expected excess returns (Giglio, Maggiori, Stroebel, and Utkus, 2021, Beutel and Weber, 2023). We, therefore, use data on portfolio holdings, along with data on household and firm locations, to estimate our model of subjective prior beliefs. Each household's portfolio choices are determined by two margins. First, there is the extensive margin that determines whether a particular stock is included in a household's portfolio; we use this to determine the threshold distance $\overline{d}$, which drives a wedge between psychological and geographical distance. Second, there is the intensive margin, which determines how much of a particular firm's stock to hold once the extensive margin condition has been satisfied; we use this to determine r and, hence, the mean radius of a familiarity region.

To estimate our model of subjective prior beliefs, we use Finnish data on the portfolio holdings of 405,628 households living in 2,923 postal codes and 125 firms. We find that the threshold distance is $\overline{d} = 143$ miles (230 km) and the mean radius of a household's familiarity region is $r = 249$ miles (401 km).[6] Hence, for distances below $\overline{d} = 143$ miles, the psychological distance between a household and a firm equals the geographical distance. Given the estimated value of r, a household's subjective expected excess return for a particular firm's stock will decrease by a quarter for every 71 miles (114 km) increase in geographical distance. Thus, the spatial distance between households and firms has a statistically and economically significant effect on the subjective prior beliefs of households about firms' stock returns. In particular, the sensitivity coefficient representing spatial distance is highly statistically significant in influencing beliefs in all regressions—univariate regressions, regressions including risk-aversion fixed effects, regressions including risk-aversion and stock-characteristic fixed effects, and panel regressions with robust standard errors double clustered at the firm and postal code level.[7]

Our estimates of subjective prior beliefs have been obtained from data on portfolio holdings. The model, however, has not been designed to match moments of stock returns. This provides an opportunity to perform an independent test of the model by investigating how well it predicts

[6] With this threshold distance, our model can correctly classify 75% of extensive margin decisions and our estimate of the mean radius is significant at the 1 percent level.

[7] A possible concern with these empirical results is that they may be driven by households in Helsinki, the main conurbation in Finland, and there may be differences in behavior between rural and urban households. To check if this is indeed the case, we run regressions *excluding* stocks and postal codes in the Helsinki area and find that the results are still both statistically and economically highly significant.

cross-sectional variation in stock-return moments. Our empirical results show that our model of endogenous subjective prior beliefs is superior to a model with rational (undistorted) prior beliefs in explaining the cross-sectional risk-return tradeoff. For instance, when predicting the volatility of stock returns across firms, our model with subjective priors has an R^2 of 50% compared to 35% for the model based on rational priors. We also predict the cross-sectional variation in the ratio of mean excess returns to the variance of returns across firms. Our model has an R^2 of 7% compared to 2% for the model with rational priors.

Finally, we show that our results are also economically significant. We prove that the welfare loss to households in deviating from rational prior beliefs is directly proportional to the relative entropy between their distorted and rational beliefs. The welfare loss can be expressed in the same units as an annualized Sharpe ratio. If households had rational beliefs, the welfare loss would be zero, while the maximum value for the welfare loss is the Sharpe ratio for the Finnish stock market, which is 0.59 per year. We find that the smallest value of the welfare loss when measured as a Sharpe ratio is 0.25 per year, which is for households in the Helsinki region. It is striking that even for households close to Helsinki, where a majority of the firms are headquartered, the value is so much greater than zero. As one moves away from Helsinki, the welfare loss increases and is about 0.57 per year for households farther away from Helsinki, which is almost equal to the entire Sharpe ratio of the Finnish market portfolio.

Related literature. Precise quantitative laws in social sciences are relatively rare compared to the natural sciences, but some laws and regularities have been formulated based on empirical data and are highly regarded for their consistency. Most such regularities are exponential or power laws (Gabaix, 2009). For instance, the seminal work of Shepard (1987) shows that the way humans and animals generalize their responses to stimuli follows an exponential law called the Universal Law of Generalization.[8] In contrast to Shepard (1987), who is interested in the distance between objects of the same type, for example, two worms of different appearance, we are interested in the psychological distance between objects of distinct categories, households and firms. Therefore, our results can also be interpreted as providing, in the context of financial decision-making, a mathematical foundation for Construal Level Theory (Trope and Liberman, 2010), which posits that the psychological distance between an individual and an object is central to decision-making.

[8]Initially rooted in the work of Pavlov (1927), who demonstrated that dogs conditioned to salivate at the sound of a bell also responded to tones of different pitches, *stimulus generalization* is a fundamental concept in psychology that describes how an agent conditioned to respond to a particular stimulus, generalizes this response to a new stimulus. Stimulus generalization is extremely well-documented empirically and is known to occur across a wide variety of agents, including birds, reptiles, amphibians, insects, mammals, and humans.

Power laws also appear in the statistical patterns present in natural languages (Mandelbrot, 1953) and a range of economic phenomena (Gabaix, 2016), such as Zipf's Law for city sizes (Gabaix, 1999), compensation for CEOs (Gabaix and Landier, 2008), and gravity models for international trade. Finding theoretical foundations for such power laws has been challenging. For instance, while the first full development of the trade equation is credited to Tinbergen (1962), its lack of theoretical foundation was a major weakness (Head and Mayer, 2014) until Chaney (2018) provided a theoretical explanation for the role of distance. To provide theoretical foundations for a quantitative law, Gabaix (2009) argues for using efficiency principles whereby an important objective is optimized. The efficiency principle we use is the Principle of Maximum Entropy, and we show that it gives rise to an exponential law, which is supported by the data.

Next, we discuss how our work is related to the literature on belief formation. Beliefs are central to financial decision-making but challenging to identify. The rational expectations paradigm (Muth, 1961, Lucas, 1976) cleverly sidesteps this challenge by assuming the decision maker can recover the objective probability distribution from the data. However, Manski (2004) has argued that instead of assuming rational expectations, one should test if the assumption of rational expectations is valid. There is overwhelming evidence from surveys, empirical studies, and experiments showing that beliefs deviate from rational expectations (cf. footnote 1).

In response to the substantial evidence against rational expectations, recent work has developed new models of expectation formation, such as diagnostic expectations (Gennaioli, Shleifer, and Vishny, 2015, Gennaioli and Shleifer, 2018, Bordalo et al., 2018, Bordalo, Gennaioli, and Shleifer, 2020b, Bordalo, Gennaioli, Ma, and Shleifer, 2020a) and adaptive expectations (Malmendier and Nagel, 2015, Adam et al., 2021, Nagel and Xu, 2022).[9] These models take subjective priors as given and develop new updating rules. In contrast to this work, we focus on the origin of subjective prior beliefs. We build on ideas from psychology to develop a theoretical framework for deviating from rational objective priors in a disciplined fashion.[10] A separate strand of the literature has focused, instead of biased expectations, on an information channel for explaining individual behavior, see, e.g., Van Nieuwerburgh and Veldkamp (2009, 2010). In these models, learning is rational, but what agents choose to learn is influenced by their priors; our model offers one explanation for why priors may differ across agents.

Our empirical results rely on the same data as Grinblatt and Keloharju (2001), who focus on the extensive-margin portfolio decision of households, i.e., the decision whether or not to

[9] For surveys of the literature on expectation formation, see Malmendier (2021) and Adam and Nagel (2023).

[10] How psychology affects decision-making in economics and finance is discussed in Barberis, Shleifer, and Vishny (1998), Shleifer (2000), Barberis and Thaler (2003), Hirshleifer (2001, 2015), Shefrin (2007, 2010), Statman (2010, 2011), Barberis (2018), Barberis, Jin, and Wang (2021), and Barberis and Jin (2023).

hold a particular stock. Grinblatt and Keloharju (2001) do not study the intensive margin, nor do they link portfolio holdings to beliefs. The intensive margin is more subtle and understudied in the context of individual stocks and has been examined only in the context of aggregate investment in the stock market via a fund or ETF (see, e.g., Giglio et al., 2021, Hvide, Meling, Mogstad, and Vestad, 2024). Empirically, different households invest different fractions of their wealth in a particular stock. Standard portfolio theory suggests this is driven by heterogeneity in households' subjective expectations about that stock's risk and return. In contrast to existing work, we derive a precise quantitative law linking subjective prior beliefs to psychological distance. In our theory, a single parameter, the mean radius of a household's familiarity region, r, governs how the psychological distance between a household and a firm impacts the household's subjective expected excess return for this firm and, hence the intensive margin.

Finally, our paper provides microfoundations for theoretical models such as Merton (1987, p. 487) that assume that "each investor knows only about a subset of the available securities." Specifically, our model shows how the subset of stocks that each investor knows about depends on the psychological distance between the household and the firm issuing that stock. Our work also provides a unifying framework for belief distortions, that is microfounded and based on psychological distance, for the large empirical literature on deviations from rational beliefs.[11]

The rest of this paper is organized as follows. In Section I, we describe the main features of our model and present our key theoretical results. In Section II, we estimate our model linking subjective prior beliefs about firm-level stock returns to psychological distance. In Section III, we use the estimated model to measure the welfare losses that arise as a consequence of deviating from rational prior beliefs and show how these losses relate to spatial distance. We conclude in Section IV. Additional details regarding our empirical results are reported in the appendix.

I. A Model of Subjective Beliefs

The principal objective of this section is to develop a parsimonious framework to show how psychological distance distorts subjective prior beliefs about expected excess returns relative to

[11]The following empirical papers in financial economics provide evidence on how individuals' decisions are influenced by the different dimensions of psychological distance: spatial distance (French and Poterba, 1991, Coval and Moskovitz, 1999a,b, Huberman, 2001, Grinblatt and Keloharju, 2001, Kuchler and Zafar, 2019, Branikas, Hong, and Xu, 2020), cultural and linguistic distance (Grinblatt and Keloharju, 2001, Guiso, Sapienza, and Zingales, 2006, Laudenbach, Malmendier, and Niessen-Ruenzi, 2018, Badarinza, Ramadorai, and Shimizu, 2022, D'Acunto, Prokopczuk, and Weber, 2019), temporal distance (Kaustia and Knüpfer, 2008, 2012, Greenwood and Nagel, 2009, Chiang, Hirshleifer, Qian, and Sherman, 2011, Malmendier and Nagel, 2011, 2015, Knüpfer, Rantapuska, and Sarvimäki, 2017), and social distance (Shive, 2010, Das, Kuhnen, and Nagel, 2020, Bailey, Cao, Kuchler, and Stroebel, 2018, Hirshleifer, 2020, Pedersen, 2022).

rational prior beliefs. Our results hold in both discrete and continuous time; for expositional ease, we present them in discrete time and consider an IID setting over time.

We consider a model of a finite number of households and stocks. The first part of this section describes our model for stock returns and households' investment opportunities. The second part defines psychological distance and shows how it affects households' subjective priors about expected excess stock returns. The third part establishes the link between these subjective priors and households' portfolio choices. The last part shows the welfare losses resulting from the deviation of subjective prior beliefs from rational beliefs.

A. Households' Investment Opportunities and Stock Returns

There are H households, indexed by $h \in \{1, \ldots, H\}$. Each household h can invest its wealth in a risk-free asset that has a (gross) interest rate R_f between dates t and $t+1$. Each household can also invest in the risky stocks of N firms, indexed by $n \in \{1, \ldots, N\}$, with the (gross) return on each stock denoted by R_n.

The proportion of household h's wealth invested in stock n at each date t is denoted by ω_{hn} and so the household's dynamic budget constraint relating date t wealth, $W_{h,t}$, to date $t+1$ wealth, $W_{h,t+1}$, is

$$W_{h,t+1} = W_{h,t}\left[\big(1 - \sum_{n=1}^{N} \omega_{hn}\big)R_f + \sum_{n=1}^{N} \omega_{hn} R_{n,}\right] = W_{h,t}\left[R_f + \sum_{n=1}^{N} \omega_{hn}(R_n - R_f)\right].$$

There is a reference probability measure $\mathbb{P}$ that represents objective prior beliefs. The expected return in excess of the risk-free rate under $\mathbb{P}$ is

$$\mu_n = \mathbb{E}[R_n] - R_f,\ n \in \{1, \ldots, N\}.$$

Denoting the N-dimensional vector of ones by $\mathbf{1}$, the N-dimensional vector of expected excess returns under the objective measure by $\boldsymbol{\mu}$, the $N \times N$ variance-covariance matrix of returns by the matrix V, and the N-dimensional vector of portfolio weights ω_{hn} by $\boldsymbol{\omega}_h$, the expected return on wealth, under *objective* prior beliefs, is

$$\mathbb{E}\left[\frac{W_{h,t+1}}{W_{h,t}}\right] = (1 - \boldsymbol{\omega}_h^\top \mathbf{1})R_f + \boldsymbol{\omega}_h^\top\, \mathbb{E}[R_n] = R_f + \boldsymbol{\omega}_h^\top \boldsymbol{\mu},$$

and the variance of the return on wealth is

$$\text{Var}\left[\frac{W_{h,t+1}}{W_{h,t}}\right] = \boldsymbol{\omega}_h^\top V \boldsymbol{\omega}_h.$$

We assume that each household h is a mean-variance investor and to choose her optimal portfolio uses, instead of objective prior beliefs about expected excess returns, $\boldsymbol{\mu}$, her *subjective* prior beliefs, $\boldsymbol{\mu}_h = (\mu_{h1}, \mu_{h1}, \ldots, \mu_{hN})$:

$$\max_{\boldsymbol{\omega}_h} \; R_f + \boldsymbol{\omega}_h^\top \boldsymbol{\mu}_h - \frac{1}{2}\gamma_h \boldsymbol{\omega}_h^\top V \boldsymbol{\omega}_h. \tag{1}$$

Below, we explain how the household forms her subjective prior beliefs about expected excess returns, $\boldsymbol{\mu}_h$.[12]

B. *From Objective to Subjective Expected Returns*

In this section, we explain how a household forms subjective priors about expected excess returns. We first describe how we go from the well-understood concept of geographical distance to psychological distance. Then, we explain that each household has a *familiarity region*, which is centered on itself. Finally, we define the *level of familiarity* a household has with the expected return measurement of a particular firm as the probability that the firm lies within the household's familiarity region and use this to obtain the relation between objective and subjective priors about expected excess returns.

B.1. *From Geographical Distance to Psychological Distance*

Each household is located at the origin in its own two-dimensional geographical space, and firms are located in the same space. We measure the *geographical distance* between a household and a firm in the usual way, using the Euclidean metric in miles (or kilometers). For example, if firm n is located at the coordinates (X_n, Y_n), then its *geographical distance* from household h, which is located at the origin $(0, 0)$, is given by

$$d_{hn} = \sqrt{X_n^2 + Y_n^2}.$$

Figure 1 illustrates a household h and two firms, $n = \{1, 2\}$.

We now introduce a new measure of distance, distinct from geographical distance, which we refer to as *psychological distance*. Psychological distance is an important concept that is used in Construal Level Theory (Trope and Liberman, 2010) to capture the perceived extent to which an object, event, or idea feels remote from an individual's direct experience, encompassing

[12]Note that we study subjective prior beliefs about expected excess returns but not the volatility of returns because it is well known (Merton, 1980) that it is much easier to obtain a precise estimate of return volatility than of return means. Moreover, Girsanov's Theorem tells us that return volatility is the same under different probability measures. For a version of Girsanov's theorem in discrete time, see Föllmer and Schied (2011, sec. 10.2).

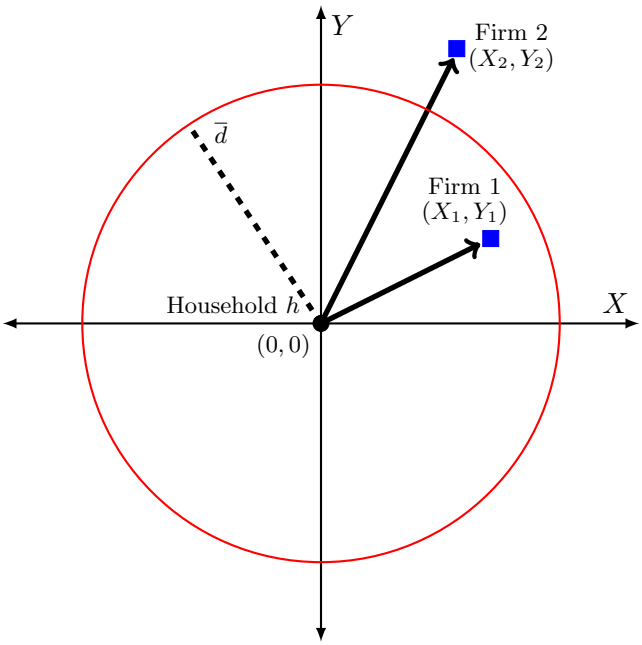


FIGURE 1. FROM GEOGRAPHICAL DISTANCE TO PSYCHOLOGICAL DISTANCE

The figure shows household h and two firms, $n = \{1, 2\}$ in two-dimensional *geographical space*, with the origin at the household's location. The geographical distance of Firm 1 from household h is $d_{h1} = \sqrt{X_1^2 + Y_1^2}$ and of Firm 2 is $d_{h2} = \sqrt{X_2^2 + Y_2^2}$. In the figure, $\overline{d}$ denotes the threshold distance. Therefore, using Definition 1, the *psychological distance* of Firm 1 from household h is $D_{h1} = d_{h1}$ and of Firm 2 is $D_{h2} = \infty$.

dimensions such as temporal, spatial, social, and hypothetical aspects. Trope and Liberman (2010, p. 440) explain that "People directly experience only the here and now. It is impossible to experience the past and the future, other places, other people, and alternatives to reality. And yet, memories, plans, predictions, hopes, and counterfactual alternatives populate our minds, influence our emotions, and guide our choice and action. How do we transcend the here and now to include distant entities? ... How do we plan for the distant future, understand other people's point of view, and take into account hypothetical alternatives to reality? Construal level theory proposes that we do so by forming abstract mental construals of distal objects. ... Psychological distance is a subjective experience that something is close or far away from the self, here, and now." Motivated by this, we define psychological distance as follows.

DEFINITION 1. *Denoting by $\overline{d}$ a threshold distance, the psychological distance between firm n and household h, D_{hn}, in terms of geographical distance, d_{hn}, is defined as*

$$D_{hn} = \begin{cases} d_{hn}, & d_{hn} \leq \overline{d} \\ \infty, & d_{hn} > \overline{d}. \end{cases}$$

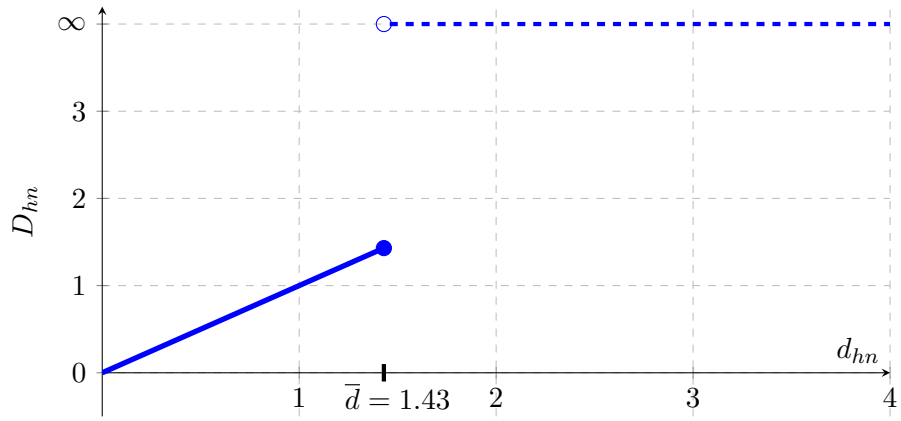


FIGURE 2. PSYCHOLOGICAL DISTANCE AS A FUNCTION OF GEOGRAPHICAL DISTANCE
This figure shows *psychological distance*, D_{hn}, as a function of geographical distance, d_{hn}. We see from the figure that $D_{hn} = d_{hn}$ if $d_{hn} \leq \overline{d}$ and equal to ∞ if $d_{hn} > \overline{d}$. In the figure, $\overline{d}$ is set equal to 1.43 based on the value of 143 miles estimated in Table 2 in Section B.1.

In our definition, the threshold distance, $\overline{d}$, drives a wedge between psychological distance, D_{hn}, and geographical distance, d_{hn}, as illustrated in Figure 1.[13] The geographical distance of Firm 1 from household h is $d_{h1} = \sqrt{X_1^2 + Y_1^2}$ and of Firm 2 is $d_{h2} = \sqrt{X_2^2 + Y_2^2}$. Therefore, using Definition 1, the *psychological distance* of Firm 1 from household h is $D_{h1} = d_{h1}$ and of Firm 2 is $D_{h2} = \infty$. This allows us to capture the idea that from a household's perspective, it is the same whether a firm is located 100 miles or 1000 miles beyond the threshold distance—both distances are very remote.

Figure 2 plots psychological distance as a function of geographical distance. When geographical distance is less than $\overline{d}$, psychological distance equals geographical distance, illustrated by the solid line in Figure 2. However, when the geographical distance exceeds $\overline{d}$, psychological distance is infinitely large, as indicated by the dashed line in Figure 2, even though the geographical distance is finite. Clearly, if the threshold distance $\overline{d}$ were very large, then the distinction between psychological and geographical distances would be meaningless. In Section B.1, we estimate the magnitude of $\overline{d}$ to confirm that the distinction between psychological and geographical distance is relevant empirically.

Note that in the above specification, we have defined psychological distance only in terms of geographical distance. It is, however, straightforward to allow for more general psychological distance functions. For instance, social-distance measures can be incorporated into a more general psychological distance. To see this, consider the case where social distance is measured as the difference between the predominant language of the household and that of the firm's CEO.

[13] Note that to distinguish between the geographical distance and the psychological distance between household h and firm n, we denote geographical distance by lowercase d_{hn} and psychological distance by uppercase D_{hn}.

Then, one could generalize the distance function to include this. For instance, in a bilingual region, one could represent the predominant language of the household h by $\ell_h \in \{0,1\}$ and that of firm n's CEO by $\ell_n \in \{0,1\}$, where the set $\{0,1\}$ represents the two spoken languages in the region. Then, the generalized psychological distance function could take the form

$$D_{hn} = \begin{cases} d_{hn} + K|\ell_h - \ell_n|, & d_{hn} + K|\ell_h - \ell_n| \leq \overline{d} \\ \infty, & d_{hn} + K|\ell_h - \ell_n| > \overline{d} \end{cases}, \tag{2}$$

where the term d_{hn} represents geographical distance and the second term, $K|\ell_h - \ell_n|$, social distance, where a higher value for the positive constant K increases the importance of social distance for psychological distance.

B.2. Endogenizing Familiarity

Construal-level theory emphasizes the centrality of psychological distance in shaping decision-making processes. Building on this framework, we now introduce the concept of a familiarity region based on psychological distance. While the existing literature treats familiarity as an exogenous parameter calibrated to align with observed data, it lacks a rigorous mathematical foundation. This gap leaves open the question of how familiarity can be connected to measurable quantities in a systematic way. We address this challenge below by developing a formal theory that defines familiarity mathematically, offering a novel approach to integrate it into empirical analysis.

We formally define the familiarity level of household h with firm n as the probability that firm n is within household h's familiarity region; this region is defined in terms of psychological distance, not geographical distance. Our definition allows us to transform an economic parameter into a measurable quantity.

DEFINITION 2. *A household's* familiarity region $\mathcal{F}_h(S) = B_S(0,0) = \left\{(x,y) : x^2 + y^2 \leq S^2\right\}$ *is a closed disk of radius (size) S, centered on the household, which is located at the origin. The random variable S is the radius of the familiarity region and has a known mean $\mathbb{E}[S] = r$, but an unknown distribution.*

The level of familiarity *household h has with firm n, f_{hn}, is the probability that firm n is within household h's familiarity region, i.e.,*

$$f_{hn} = \Pr(\text{firm } n \in \mathcal{F}_h(S)). \tag{3}$$

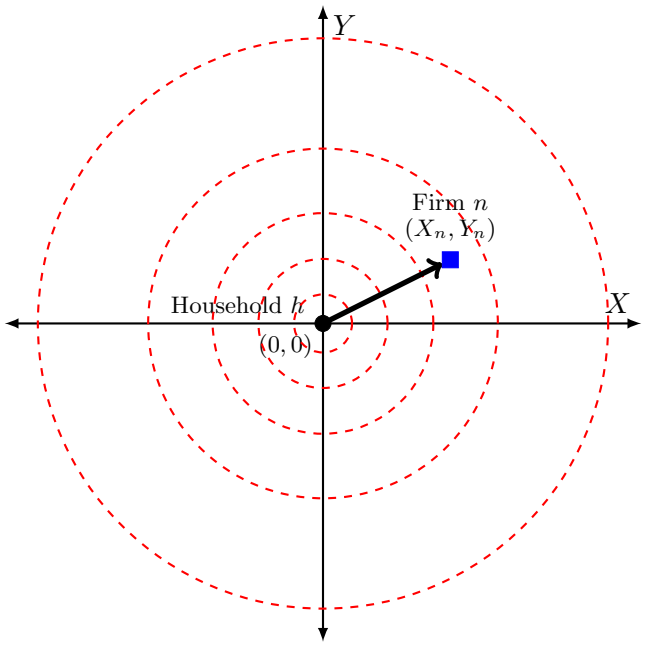


FIGURE 3. FAMILIARITY REGION

The figure shows household h located at the origin. The concentric circles represent possible boundaries for the household's familiarity region. The radius of the familiarity region is a random variable. As we will show below in Proposition 1, this random variable has an exponential distribution. The spacing of the circles in the figure corresponds to probability quantiles of the exponential distribution governing the familiarity radius. Because smaller distances are more likely under this distribution, the circles are more closely spaced near the center and become sparser as the radius grows.

Figure 3 illustrates a household h located at the origin. The radius of the familiarity region is a random variable, and the concentric circles in the figure represent possible boundaries for the household's familiarity region.

To capture the idea that a household has a sense of how large its familiarity region is, in our definition, we assume the mean radius of a familiarity region, $\mathbb{E}[S]$, is known. We denote this mean radius by r. However, households do not consciously work with probability density functions, so in our definition, we have assumed that the probability density function for the familiarity region's radius is unknown.

All households observe the same measurement of expected excess returns, μ_n, for each of the n firms. A given household h will subconsciously gauge its familiarity with μ_n. We model the process of assessing the familiarity a household has with a measurement of a firm as a probabilistic assessment of whether the firm is within the household's familiarity region.

We assume that if firm n lies within household h's familiarity region, the household will believe the expected excess return measurement for the firm, and the household's expected excess return prior belief will not be distorted. However, if the firm lies outside the household's

familiarity region, the household will not believe the expected excess return measurement and will use a distorted belief, where the household believes the expected excess return to be zero.

We hence obtain the following lemma.

LEMMA 1. *The relation between household h's subjective prior expected excess return for firm n, μ_{hn}, and the objective prior expected excess return, μ_n, is given by*

$$\mu_{hn} = f_{hn}\mu_n, \tag{4}$$

where f_{hn} is the level of familiarity household h has with firm n.

Proof. The proof is trivial. If the probability firm n lies within household h 's familiarity region is $\Pr(\text{firm } n \in \mathcal{F}_h(S))$, then the household's subjective prior belief about the expected excess return is given by

$$\begin{aligned}\mu_{hn} &= \Pr(\text{firm } n \in \mathcal{F}_h(S))\mu_n + (1 - \Pr(\text{firm } n \in \mathcal{F}_h(S))) \times 0 \\ &= \Pr(\text{firm } n \in \mathcal{F}_h(S))\mu_n.\end{aligned}$$

Using the definition of familiarity given in (3), we obtain (4). ∎

We have assumed the probability distribution of the familiarity region's radius is unknown. When we compute the probability in the definition of familiarity in (3), we want to minimize what we assume the decision-maker knows. This is particularly important because we are modeling the behavior of non-experts. We, therefore, select the probability distribution for the radius of a household's familiarity region according to the Principle of Maximum Entropy (Jaynes, 1957, 1986). The Principle of Maximum Entropy is a method used in various fields, such as statistics, physics, and information theory, to derive the most unbiased probability distributions possible given a set of known constraints. This principle is founded on the premise that when selecting a probability distribution, one should choose the distribution with the maximum entropy among all those that satisfy the given constraints. Here, entropy is a measure of uncertainty or randomness in the distribution; therefore, by using the Principle of Maximum Entropy, we are choosing the distribution that preserves the maximum amount of uncertainty (or entropy) given known constraints, thereby avoiding unwarranted assumptions.[14] The proposition below follows from the Principle of Maximum Entropy.

[14] Jaynes (1957, p. 623) "The maximum-entropy distribution may be asserted for the positive reason that it is uniquely determined as the one which is maximally noncommittal with regard to missing information, instead of the negative one that there was no reason to think otherwise."

PROPOSITION 1. *The radius of a household's familiarity region $\mathcal{F}_h(S) = B_S(0,0)$ is exponentially distributed with parameter r, $S \sim \text{Exp}(r)$. That is, the probability density function of the radius S is*

$$p(s) = \frac{1}{r} e^{-\frac{s}{r}},\ s \geq 0. \tag{5}$$

Proof. Applying the Principle of Maximum Entropy, the probability density function for S, denoted by $p(s)$ for $s \geq 0$, has the maximum possible entropy subject to the constraint $\mathbb{E}[S] = r$, i.e., $\int_0^\infty s\, p(s) ds = r$. We also note that $p(s)$ must be a probability density function, and so we obtain a second constraint $\int_0^\infty p(s) ds = 1$. Consequently, the following static optimization problem determines $p(s)$:

$$\max_{p(s)} - \int_0^\infty p(s) \ln p(s) ds,$$

$$\text{subject to:} \qquad \int_0^\infty p(s) ds = 1, \tag{6}$$

$$\text{and} \qquad \int_0^\infty s\, p(s) ds = r. \tag{7}$$

To solve the above constrained-maximization problem, we form the Lagrangian

$$\mathcal{L} = - \int_0^\infty p(s) \ln p(s) ds + k_0 \left(1 - \int_0^\infty p(s) ds\right) + k \left(r - \int_0^\infty s p(s) ds\right),$$

where k_0 and k are the Lagrange multipliers for the two constraints.

We have the first-order condition for the probability density function $p(s)$

$$0 = - \ln p(s) - 1 - k_0 - ks,$$

$$\text{and therefore,} \qquad p(s) = e^{-(1+k_0)} e^{-ks},\ s \in [0, \infty).$$

From (6), we see that $e^{-(1+k_0)} = k$, so

$$p(s) = k e^{-ks},\ s \in [0, \infty].$$

Then, we use the constraint in (7) to determine k:

$$r = \mathbb{E}[S] = \int_0^\infty s p(s) ds = k \int_0^\infty s e^{-ks} ds = \frac{1}{k}.$$

It follows that

$$k = \frac{1}{r},$$

implying that the probability density function of S is the expression in (5). ∎

We now use the probability density function for the radius of a household's familiarity region, derived in the proposition above, to compute the probability of a firm being within the familiarity region. From Definition 2, this probability is the level of familiarity that a household has with the firm's expected excess return measurements.

PROPOSITION 2. *The level of familiarity that household h has with expected excess return measurements for a firm at psychological distance D_{hn} from itself is given by*

$$f_{hn} = e^{-\frac{D_{hn}}{r}}, \tag{8}$$

where r is the mean radius of a familiarity region.

Proof. By combining Proposition 1 with Definition 2 for the familiarity of household h with measurements about expected excess returns for firm n, we see that

$$f_{hn} = \Pr(D_{hn} \leq S) = \int_{D_{hn}}^{\infty} \frac{1}{r} e^{-\frac{1}{r}s} ds.$$

Evaluating the above integral results in Proposition 2. ∎

We see from equation (8) that familiarity decays exponentially in D_{hn}, the psychological distance of the firm from the household, and this exponential decay is more rapid when the mean radius of the familiarity region, r, is smaller. Equation (8) also implies that f_{hn} is bounded above by one and below by zero.

The following corollary gives the familiarity of household h with firm n in terms of geographical distance, d_{hn}.

COROLLARY 1. *Household h's level of familiarity with firm n as a function of the geographical distance between household h and firm n, d_{hn}, is given by*

$$f_{hn} = \begin{cases} e^{-\frac{d_{hn}}{r}}, & d_{hn} \leq \overline{d} \\ 0, & d_{hn} > \overline{d}. \end{cases} \tag{9}$$

Proof. Equation (9) follows from the definition of psychological distance (Definition 1) and Proposition 2. ∎

We can see from the above corollary that the way familiarity decreases with geographical distance, d_{hn}, depends on both $\overline{d}$ and r, where $\overline{d}$ determines whether familiarity is equal to zero or not, and, for the case where familiarity is nonzero, the ratio of d_{hn} to r determines its level. Thus, the mean radius r gives us natural units in which to measure psychological distance.

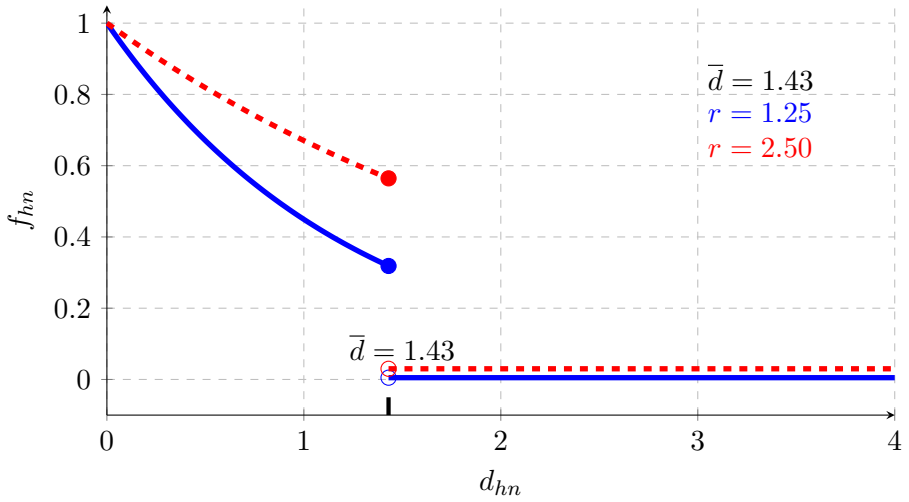


FIGURE 4. FAMILIARITY LEVEL OF HOUSEHOLD h WITH FIRM n, f_{hn}
This figure shows the familiarity level of household h with firm n, f_{hn}, as a function of geographical distance, d_{hn}. The red dashed line is for the case of $r = 2.50$ (which corresponds to the value of $r = 250$ miles estimated in column (4) of Panel A in Table 3), and the blue solid line is for the (hypothetical) case of $r = 1.25$; these lines show that familiarity level declines faster as r decreases. The figure shows that the familiarity level is exponentially decreasing with geographical distance if $d_{hn} \leq \overline{d}$ (which, in the figure, is equal to 1.43, based on the value of 143 miles estimated in Table 2). If $d_{hn} > \overline{d}$, then the psychological distance is infinitely large, and the familiarity level drops to zero.

Figure 4 illustrates the familiarity level of household h with firm n, f_{hn}, as a function of geographical distance, d_{hn}. The figure shows that the familiarity level is exponentially decreasing with geographical distance if $d_{hn} \leq \overline{d}$. If $d_{hn} > \overline{d}$, then the psychological distance is infinitely large, and the familiarity level drops to zero. The red dashed line is for the case of $r = 2.50$ and the blue solid line is for the case of $r = 1.25$; these lines show that the familiarity level declines faster as r decreases.

The following corollary provides a precise, theoretically justified, quantitative law linking a household's subjective prior beliefs about a firm's excess stock returns to the geographical distance between the household and the firm.

COROLLARY 2. *The subjective prior beliefs about expected excess return of household h for stock n, i.e., μ_{hn}, is related to the objective prior expected excess return, μ_n, by*

$$\mu_{hn} = f_{hn}\mu_n = \begin{cases} e^{-\frac{d_{hn}}{r}}\mu_n, & d_{hn} \leq \overline{d} \\ 0, & d_{hn} > \overline{d}. \end{cases} \tag{10}$$

Proof. Equation (10) follows from equation (4) for prior beliefs in Lemma 1, combined with the expression for familiarity, given in Corollary 1. ∎

Equation (10) predicts that a household's prior beliefs about a firm's expected excess returns decay exponentially as the geographical distance between the household and the firm increases,

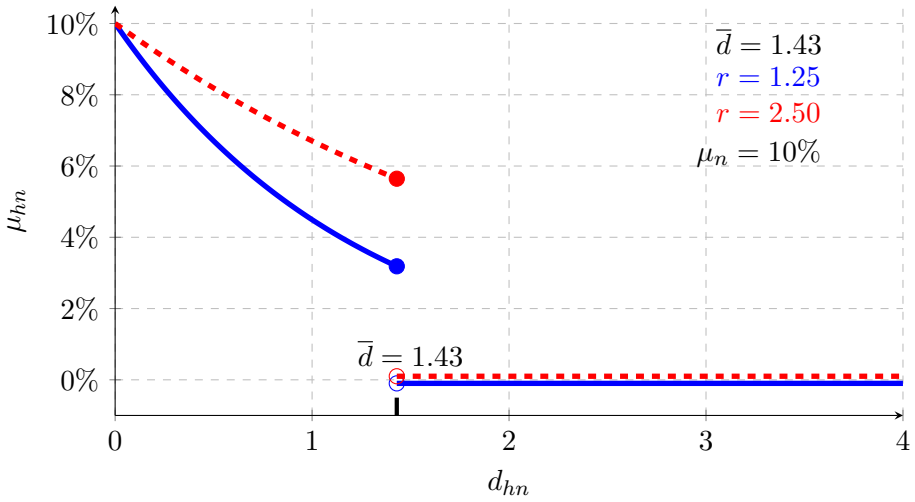


FIGURE 5. SUBJECTIVE PRIOR BELIEFS ABOUT FIRMS' EXPECTED EXCESS RETURNS

This figure, which mirrors Figure 4, shows household h's subjective prior beliefs about the expected excess stock returns for firm n, μ_{hn}, as a function of geographical distance, d_{hn}. In the figure, it is assumed that the objective prior expected stock return is $\mu_n = 10\%$. The plot shows that the subjective prior belief about expected excess returns declines exponentially with d_{hn} until the threshold $\overline{d}$ and then drops to zero. In the figure, the threshold distance $\overline{d}$ is equal to 1.43, based on the value of 143 miles estimated in Table 2. The red dashed line is drawn for the case of $r = 2.50$, which corresponds to the value of $r = 250$ miles estimated in column (4) of Panel A in Table 3, and the blue solid line is for the (hypothetical) case of $r = 1.25$. These lines show that the subjective prior beliefs decline faster when r is smaller.

until the threshold $\overline{d}$ is reached. If $d_{hn} \leq \overline{d}$, the subjective expected excess return for a given stock n halves every $r \ln 2$ units of geographical distance (miles if r is given in miles). When geographical distance reaches a threshold $\overline{d}$, psychological distance becomes infinite (cf. Definition 1 and Figure 2), reducing prior beliefs about a firm's expected excess returns to zero, as shown in Figure 5. Therefore, we see from Figure 5, which closely mirrors Figure 4, that the impact of distance on subjective expected excess return is extremely strong, exponential rather than linear, because subjective prior beliefs inherit the properties of familiarity.

C. Households' Portfolio Choice

Our theory provides a precise quantitative law for households' subjective prior beliefs about stock returns. However, subjective prior beliefs are not observable. The portfolio choices of each household are observable, and reflect its beliefs about firm-level expected excess returns (Giglio et al., 2021, Beutel and Weber, 2023). We now explain how we use portfolio holdings to estimate the two key parameters, $\overline{d}$ and r, underlying our quantitative law.

Recall from equation (1) that each household is a mean-variance investor and uses her subjective prior beliefs about expected excess returns to choose her optimal portfolio. The proposition below gives household h's optimal portfolio.

PROPOSITION 3. *The optimal portfolio of household h is given by the vector of weights:*

$$\boldsymbol{\omega}_h = \frac{1}{\gamma_h} V^{-1} \boldsymbol{\mu}_h = \frac{1}{\gamma_h} V^{-1} F_h \boldsymbol{\mu}, \tag{11}$$

where, from Lemma 1, $\boldsymbol{\mu}_h = F_h \boldsymbol{\mu}$, with F_h being the diagonal matrix $\text{diag}(f_{h1}, \ldots, f_{hN})$*, and*

$$f_{hn} = \begin{cases} e^{-\frac{d_{hn}}{r}}, & d_{hn} \leq \overline{d} \\ 0, & d_{hn} > \overline{d}. \end{cases}$$

For the special case where asset-returns are uncorrelated, equation (11) simplifies to the following expression for the portfolio weight of household h in stock n:

$$\omega_{hn} = \frac{1}{\gamma_h} \frac{\mu_{hn}}{\sigma_n^2} = \frac{1}{\gamma_h} \frac{f_{hn}\, \mu_n}{\sigma_n^2} = \begin{cases} \frac{1}{\gamma_h} e^{-\frac{d_{hn}}{r}} \frac{\mu_n}{\sigma_n^2}, & d_{hn} \leq \overline{d} \\ 0, & d_{hn} > \overline{d}. \end{cases} \tag{12}$$

Proof. We maximize the mean-variance objective function in (1) with respect to the vector of portfolio weights $\boldsymbol{\omega}_h$, which leads to the well-known optimal solution (11), where the second equality follows from Lemma 1. ∎

In our empirical analysis, we shall exploit data on portfolio holdings along with data on household and firm locations to estimate our model of subjective prior beliefs. We will estimate the two key parameters, $\overline{d}$ and r, using the joint cross-sectional variation in portfolio weights, ω_{hn}, and psychological distances of households from firms, D_{hn}. Each household's portfolio choices are determined by two margins. First, there is the extensive margin that determines whether a particular stock is included in a household's portfolio; we use this to determine the threshold distance $\overline{d}$, which drives a wedge between psychological and geographical distance. Second, there is the intensive margin, which determines how much of a particular firm's stock to hold once the extensive margin condition has been satisfied; we use this to determine r and, hence, the mean radius of the familiarity region.

D. Household Welfare under Subjective Prior Beliefs

To study the impact of psychological distance on subjective prior beliefs, and through that, on welfare, we compute the *welfare loss* to households in deviating from objective prior beliefs

and show that it is related to the relative entropy from the distorted belief about expected excess returns, denoted by $\boldsymbol{\mu}_h$, relative to the rational belief about expected excess returns, denoted by $\boldsymbol{\mu}$.

The mean-variance utility of a household with objective prior beliefs about expected excess returns denoted by $\boldsymbol{\mu}$, for an arbitrary portfolio vector $\boldsymbol{\omega}_h$, is given by

$$U^{MV}\big(\boldsymbol{\omega}_h\big) = R_f + \boldsymbol{\mu}^\top \boldsymbol{\omega}_h - \frac{1}{2}\gamma_h \boldsymbol{\omega}_h^\top V \boldsymbol{\omega}_h, \tag{13}$$

which is the expected portfolio rate of return minus a penalty for portfolio variance.

We denote the optimal portfolio under objective prior beliefs by $\boldsymbol{\omega}_h(\boldsymbol{\mu})$, and so

$$\boldsymbol{\omega}_h(\boldsymbol{\mu}) = \frac{1}{\gamma_h} V^{-1} \boldsymbol{\mu}.$$

Substituting the optimal portfolio under objective beliefs into the mean-variance utility in (13) and simplifying gives

$$U^{MV}\big(\boldsymbol{\omega}_h(\boldsymbol{\mu})\big) = R_f + \frac{1}{2}\frac{1}{\gamma_h} \boldsymbol{\mu}^\top V^{-1} \boldsymbol{\mu}. \tag{14}$$

Denoting the optimal portfolio under household h's subjective prior beliefs by $\boldsymbol{\omega}_h(\boldsymbol{\mu}_h)$, the mean-variance welfare for a household with subjective priors is given by

$$U^{MV}\big(\boldsymbol{\omega}_h(\boldsymbol{\mu}_h)\big) = R_f + \boldsymbol{\mu}^\top \boldsymbol{\omega}_h(\boldsymbol{\mu}_h) - \frac{1}{2}\gamma_h \boldsymbol{\omega}_h(\boldsymbol{\mu}_h)^\top V \boldsymbol{\omega}_h(\boldsymbol{\mu}_h).$$

We can then compute the *welfare loss* in deviating from objective prior beliefs

$$\Delta U^{MV}(\boldsymbol{\mu}, \boldsymbol{\mu}_h) = U^{MV}\big(\boldsymbol{\omega}_h(\boldsymbol{\mu})\big) - U^{MV}\big(\boldsymbol{\omega}_h(\boldsymbol{\mu}_h)\big). \tag{15}$$

An elegant way to express this welfare loss is to use the concept of relative entropy, also known as Kullback-Leibler (KL) divergence.[15]

Proposition 4. *The* welfare loss *from having subjective prior beliefs instead of objective prior beliefs is given by*

$$\Delta U^{MV}(\boldsymbol{\mu}, \boldsymbol{\mu}_h) = \frac{1}{\gamma_h} \mathrm{KL}(\boldsymbol{\mu}, \boldsymbol{\mu}_h), \tag{16}$$

where the relative entropy from subjective to objective priors is the Kullback-Leibler (KL) divergence

$$\mathrm{KL}(\boldsymbol{\mu}, \boldsymbol{\mu}_h) = \frac{1}{2}(\boldsymbol{\mu} - \boldsymbol{\mu}_h)^\top V^{-1} (\boldsymbol{\mu} - \boldsymbol{\mu}_h), \tag{17}$$

[15] The concept of entropy has been used in economics at least as early as Marschak (1959); Veldkamp (2011) and Cabrales, Gossner, and Serrano (2013, sec. IV) present excellent reviews of the related literature, and Gârleanu and Pedersen (2022, prop. 9) show how entropy can be used to measure the inefficiency of a portfolio in a two-date asymmetric-information model.

and $(\boldsymbol{\mu}-\boldsymbol{\mu}_h)^\top V^{-1}(\boldsymbol{\mu}-\boldsymbol{\mu}_h)$ *is the difference in the squared Sharpe ratio of the portfolios under objective and subjective priors about expected excess returns. For the special case where stock returns are uncorrelated,*

$$\text{KL}(\boldsymbol{\mu},\boldsymbol{\mu}_h)=\frac{1}{2}\left[\sum_{n:\,d_{hn}\leq\overline{d}}\left(\frac{\mu_n}{\sigma_n}\right)^2\left(1-e^{-\frac{d_{hn}}{r}}\right)^2+\sum_{n:\,d_{hn}>\overline{d}}\left(\frac{\mu_n}{\sigma_n}\right)^2\right]. \tag{18}$$

Proof. To compute the welfare loss defined in (15), we first simplify $U^{MV}\big(\boldsymbol{\omega}_h(\boldsymbol{\mu}_h)\big)$ by noting that $\boldsymbol{\omega}_h(\boldsymbol{\mu}_h)=\frac{1}{\gamma_h}V^{-1}\boldsymbol{\mu}_h$. Therefore,

$$U^{MV}\big(\boldsymbol{\omega}_h(\boldsymbol{\mu}_h)\big)=R_f+\frac{1}{\gamma_h}\boldsymbol{\mu}^\top V^{-1}\boldsymbol{\mu}_h-\frac{1}{2\gamma_h}\boldsymbol{\mu}_h^\top V^{-1}\boldsymbol{\mu}_h. \tag{19}$$

To make the algebra easier to follow, we define the inner product $\langle\cdot,\cdot\rangle:\mathbb{R}^N\times\mathbb{R}^N\to\mathbb{R}$ via

$$\langle\boldsymbol{a},\boldsymbol{b}\rangle=\boldsymbol{a}V^{-1}\boldsymbol{b},$$

where $\boldsymbol{a},\boldsymbol{b}\in\mathbb{R}^N$. We can now rewrite $U^{MV}\big(\boldsymbol{\omega}_h(\boldsymbol{\mu})\big)$ in (14) and $U^{MV}\big(\boldsymbol{\omega}_h(\boldsymbol{\mu}_h)\big)$ in (19) as

$$U^{MV}\big(\boldsymbol{\omega}_h(\boldsymbol{\mu})\big)=R_f+\frac{1}{2\gamma_h}\langle\boldsymbol{\mu},\boldsymbol{\mu}\rangle,$$

and

$$U^{MV}\big(\boldsymbol{\omega}_h(\boldsymbol{\mu}_h)\big)=R_f+\frac{1}{\gamma_h}\langle\boldsymbol{\mu},\boldsymbol{\mu}_h\rangle-\frac{1}{2\gamma_h}\langle\boldsymbol{\mu}_h,\boldsymbol{\mu}_h\rangle.$$

Therefore, the welfare loss $\Delta U^{MV}(\boldsymbol{\mu},\boldsymbol{\mu}_h)$ is

$$\begin{aligned}\Delta U^{MV}(\boldsymbol{\mu},\boldsymbol{\mu}_h)&=\frac{1}{2\gamma_h}\left[\langle\boldsymbol{\mu},\boldsymbol{\mu}\rangle+\langle\boldsymbol{\mu}_h,\boldsymbol{\mu}_h\rangle-2\langle\boldsymbol{\mu},\boldsymbol{\mu}_h\rangle\right]\\&=\frac{1}{2\gamma_h}\langle\boldsymbol{\mu}-\boldsymbol{\mu}_h,\boldsymbol{\mu}-\boldsymbol{\mu}_h\rangle.\end{aligned}$$

Hence, we obtain (16). Recalling from Lemma 1 that $\boldsymbol{\mu}_h=F_h\boldsymbol{\mu}$, we see that the relative entropy from subjective to objective priors in equation (17) can also be written as

$$\text{KL}(\boldsymbol{\mu},\boldsymbol{\mu}_h)=\frac{1}{2}\boldsymbol{\mu}^\top(I-F_h)V^{-1}(I-F_h)\boldsymbol{\mu},$$

which, for the special case of uncorrelated stock returns, then simplifies to (18). ∎

Proposition 4 shows that the mean-variance welfare loss is given by the relative entropy measure multiplied by the household's risk tolerance, $1/\gamma_h$. The reason that the welfare loss depends on risk tolerance is because households that have a low risk tolerance (i.e., high risk

aversion, γ_h) invest little in risky assets, and hence, their welfare loss from distorted subjective prior beliefs about the return distribution of risky assets is smaller.

To estimate the expression in equation (18) for relative entropy and, therefore, household welfare losses, we need to estimate $\overline{d}$ and r (in addition to measuring firm-level Sharpe ratios and geographical distance d_{hn} for each household-firm pair). We explain how to estimate $\overline{d}$ and r in Section II. Then, in Section III, we use these estimates to compute the welfare losses resulting from distorted subjective prior beliefs for households in different parts of Finland.

II. Estimation of Subjective Prior Beliefs

In this section, we estimate the threshold distance, $\overline{d}$, which drives a wedge between psychological and geographical distance, and the parameter r, which determines how rapidly familiarity declines exponentially with distance, by exploiting the expression for optimal portfolio weights in equation (12) of Proposition 3 and using Finnish portfolio holdings data. Armed with these estimates, we can construct subjective prior beliefs using equation (10) in Corollary 2.

Our empirical analysis is described in four parts. We describe our data in Section II.A. Then we explain in Section II.B how we use data on portfolio holdings to estimate the two parameters $\overline{d}$ and r. The last two parts of this section provide further tests of these two parameters, which depend on the extensive and intensive margins of portfolio holdings.

A. Data

We obtained portfolio holdings for all accounts on the Helsinki Stock Exchange as of January 2, 2003, from Euroclear, which acquired the Finnish Central Securities Depositary in 2008.[16] The data contain portfolio holdings and postal-code information, as well as further characteristics (age, gender, and sector-code classification) of all account holders in the market. There are altogether 3,036 valid postal codes in the data set and the data contains over 60 million trades during the time period 1995-2004, and about 1.2 million accounts, most of which represent the household sector.

We obtain spatial coordinates for each postal code area from the Finnish postal services company Posti Group Corporation. These postal codes make up a fine-grained representation of Finland, as shown in Figure 6. The figure shows that even rural areas far from Helsinki have significant population densities. This is partially a result of Finland's post-World War II

[16] This dataset is similar to the one used in Grinblatt and Keloharju (2000, 2001) and Walden (2019).

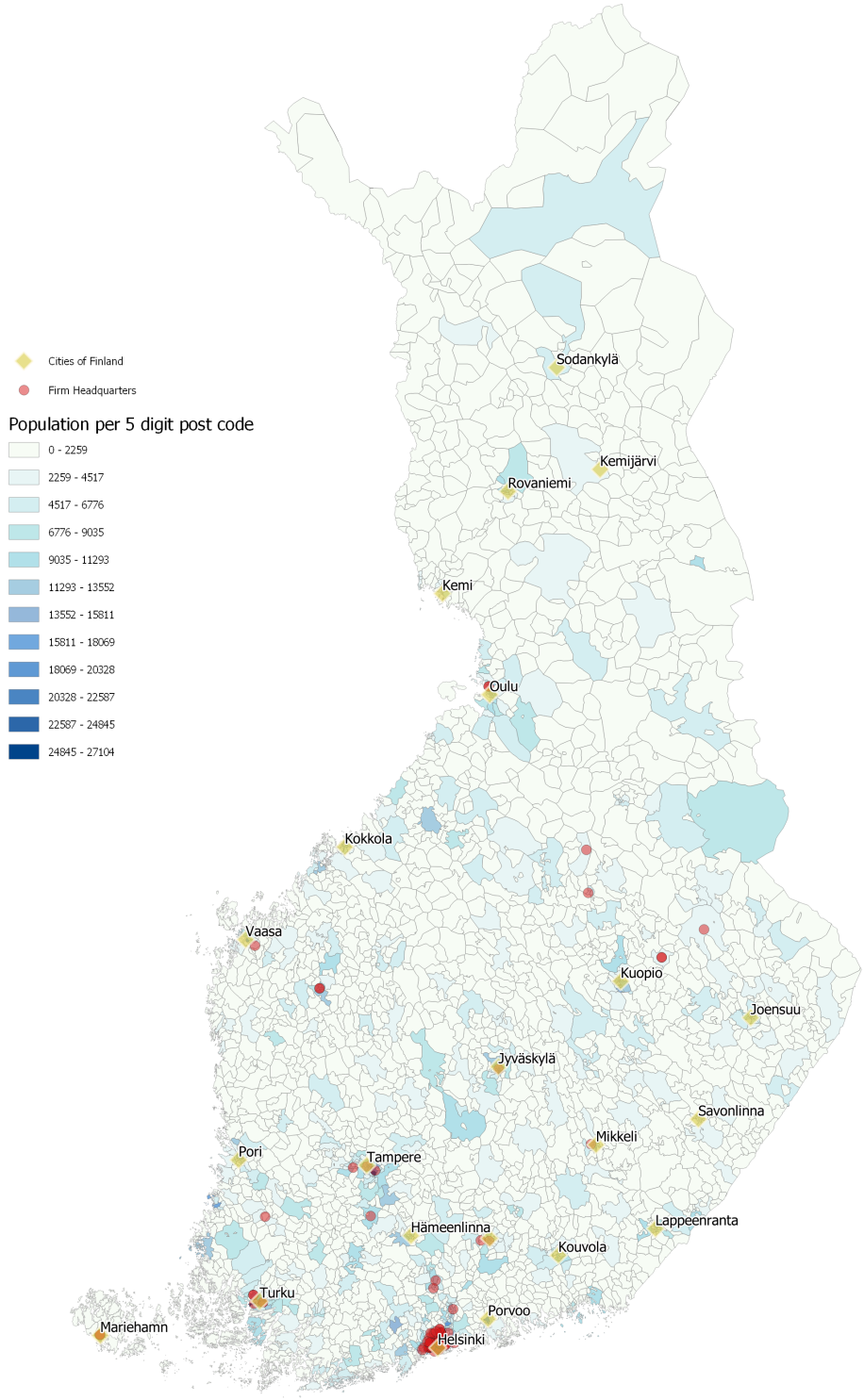


FIGURE 6. POSTAL CODES, FIRMS, AND POPULATION IN FINLAND

This figure shows the 3036 postal code regions (at the five-digit level), which are obtained from the Finnish postal services company Posti Group Corporation. The figure also shows the location of the firm headquarters (orange circles) and the major cities of Finland (yellow diamonds). Finally, the choropleth map shows the population of Finland across different postal codes. We see from the map that the population is dispersed across postal codes, while a majority of firm headquarters (80%) are in the Helsinki region.

doctrine of Total Defense (known as "kokonaismaanpuolustu"), which includes policies aimed at maintaining rural populations. This strategy emerged as a response to the geopolitical threats faced by Finland, particularly the proximity to the Soviet Union and, later, Russia.

We obtain information about the postal codes of the company headquarters from Thomson One Reuters. We exclude companies headquartered outside of Finland and also companies with shares that were not traded within the previous month. Finally, we exclude the telecommunications company Elisa Oyj, which until 1999 had been a privately held mutual association with broad ownership among its association members and, therefore, had quite a different ownership history and structure than the rest of the firms.[17] This leaves us with 125 stocks, which are listed in Table A.1 of Appendix A.[18]

We include accounts that are classified as households (these are accounts associated with sector codes between 500 and 599), that are associated with a valid postal code, and that owned shares in at least one of the 125 stocks on January 2, 2003. This leaves us with 405,868 households associated with altogether $P = 2,923$ postal codes.

The postal code associated with household h is denoted p_h. We assume that each agent resides at the center of gravity of his/her respective postal code and also that each firm is headquartered at the center of gravity of its postal code. Thus, all agents within a postal code are assumed to be at the same distance from each of the firms, with d_{pn} denoting the geographical distance between the center of gravity of postal code area p, (X_p, Y_p), and the center of gravity of the postal code area in which firm n, (X_n, Y_n), is located, i.e.

$$d_{pn} = \sqrt{(X_n - X_p)^2 + (Y_n - Y_p)^2}. \tag{20}$$

For the estimation, we normalize the distance function so that all geographical coordinates lie in the unit square, $[0,1] \times [0,1]$. The household-firm pair that are farthest apart are, therefore, at a distance somewhere between 1 and $\sqrt{2}$ from each other (in our sample, the maximum distance is 1.175), and 1 normalized unit corresponds to 795 miles (1279 km).

[17] Elisa Oyj was formed on July 1, 2000, with the merger of the Helsinki Telephone Corporation (in Finnish, "Helsingin Puhelin") and its holding company, HPY Holding Corporation. Helsinki Telephone Corporation had been a privately held telephone cooperative with broad ownership among its 550,000 "association members." Subscribers to its telephone services automatically became association members. When the company was listed on the Helsinki Stock Exchange in 1997, these owners became shareholders, which then carried over to Elisa Oyj after the merger (Source: Annual Reports, 1997-2000). Most of these shareholders only held this one stock and thus seem to be shareholders for different reasons than the rest of the investor population. The results about the estimates of $\frac{1}{r}$ and $\overline{d}$ are very similar when Elisa Oyj is included.

[18] Some of these stocks represent A and B shares in the same company. An A share in Finland typically comes with greater voting rights than a B share. There were significant differences in share prices and returns between A and B shares of the same companies and we therefore include both A and B shares in our sample for companies with both types of shares.

Item	Value
Number of stocks	125
Number of household accounts	405,628
Number of postal codes	2,923
Average number of accounts in a postal code	139
Total number of observations	364,750
Number of nonzero observations	132,811
Maximum portfolio holdings	FIM 178.7 million
Minimum portfolio holdings	FIM 0
Average stock holdings by postal code	FIM 30,617
Median number of stocks held by an account	2
Mean number of stocks held by an account	2.75

TABLE 1—SUMMARY STATISTICS

Notes. This table gives the summary statistics for the data used in our empirical analysis.

The spatial coordinates of postal codes and firms (orange circles) are shown in Figure 6. As can be seen in the figure, most firms (about 80%) are headquartered in the far south around the capital, Helsinki (with associated five-digit postal codes between 00100 and 09900), whereas about 20% of the firms have headquarters elsewhere. Summary statistics of the data we use are provided in Table 1.

Despite the detailed dataset that we have, it has some limitations, which have implications for how we undertake our empirical analysis. One, the portfolios of the retail investors we study are very persistent at the postal code level, which is the level of resolution we use for our tests, to the degree that they are almost perfectly correlated in the time series. Therefore, we focus on a single point in time: January 2003. So, our panel is defined across postal codes and stocks, which is used to draw inferences about the parameters in (12), but not across time. Two, our dataset does not contain information about households' total wealth, bond holdings, or savings in retirement accounts and mutual funds, information that would allow us to draw further inferences about risk aversion and allocation between risky and risk-free assets. Three, although postal codes, in principle, should have been updated for households that moved during the period, this almost never happened in our dataset. Postal codes for fewer than 100 households changed during the entire period 1996–2004, corresponding to less than 0.04% of the households in the sample.[19] So, we were unable to study whether portfolios changed for households that moved, even though that would be an interesting analysis to undertake.[20] Finally, our data contains no information that would allow the identification of individual households

[19]Moreover, several of these changes seem to be erroneous, for example, a switch for one trade but then a switch back for the next and onward.

[20]The effect of a change in residence on investors' portfolio is studied in Bodnaruk (2009). Consistent with our hypothesis that beliefs are influenced by psychological distance, he finds that the farther investors move away from a firm, the more of its shares they sell compared to investors who do not move. He also finds that, after moving, investors increase ownership in firms closer to their new location.

and, thereby, the possibility of using other data sources to gain additional information at the individual household level.

B. Estimating the Parameters Driving Subjective Beliefs

We now explain how we estimate the threshold parameter, $\overline{d}$, and the mean radius of a household's familiarity region, r, that determine the subjective prior beliefs of household h about stock n's expected excess return. Our theoretical result in Proposition 3 allows us to disentangle the extensive and intensive margins, with one distinct parameter, $\overline{d}$, governing the extensive margin and a second distinct parameter, r, governing the intensive margin. Data about the extensive margin, i.e., whether or not households purchase the equity of a particular firm, allows us to test whether psychological distance is distinct from geographical distance and also identify the threshold, $\overline{d}$, at which this distinction becomes consequential. Data on the intensive margin, i.e., the extent to which a household invests in the equity of a particular firm, allows us to identify the mean radius, r, of the familiarity region.

In our estimation, we exploit equation (12) in Proposition 3, which is the first-order condition linking portfolio weights to subjective prior beliefs for the special case where stock returns are uncorrelated. We consider the case of uncorrelated stock returns because this allows us to simplify the estimation—if one were to consider the case of correlated stock returns, one would need to estimate an additional 7,750 covariance parameters.[21] The assumption of uncorrelated stock returns is reasonable also because the average correlation across stocks for our sample period is less than 0.10. Moreover, the median number of stocks held by a household is two, suggesting that correlation does not play a major role in a household's portfolio choice.

B.1. Estimating $\overline{d}$

We estimate the magnitude of the threshold distance, $\overline{d}$ by exploiting data on the extensive margin and using the result in equation (12), which states that the investment in firms that are beyond the threshold distance of $\overline{d}$ should be zero. Specifically, for each of the 125 stocks, we choose a value for $\overline{d}$ that maximizes the number of correctly classified postal codes with respect to whether the stock holdings in the firm are positive or zero. The results are shown in Table 2. The average estimated $\overline{d}$ is 0.1799 in standardized units, corresponding to a threshold distance of about 0.1799×795 miles $= 143$ miles (230 km). Beyond this threshold distance from

[21] The number of covariance terms in the variance-covariance matrix V is $\frac{N^2-N}{2} = \frac{125^2-125}{2} = 7,750$.

Item	Value
Average threshold, $\overline{d}$	143 miles (230 km)
Fraction of zero holdings	0.6359
Fraction correctly classified	0.7534

TABLE 2—ESTIMATE OF $\overline{d}$, THE THRESHOLD PARAMETER

Notes. This table shows the estimated magnitude of the threshold distance, $\overline{d}$. The table also reports the fraction of zero holdings and the fraction of holdings correctly classified if one were to use the estimated threshold distance.

a firm's headquarters, a household's prior beliefs are strongly distorted: its subjective expected risk premium is zero, and it completely avoids investing in that stock.

We now explain how one can evaluate the quality of our estimate for $\overline{d}$. Note that each postal-code/firm pair (p, n) is associated with an observation that tells us the holdings of households in postal code p in firm n. There are $P \times N = 2,923 \times 125$ such pairs, and for 63.59% of them, the recorded portfolio holding is zero, indicating that households have sparse portfolios concentrated in a small number of assets. When the estimated threshold distance $\overline{d}$ is used to predict whether a postal code/firm portfolio holding is zero, the fraction of correct classifications is 75.34%. Thus, our model is good at identifying whether or not households in a particular postal code invest in a stock. In Section II.C, we report further tests of the extensive margin.

B.2. Estimating r

Equation (12), when expressed at the postal code level, is

$$\omega_{pn} = \frac{\text{amt}_{pn}}{W_p} = \begin{cases} \frac{1}{\gamma_p}\frac{\mu_n}{\sigma_n^2}e^{-\frac{1}{r}d_{pn}}, & d_{pn} \leq \overline{d} \\ 0, & d_{pn} > \overline{d}, \end{cases}$$

where amt_{pn} is the Finnish mark (FIM) amount invested in stock n by households in postal code p, W_p is the wealth of the households in that postal code, and γ_p is the wealth-weighted harmonic mean of the relative risk aversion coefficients for agents living in postal code p, $\frac{1}{\gamma_p} = \frac{\sum_{\{h:p_h=p\}}\frac{W_h}{\gamma_h}}{W_p}$.

The equation above implies that

$$\text{amt}_{pn} = \begin{cases} \frac{W_p}{\gamma_p}\frac{\mu_n}{\sigma_n^2}e^{-\frac{1}{r}d_{pn}}, & d_{pn} \leq \overline{d} \\ 0, & d_{pn} > \overline{d}. \end{cases} \tag{21}$$

Defining $a_{pn} = \ln(\text{amt}_{pn})$, $s_n = \ln\left(\frac{\mu_n}{\sigma_n^2}\right)$, and $g_p = \ln(\gamma_p / W_p)$, then implies that, when the geographical distance d_{hn} is less than $\overline{d}$, we can rewrite (21) as

$$a_{pn} = -g_p + s_n - \frac{1}{r}\, d_{pn}. \tag{22}$$

Equation (22) thus consists of $P \times N$ postal-code/firm holdings. The $\frac{1}{r}$ coefficient in (22), which is constant across postal codes and firms, acts as a cross-equation restriction across both dimensions of the data, which allows us to estimate it from portfolio-holdings data. Similarly, g_p imposes a cross-equation restriction across firms and s_n a cross-equation restriction across postal codes. Thus, equation (22) can be viewed as a panel with fixed effects for postal codes (representing the log of risk-aversion scaled by wealth, g_p) and companies (representing the log of expected excess returns scaled by variance, s_n). We, therefore, use panel regressions to estimate the sensitivity parameter $\frac{1}{r}$.

We obtain an estimate for r, which governs the intensive margin—how large a household's subjective prior belief about a firm's expected excess return—and, therefore, how much wealth a household invests in that firm.[22]

We now explain the two approaches we use to handle portfolio amounts of zero, where the logarithm is not defined. Under the first approach, we include these observations but replace the zero with a small positive threshold, namely one Finnish mark (corresponding to about USD 0.17). Under the second approach, we exclude such observations and run unbalanced panel regressions. The disadvantage of the former approach is that it introduces an arbitrary lower threshold, whereas the disadvantage of the latter is that it does not use information about zero holdings.

The estimation results are shown in Table 3. We see that the sensitivity coefficient, $\frac{1}{r}$, is highly statistically significant in all four regression specifications (univariate, including risk-aversion fixed effects, including risk-aversion and stock-characteristic fixed effects, and panel regression with robust standard errors double clustered at the firm and postal-code level). The results are also economically significant. For the estimation that includes risk-aversion, stock-return distribution, and all observations (first row in Panel A, Column (4)), $r = 250$ miles (402 km). The R^2 for the univariate regression in Column (1) of Panel A is 6.54%, corresponding to a correlation between proximity and log-portfolio holdings of about 26%, while for the

[22] The model is not completely identified because the mapping $g_p \mapsto g_p + c$, $s_n \mapsto s_n + c$ yields the same portfolio weights for an arbitrary constant c. Intuitively, higher risk aversion coefficients are offset by more favorable investment opportunities. We obtain unique identification by normalizing the results so that the average s_n coefficient is 0 ($s_n = 0$ is, for example, obtained with $\mu_n = 0.09$, $\sigma_n = 0.3$ so that the ratio $\frac{\mu_n}{\sigma_n^2} = 1$).

	(1)	(2)	(3)	(4)
Panel A: Including all observations				
Estimate of $\frac{1}{r}$ (normalized units)	5.873***	3.861***	3.188***	3.185***
Standard error of $\frac{1}{r}$	0.037	0.058	0.056	0.434
Mean radius, r (miles)	135	206	249	250
Mean radius, r (km)	218	331	401	402
$g_p \equiv \ln(\gamma_p/W_p)$				
-average		−4.330	−4.120	
-max		−0.382	−0.325	
-min		−12.887	−12.834	
$s_n \equiv \ln\left(\mu_n/\sigma_n^2\right)$				
-average			0	
-max			7.258	
-min			−2.658	
R^2	0.065	0.385	0.591	0.591
Adj. R^2	0.065	0.380	0.588	0.588
$N = 368,298$				
Panel B: Excluding observations with $amt_{pn} = 0$				
Estimate of $\frac{1}{r}$ (normalized units)	2.251***	2.123***	2.669***	2.669***
Standard error of $\frac{1}{r}$	0.035	0.061	0.046	0.403
Mean radius, r (miles)	353	374	298	298
Mean radius, r (km)	568	602	479	479
$g_p \equiv \ln(\gamma_p/W_p)$				
-average		−8.572	−7.979	
-max		−4.563	−2.638	
-min		−12.845	−12.883	
$s_n \equiv \ln\left(\mu_n/\sigma_n^2\right)$				
-average			0	
-max			4.166	
-min			−3.985	
R^2	0.030	0.210	0.626	0.626
Adj. R^2	0.030	0.191	0.618	0.618
$N = 134,902$				

TABLE 3—ESTIMATE OF r, THE MEAN RADIUS OF THE FAMILIARITY REGION

Notes. This table shows estimates of $\frac{1}{r}$ from equation (22) based on normalized units of distance, which are then converted into estimates for r in both miles and km. Note that $g_p \equiv \ln(\gamma_p/W_p)$ denotes the log of risk aversion scaled by wealth and $s_n \equiv \ln\left(\mu_n/\sigma_n^2\right)$ denotes the log of expected excess return scaled by return variance. Panel A includes observations with $\text{amt}_{pn} = 0$ replaced with an investment of one Finnish mark, corresponding to about USD 0.17. Panel B excludes observations with $\text{amt}_{pn} = 0$. Univariate regression results are reported in Column (1), including risk aversion in Column (2), including risk aversion and expected excess stock returns scaled by variance of returns in Column (3), panel regression with postal code and stock fixed effects and robust standard errors double-clustered at the postal code and firm level in Column (4). Statistical significance levels: * = 0.01, ** = 0.001, *** = 0.0001.

panel regression (Column (4) of Panel A), the R^2 is 62%. The standard deviation of the distance between headquarters and household is 0.312, so a one standard deviation increase in a household's distance to a firm's headquarters shrinks its subjective prior expected risk premium by a factor of $e^{-3.185\times 0.312} = 0.37$, which is substantial; e.g., an objective risk-premium of 10% would be reduced to a risk premium of only 3.7%.

B.3. Discussion

As we can see, our results show that the distinction between psychological and geographical distance is relevant empirically. When the geographical distance between a household and the firm's headquarters exceeds the threshold distance of $\overline{d} = 143$ miles (230 km), the psychological distance between the household and the firm becomes infinite, and so the household's subjective prior expected excess return for a firm's stock is zero—the household decides it is optimal not to hold the firm's stock. We are thus able to quantify the extent to which the geographical distance between a household governs the extensive margin, i.e., the decision whether or not to hold a particular stock. For distances below $\overline{d} = 143$ miles (230 km), the psychological distance between a household and a firm equals the geographical distance, and a household's subjective expected excess return for a given firm's stock will decrease by a quarter every $r \ln \frac{4}{3} = 250 \ln \frac{4}{3} = 71.46$ miles (115 km).[23] We can, therefore, see how the radius r of the familiarity region governs a household's subjective prior expected excess return for a given firm's stock and, hence, its intensive margin, i.e., how much to invest in that particular firm's stock.

C. Further Tests of the Extensive Margin

In this section, we test some further predictions of our estimated model for the extensive margin.

C.1. Predicting extent of diversification

A prediction of our theory—see equation (10) in Corollary 2—is that if subjective prior beliefs about expected excess returns are impacted by household-firm distances, then households farther away from clusters of firms should hold less well-diversified portfolios. This is a new test

[23] From Corollary 2, we can see that when $d \leq \overline{d}$, household h's subjective expected excess return for firm n's stock is given by $\mu_{hn} = \mu_n e^{-\frac{d_{hn}}{r}}$. Therefore, for distances below $\overline{d}$, household h's subjective expected excess return for firm n's stock will decrease by a quarter every $d_{1/4}$ miles, where $e^{-\frac{d_{1/4}}{r}} = \frac{3}{4}$. Hence, $d_{1/4} = r \ln \frac{4}{3}$.

	Equally weighted		Value weighted	
	(1)	(2)	(3)	(4)
Distance, d_p	-1.011^{***}	-0.306^{***}	-1.024^{***}	-0.313^{***}
Standard error	0.084	0.072	0.082	0.070
Portfolio size, $\ln(W_p)$		0.446^{***}		0.445^{***}
Standard error		0.012		0.012

TABLE 4—PREDICTING DIVERSIFICATION BASED ON DISTANCE

Notes. This table shows how the average number of stocks households hold in a postal code n_p is related to the distance of the postal code to the firms' center-of-gravity (CoG), d_p. Columns 1 and 2 use an equally weighted definition of CoG, whereas Columns 3 and 4 use a value-weighted definition. Univariate regressions are used in Columns 1 and 3, and bivariate regressions, also including log-average portfolio size, $\ln(W_p)$, are used in Columns 2 and 4.

of the effect of subjective priors on the extensive margin that has not been undertaken in the literature.

To test if households tend to be more underdiversified the farther away they are located from firm headquarters, we define the center of gravity (CoG) of all the firms in our data set to be the mean of their individual locations

$$(x^C, y^C) = \frac{1}{\sum_{n=1}^{N} W^n} \left(\sum_{n=1}^{N} W^n x^n, \sum_{n=1}^{N} W^n y^n \right),$$

where (x^n, y^n) are the coordinates for firm n. We use both *equally-weighted* CoG ($W^n = 1$ for all firms) and *value-weighted* CoG, (a firm's weight is defined as the total value of household portfolio holdings in that firm).

We further define n_p to be the average *number* of stocks in households' portfolios in postal code p. We also define $d_p = D((x_p, y_p), (x^C, y^C))$, to be the *distance* between postal code area p and the firms' CoG. Then, we estimate how n_p is related to d_p.

Table 4 shows that the relation between n_p and d_p is significantly negative, both economically and statistically. A household located at the maximum distance from the firms' CoG is predicted to hold about one fewer stock in its portfolio than a household located right at the CoG—a major effect because the median number of stocks held in a household portfolio, as reported in Table 1, is only two. The results are very similar whether one uses the value-weighted or equally weighted definition of CoG.

We also control for portfolio size. Specifically, if wealthier households tend to be better diversified and are also located closer to firms on average, similar results would arise, but the results would be influenced by this omitted variable. We therefore include the logarithm of

average portfolio size within a postal code area, $\ln(W_p)$, in the regression. The estimated coefficient decreases by about two-thirds when $\ln(W_p)$ is included, both in the value-weighted and equally weighted CoG specification, but still remains highly significant.

C.2. Predicting overlap of portfolios

Our theory suggests that households located close to each other and, hence, in proximity to the same set of firms should have similar prior beliefs and hold similar investment portfolios. Therefore, households located in the same postal code should hold portfolios with more overlap (i.e., more common stocks) than if the portfolios were chosen randomly.

For example, for two households that each randomly and independently invest in one of N stocks, with probability $\frac{1}{N}$ of choosing each stock, the probability that the two portfolios overlap would also be $\frac{1}{N}$. In other words, the expected value of the random value $\tilde{N}^c$, which denotes the number of common stocks in their portfolios, would be $\frac{1}{N}$. More generally, if household h_1 randomly chooses N_{h_1} stocks and household h_2 randomly and independently chooses N_{h_2} stocks, then the expected overlap is

$$E\left[\tilde{N}^c_{h_1,h_2}\right] = \frac{N_{h_1} N_{h_2}}{N}.$$

This leads to the following prediction: two households in proximity should have similar prior beliefs and, hence, should hold more similar investment portfolios than two randomly chosen households.

This prediction can be tested by studying the actual versus expected overlap of the portfolios of all households located within the same postal code area, and summing up these overlaps over all postal codes, that is, by calculating the actual total overlap

$$N^c_{TOT} = \sum_{p} \sum_{\substack{h_1,h_2 \in \mathcal{H}_p \\ h_1 \neq h_2}} N^c_{h_1,h_2},$$

where $\mathcal{H}_p = \{h : p_h = p\}$ is the set of households in postal code area p, and comparing it with the expected total overlap.

The actual total overlap in the data is $N^c_{TOT} = 51,604,247$, whereas the expected total overlap under the independent, $\frac{1}{N}$ probability-per-stock, assumption is $3,478,029$. Thus, the likelihood that two randomly chosen households within the same randomly selected postal code area invest in the same stock is almost 15 times higher than expected. This strongly suggests that households in the same location hold similar prior beliefs about expected stock returns, while households in different locations do not.

Max. portf. size	Number of households	Actual overlap	Expected overlap	Ratio
1	188,535	6,324,570	2,649,371	2.387
2	268,268	12,989,232	6,096,314	2.130
5	357,772	28,450,235	16,782,239	1.695
10	393,606	42,315,889	27,935,744	1.515
20	404,277	49,978,463	34,481,911	1.449
125	405,628	51,604,247	35,952,390	1.436

TABLE 5— PREDICTING OVERLAP OF PORTFOLIOS WITHIN A POSTAL CODE

Notes. This table tests whether portfolio overlaps within a postal code area is higher than expected if households were randomly assigned to the area. Column 1 shows the maximum portfolio size included in test, Column 2 the number of households included in the sample, Column 3 the expected number of overlaps, Column 4 the actual number of overlaps, and Column 5 the ratio between actual and expected overlaps.

A limitation of the above test is that it assumes that each stock is chosen with the same probability, $\frac{1}{N}$, whereas, in practice, some stocks (for example, the telecommunications company Nokia in our dataset) are much more broadly held than others. The higher overlap will, therefore, partly be a consequence of the $\frac{1}{N}$ assumption. We, therefore, use a more sophisticated bootstrapping method based on the actual distribution of portfolio holdings among the households to test the prediction.

Briefly, we assume that the empirical distribution of household portfolio holdings represents the underlying data-generating process and compare the expected overlap if households and their portfolios were randomly assigned to postal codes with what is observed in the data. An interesting property of this test is that the maximum portfolio size, measured by the number of stocks in the portfolio, can be capped so that the test is applied to a subpopulation of households whose portfolios contain no more than 1, 2, 5, etc., stocks. Because location, via subjective prior beliefs, drives both underdiversification and the choice of similar portfolios for nearby households, we expect higher-than-expected overlaps to be more pronounced among households that hold few stocks.[24] Further details of the test are provided in the appendix.

The results of the bootstrapping method are shown in Table 5. The ratio of actual-to-expected overlap (the right-most column in the table) is the highest, 2.387 when only households holding one stock are included in the test, and then gradually decreases as the maximum portfolio size increases. The ratio is 1.436 when the full sample of households is included. These ratios, while lower than the ratio based on the $\frac{1}{N}$ assumption, remain highly significant in support of our model's prediction.

[24]There is also a purely mechanical effect in that the actual overlap cannot be much higher than the expected overlap when households hold large portfolios. For example, if a household holds *all* stocks in its portfolio, *every* stock in the other household's portfolio is common for the two portfolios, so actual and expected overlap must coincide in that case.

	Zero holding	Positive holding	Difference
Average distance to HQ	0.332	0.224	0.108
Average t-stat	−3.047	14.080	13.258
Number of firms	6	119	

TABLE 6—PREDICTING ZERO AND NON-ZERO STOCK HOLDINGS

Notes. This table shows results from two-sample t-tests of the difference in means between the distance from postal codes with zero holdings to firm headquarters and from postal codes with positive holdings.

C.3. Predicting zero and non-zero stock holdings

According to our theory—see equation (10)—a household's belief distortions about firms that are distant from it should be larger than those for firms closer to it. In particular, if a household-firm distance exceeds the threshold $\bar{d}$, then the household's prior beliefs should be distorted so much that it will not include that firm in its portfolio. This leads to the prediction that the distance between postal codes and headquarters for stocks with positive stock holdings should be smaller than that for zero holdings of a stock.

To test this prediction, for each stock, we perform a two-sample t-test, comparing the average distances of postal codes with zero and with positive holdings from the firms' headquarters. The results are shown in Table 6. The average distance for postal codes with zero holdings is about 0.332, whereas the average distance for postal codes with positive holdings is about 0.224, corresponding to a difference of 0.108—about 85 miles (137 km). The average t-statistic for the difference of means being positive is 13.3.

At the individual firm level, the average distance from a postal code with zero holdings is higher than the distance for positive holdings for 119 of the 125 stocks. For 116 of these firms, the difference is statistically significant at the 0.01% level. For the remaining 6 firms, for which the average distance is higher for postal codes with positive holdings compared to the distance for zero holdings, only one is significant at the 0.01% level. Thus, the data strongly support the prediction that the farther away a household is from a firm's headquarters, the more distorted are its prior beliefs, and hence, the higher the likelihood of zero portfolio holdings.

D. Further Tests of the Intensive Margin

In this section, we test some further predictions of our estimated model for the intensive margin.

D.1. Predicting stock-return moments

Our model has not been designed to match moments of stock returns; instead, we estimated the parameters r and $\overline{d}$ to fit the data on portfolio holdings. Therefore, to provide an independent test of our model, we now investigate how well it predicts a different set of data—the cross-sectional variation in moments of stock returns. To do this, we test if the data on portfolio holdings and location are informative also about out-of-sample cross-sectional stock-return distributions at the firm level. That is, we test if the estimated $s_n = \ln\left(\frac{\mu_n}{\sigma_n^2}\right)$ coefficients in (22) are informative about the N stock-return distributions. If the predictions of our model with distorted prior beliefs are superior to those under rational beliefs, it will provide significant support for our belief-based explanation of investor behavior because we are using only data on portfolio holdings and location to predict out-of-sample stock-return distributions.

To test whether the estimated s_n coefficients (the firm fixed effects) from the model with subjective prior beliefs are informative about actual stock-return distributions out of sample, we calculate daily mean excess returns, $\hat{\mu}_n$, and volatility, $\hat{\sigma}_n$, over a five-year period from 2003–2008, which is subsequent to the period used in the panel regressions. We first compare the relation between estimated s_n and realized volatility, $\ln(\hat{\sigma}_n)$, because realized volatility is the part of $\ln\left(\frac{\hat{\mu}_n}{\hat{\sigma}_n^2}\right)$ that is easiest to estimate. This relation should be negative. As shown in Column (1) in Panel A of Table 7, the relation is strongly negatively significant, with an R^2 of over 50%.

We compare this with the prediction of the rational-expectations model. In the rational-expectations model, all households choose the same risky portfolio, i.e., $f_{hn} \equiv 1$ for all h and n, and by summing (22) over households, it follows that s_n is directly related to a firm's log-size. Column (2) in Panel A of Table 7 shows that firm log-size is also informative about the stock-return volatility in our data but with lower explanatory power than the subjective-belief-based model. Moreover, when both the subjective-beliefs and rational-expectations estimates are included in a bivariate regression, as done in Column (3) of Panel A, the subjective-belief-based estimate dominates, remaining significant, whereas the log-firm size coefficient switches signs and becomes insignificant. That is, our model of subjective prior beliefs is better at explaining the risk-return tradeoff perceived by households from investing in stocks than the model with rational prior beliefs.

In Panel B of the table, we do the same estimation for $\ln\left(\frac{\hat{\mu}_n}{\hat{\sigma}_n^2}\right)$ as we did for $\ln(\hat{\sigma})$, including the 100 stocks that had positive excess realized returns during the period (for which the loga-

	(1)	(2)	(3)
Panel A: $\ln(\hat{\sigma}_n)$			
Rational expectations, s_n^{RE}		−0.149***	0.036
Belief-based, s_n^{BB}	−0.185***		−0.219***
R^2	0.506	0.356	0.510
N	108		
Panel B: $\ln\left(\frac{\hat{\mu}_n}{\hat{\sigma}_n^2}\right)$			
Rational expectations, s_n^{RE}		0.075	−0.296*
Belief-based, s_n^{BB}	0.149**		0.426***
R^2	0.068	0.019	0.121
N	100		

TABLE 7—PREDICTIVE POWER OF THE ESTIMATED s_n COEFFICIENTS

Notes. This table tests whether the s_n coefficients estimated from portfolio holdings predict realized volatility (Panel A) and return over variance (Panel B) in the subsequent 5-year period. Column 1 uses the subjective-belief-based model, Column 2 the rational-expectations model, and Column (3) both models. Realized volatility and returns are measured using daily data over the 3-year period, 2003–2005. In Panel A, $N = 108$ because this is the number of firms for which stock-market data was available to compute volatility. In Panel B, $N = 100$ because eight firms had negative realized excess returns for which the log is not defined. Statistical significance levels: * = 0.01, ** = 0.001, *** = 0.0001.

rithm is defined). The explanatory power is lower both for the subjective-belief-based coefficient and the coefficient based on the rational-expectations model due to the well-known challenges of estimating stocks' expected excess returns from realized returns. However, the subjective-belief-based estimate remains significant at the 0.1% level in the univariate regression and the 0.01% level in the bivariate regression, while the rational-expectations coefficient switches signs in the bivariate regression. The three-fold improvement in R^2 from 1.9% to 6.8% is striking because, as Campbell and Thompson (2008) explain, even small improvements in R^2 can lead to substantial utility gains for a mean-variance investor. As a robustness check, we also run the same tests using three years of realized returns. The results (not reported) are similar, the main difference being that the subjective-belief-based coefficient in the bivariate regression in Panel B is significant only at the 10% level. We emphasize that only data on portfolio holdings and location is used to estimate the s_n coefficients. That these are informative about out-of-sample stock-return moments therefore lends significant support for our subjective-belief-based explanation of investor behavior.

D.2. Estimating r after excluding Helsinki

A possible concern with the test of our key result reported in Table 3, which tests the relation between subjective prior beliefs and household-firm distance, is that it may be driven by different behaviors of households in urban areas (specifically, around Helsinki) relative to rural areas. For example, households in the Helsinki area may have a preference for stocks

headquartered in an urban area for some reason other than the effect of distance on beliefs, which will then lead to results similar to those reported above. To check if this is indeed the case, we run the regression in (22) *excluding* stocks and postal codes in the Helsinki area (postal codes with fewer than 5 significant digits). The results are reported in Table A.2 in Appendix A. We see that the results are qualitatively similar to before and, specifically, still both statistically and empirically highly significant. We also exclude households in the Helsinki area but not stocks, with similar results (not reported).

D.3. Estimating r controlling for employment effects

A second concern could be that a potential alternative explanation for the results is that it may not be psychological distance per se that drives subjective prior beliefs, but rather employment. That is, if households tend to invest in the firms they work for—which they likely also live close to—similar results may arise. To rule out such an explanation, we exclude observations for which the postal codes of account holders and firm headquarters are close. Specifically, we run the regression in (22) excluding all observations for which the normalized distance is less than some d_0. Table A.3 in Appendix A, shows that the results remain qualitatively similar when $d_0 = 0.01$ (corresponding to a minimal distance of about 8 miles (12.8 km) between the postal code of the account holder and firm headquarters for an observation to be included), and $d_0 = 0.03$ (corresponding to a minimal distance of about 24 miles). Thus, an employment effect does not seem to be driving the results.

D.4. Estimating r controlling for hedging effects

Our approach provides a tightly specified model that links households' subjective prior beliefs about expected stock returns and households' psychological distances from firms. A third concern could be that other explanations proposed in the literature, such as transaction costs and hedging demands, could drive these portfolio choices. We argue that transaction costs are unlikely to play a major role within our sample, which is focused on one country with all stocks traded on the same exchange.

With respect to hedging demand, an alternative explanation for why agents prefer to invest in nearby stocks is that they provide a hedge against local shocks. For example, if a local firm performs well, prices of services and goods (e.g., housing) may increase because of increased demand from the employees at the firm who are now wealthier. Investing in the local firm provides a hedge against such price shocks. Inasmuch as such hedging demand is related to the

age and gender of the population, we can assess its effect because account-level information is available in the data. For example, younger investors—who are less likely to own their homes—are likely to have different exposure to real-estate price shocks compared with older investors. We create variables for the average birth year (YOB) of the investors in a specific stock and postal code and for their gender (GEN, which is 1 for male and 2 for female). The correlations between the distance to firm headquarters and these variables are both low, $\rho_{d,\text{YOB}} = -0.049$, and $\rho_{d,\text{GEN}} = -0.056$, suggesting that any hedging demand that varies with age and/or gender is not captured by the distance to firm headquarters. To further explore a potential relation, we rerun the tests from Table 3, Panel B, but including birth year and gender, and also from Table A.3 with $d_0 = 0.05$, to rule out hedging demand for local shocks within a 40-mile (64-km) radius. As seen in Table A.4, the estimates for the sensitivity coefficient $\frac{1}{r}$ barely change and are still highly significant. We conclude that it is unlikely that our results are driven by hedging demand against local shocks, at least within a 40-mile (64-km) radius of the investor, and against shocks that are related to age and/or gender.

D.5. Estimating r Controlling for Nokia and Stockmann

Another concern may be that headquarters provides a very rough measure of a firm's location. For example, some firms have operations spread out over the whole country and will be familiar to households far away from their headquarters. The challenges of developing an objectively superior alternative measure of firm location are significant, though, which is why we use the well-established headquarters measure of location. As a robustness check, we ensure that the results do not change when excluding the two "least local" companies during the period: the global telecommunication company Nokia, which made up over half of the stock market value in the early 2000s, and the retail store chain Stockmann, which had stores all over Finland. The results (not reported) are very similar when excluding those two companies.

III. Estimating the Effect of Belief Distortions on Welfare

In this section, we use the results of our empirical analysis to estimate the spatial distribution of deviations of subjective prior beliefs from objective beliefs and their consequences for welfare and household inequality. In particular, we show how cross-sectional differences in psychological distance give rise to cross-sectional heterogeneity in households' subjective priors about stock returns and, thus, inequality in household welfare.

From Proposition 4, the mean-variance *welfare loss* from having distorted subjective prior beliefs $\boldsymbol{\mu}_p$ (at the postal-code level) instead of rational beliefs, is given by

$$\Delta U^{MV}(\boldsymbol{\mu}, \boldsymbol{\mu}_p) = \frac{1}{\gamma_p} \mathrm{KL}(\boldsymbol{\mu}, \boldsymbol{\mu}_p) = \frac{1}{2} \frac{1}{\gamma_p} (\boldsymbol{\mu} - \boldsymbol{\mu}_p)^\top V^{-1} (\boldsymbol{\mu} - \boldsymbol{\mu}_p).$$

In order to interpret the magnitude of the welfare loss resulting from the deviation of subjective prior beliefs from rational beliefs, it will be convenient to define *transformed relative entropy*, which is a useful measure for financial economists because it has the same units as a Sharpe ratio. This measure of welfare loss is also attractive because it is independent of leverage and the risk aversion of the household.

DEFINITION 3. *The transformed relative entropy, at the level of postal codes, is given by*

$$\mathrm{TKL}(\boldsymbol{\mu}, \boldsymbol{\mu}_p) = \sqrt{2 \frac{\mathrm{KL}(\boldsymbol{\mu}, \boldsymbol{\mu}_p)}{N}}, \tag{23}$$

where the relative entropy (Kullback-Leibler distance) is defined in equation (17) and N is the total number of firms.

For the special case in which stock returns are uncorrelated, the transformed relative entropy is the root mean square of the differences in individual stock-return Sharpe ratios:

$$\begin{aligned} \mathrm{TKL}(\boldsymbol{\mu}, \boldsymbol{\mu}_p) &= \sqrt{\frac{1}{N} \sum_{n=1}^{N} \left(\frac{\mu_n - \mu_{pn}}{\sigma_n} \right)^2} \\ &= \sqrt{\frac{1}{N} \left[\sum_{n:\, d_{pn} \leq \overline{d}} \left(\frac{\mu_n}{\sigma_n} \right)^2 (1 - e^{-\frac{1}{r} d_{pn}})^2 + \sum_{n:\, d_{pn} > \overline{d}} \left(\frac{\mu_n}{\sigma_n} \right)^2 \right]}. \end{aligned} \tag{24}$$

To compute $\mathrm{TKL}(\boldsymbol{\mu}, \boldsymbol{\mu}_p)$ at the level of each postal code, we first compute in miles the spatial distance between firm headquarters and the CoG for each postal code using equation (20). We standardize this distance by dividing it by 795 miles so that it is in the same units as our empirical work. We then compute the trust of each postal code to the 125 firms in our dataset, using the value of $\overline{d} = 0.1799$ estimated in Table 2 and the value of $\frac{1}{r} = 3.185$ estimated in Table 3. Then, we take the moments of daily stock returns and annualize them. With these annualized moments, we compute the deviation in prior beliefs at the postal code level, $\mu_n - \mu_{pn}$. Finally, using the estimates of $\mu_n - \mu_{pn}$ and σ_n^2, we compute $\mathrm{TKL}(\boldsymbol{\mu}, \boldsymbol{\mu}_p)$ as defined in (24).

Computing $\mathrm{TKL}(\boldsymbol{\mu}, \boldsymbol{\mu}_p)$, we find that the smallest value the welfare-loss measure takes is about 0.25, which is for the Helsinki region (postal codes below 00990). It is striking that even

for postal codes close to Helsinki, the value of the welfare-loss measure is substantially greater than zero, which is the value under rational beliefs. As one moves away from Helsinki, the welfare loss increases: for postal codes greater than 20000, we find that $\text{TKL}(\boldsymbol{\mu}, \boldsymbol{\mu}_p)$ is about 0.50, double that of the value for the Helsinki region. For postal codes greater than 40000, $\text{TKL}(\boldsymbol{\mu}, \boldsymbol{\mu}_p)$ is about 0.57, which is close to its maximum value of 0.59.[25] This indicates that for these postal codes, prior beliefs about firm-level expected excess returns are close to zero. That is, the effect of psychological distance is so great that households in these postal codes perceive the risk-premium from investing in risky assets to be zero and, hence, do not invest much in any of the risky assets. As shown in equation (10), this is a direct consequence of subjective prior beliefs decaying rapidly because the functional form of the familiarity of household h with firm n is exponential in psychological distance.

A choropleth map displaying these values of $\text{TKL}(\boldsymbol{\mu}, \boldsymbol{\mu}_p)$ for different postal codes is given in Figure 7. Recall from Figure 6 that during the period of our study, a significant proportion of the Finnish population (more than 70%) resided outside of Helsinki, with over half of Finland's population in rural areas. From Figures 7, it is apparent that there is a significant variation in welfare levels across the population of Finland. In particular, the segment of the population residing close to Helsinki has subjective prior beliefs that are much less distorted than the population residing in regions that are distant from Helsinki. As a result of this belief distortion based on spatial distance from firms, Figure 7 paints a stark picture of the substantial inequality in the welfare levels of the population residing close to Helsinki compared to the population in the rest of the country.

IV. Conclusion

In conclusion, our paper provides a novel theoretical framework to explain how households form subjective prior beliefs, addressing a significant gap in the literature on expectation formation. While much of the existing research has focused on how beliefs are updated, our approach endogenizes the formation of *prior* beliefs. A household's subjective prior beliefs about a firm's expected excess returns differ from rational prior beliefs because subjective priors are impacted by how familiar the household is with the firm. We provide a formal (mathematical) definition of *familiarity*. We show that a household's familiarity with a firm is explained by an exponential law that depends on only two parameters. One parameter governs the relation between psy-

[25] From the definition in (23), the $\text{TKL}(\boldsymbol{\mu}, \boldsymbol{\mu}_p)$ quantities of $\{0.25, 0.50, 0.57, 0.59\}$ reported in the text can also be expressed in terms of the Kullback-Leibler divergence; the corresponding $\text{KL}(\boldsymbol{\mu}, \boldsymbol{\mu}_p)$ quantities are $\{3.90, 15.63, 20.31, 21.76\}$.

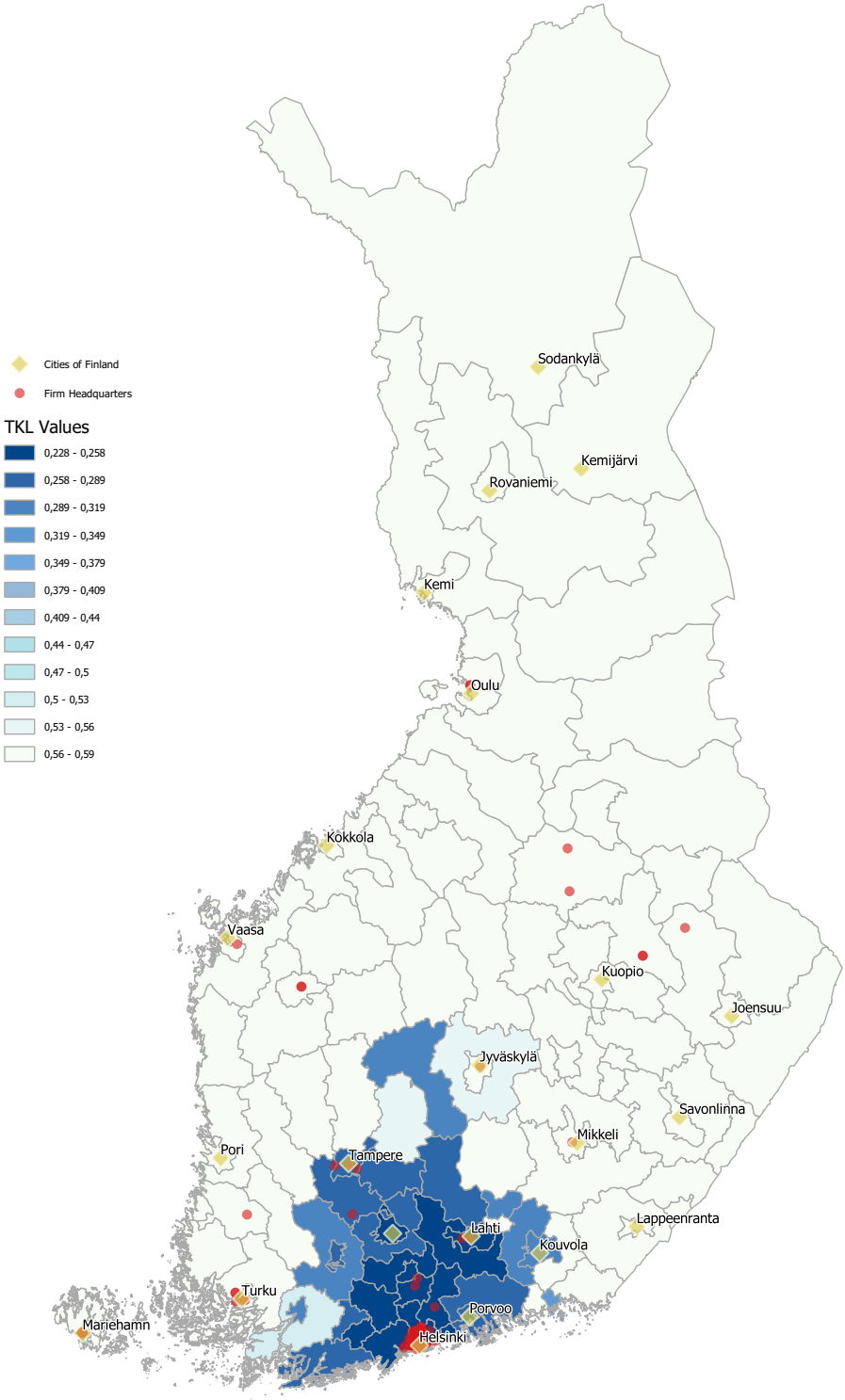


FIGURE 7. TRANSFORMED RELATIVE ENTROPY ACROSS POSTAL CODES

This choropleth map displays for different postal codes (that have been aggregated to the 2-digit level) the values of transformed relative entropy, $\mathrm{TKL}(\boldsymbol{\mu}, \boldsymbol{\mu}_p)$, which is defined in equation (24).

chological and geographical distance, while the other determines how rapidly subjective prior beliefs decay with psychological distance.

To make the model testable, our theory establishes the relation between unobservable household prior beliefs and observable portfolio choices. We estimate the two parameters underpinning our exponential law using Finnish portfolio data. Doing so reveals that psychological distance, which in our empirical estimation is a function of geographical distance, has a substantial impact on belief distortions about firm-level expected stock returns. We also show that the estimated belief distortions result in substantial household welfare losses. Moreover, households living farther from major financial centers like Helsinki experience larger welfare losses, demonstrating that inequality is linked to geography.

Our results provide a micro-founded explanation for observed deviations from rational expectations in financial economics. We explain how psychological distance can encompass temporal, spatial, cultural, and social distance. Our use of psychological distance, therefore, opens up new directions for incorporating behavioral factors into models of economic decision-making. The exponential law we develop provides a precise hypothesis to test. Our framework also highlights the economic significance of belief distortions linked to geography. In summary, we contribute to the literature on belief formation, offering insights into the endogenous mechanisms that shape cross-sectional differences in subjective priors and advancing the discussion on how economic agents perceive and act on financial information.

A. Appendix

In this appendix, we provide additional information about the empirical tests and results. Section A.A.1 provides details of the bootstrapping method used to test the prediction about the overlap of portfolios reported in Section C.2. Section A.A.2 contains the table listing the 125 stocks in our sample and additional tables with the results of tests reported in Section II.D.

A.1. Bootstrapping Method

Consider a finite multi-set of vectors, $\mathcal{V} = \{\mathbf{v}_m\}_{m\in\mathcal{M}}$, $|\mathcal{M}| \in \mathbb{N}$, where $\mathbf{v}_m \in \{0,1\}^N$, $N \in \mathbb{N}$. In our test, m will be associated with a household and $(\mathbf{v}_m)_n$ will represent whether it holds stock n (in which case $(\mathbf{v}_m)_n = 1$) or not (in which case $(\mathbf{v}_m)_n = 0$). The object $\mathcal{V}$ is a multi-set, since there may be multiple households with the same stocks in their portfolios. The nonzero elements in $\mathbf{v} \in \mathcal{V}$ are denoted the vector's *constituents*, and $c_{\mathbf{v}} = |\{\ell : (\mathbf{v})_\ell = 1\}|$ is defined as the number of such constituents.

For two elements, $\mathbf{v}^a \in \mathcal{V}$, $\mathbf{v}^b \in \mathcal{V}$, define the vector of overlaps, $\mathcal{O}(\mathbf{v}^a, \mathbf{v}^b) \in \{0,1\}^N$, such that $\mathcal{O}(\mathbf{v}^a, \mathbf{v}^b)_n = (\mathbf{v}^a)_n \times (\mathbf{v}^b)_n$, and the overlap $o(\mathbf{v}^a, \mathbf{v}^b) = \sum_n \mathcal{O}(\mathbf{v}^a, \mathbf{v}^b)_n \in \{0, 1, \ldots, N\}$.

Consider a multi-set $\mathcal{A}$ of (at least two) elements in $\mathcal{V}$, ordered from 1 to $r = |\mathcal{A}|$, $\mathbf{a}_1, \ldots, \mathbf{a}_r$. This set will correspond to the set of household portfolios in a postal code area in our test. The overlap in $\mathcal{A}$ is

$$o(\mathcal{A}) = \frac{1}{2} \sum_{\substack{k,\ell=1,\ldots,r \\ k\neq\ell}} o(\mathbf{a}_k, \mathbf{a}_\ell). \tag{25}$$

Define $\mathcal{Z}^k = \{\mathbf{v} \in \mathcal{V} : c_{\mathbf{v}} = k\}$, the set of all elements in $\mathcal{V}$, with k constituents, and $z^k = |\mathcal{Z}^k|$, the number of such elements. Also define $K = \max\{k : z^k > 0\}$. For simplicity, we assume that $z^k > 0$ for all $k < K$. Our analysis also holds if this assumption is not satisfied but with the extra notational burden of excluding such k's for which $z^k = 0$ in some of the sums below, which is why we make this assumption.

Consider a random data generating process to generate a vector $\tilde{\mathbf{a}}$ of k constituents from the elements in $\mathcal{Z}^k$, where each element in $\mathcal{Z}^k$ is chosen with the same probability. Thus, if the elements in $\mathcal{Z}^k$ are ordered as $\mathbf{v}^k_1, \ldots, \mathbf{v}^k_{z_k}$, then

$$\mathbb{P}(\tilde{\mathbf{a}} = \mathbf{v}^k_\ell) = \frac{1}{z_k}, \qquad \ell = 1, \ldots, k.$$

Now, consider two randomly chosen such elements, $\tilde{\mathbf{a}} \in \mathcal{Z}^k$ and $\tilde{\mathbf{b}} \in \mathcal{Z}^\ell$, $1 \leq k, \ell \leq K$. The expected overlap of these two elements, given the above data-generating process, is then

$$o^{\text{Exp}}_{k,\ell} = \mathbb{E}\left[o(\tilde{\mathbf{a}}, \tilde{\mathbf{b}})\right] = \frac{1}{z^k z^\ell} \sum_{s=1}^{z_k} \sum_{t=1}^{z_\ell} o(\mathbf{v}^k_s, \mathbf{v}^\ell_t).$$

Moreover, given the set $\mathcal{A}$ with $r \geq 2$ elements, and the ordered elements, $\mathbf{a}_1, \ldots, \mathbf{a}_r$, the expected overlap, when $\mathcal{A}$ is chosen from the above data generating process, is

$$o^{\text{Exp}}(\mathcal{A}) = \frac{1}{2} \sum_{\substack{k,\ell=1,\ldots,r \\ k \neq \ell}} o^{\text{Exp}}_{c_{\mathbf{a}_k}, c_{\mathbf{a}_\ell}}. \tag{26}$$

By comparing the actual overlap given in equation (25) with the expected overlap given in (26), we can thus draw inferences about whether the elements in $\mathcal{A}$ were randomly selected according to the above data generating process, or whether they have too much (or too little overlap) compared with what would be expected.

Note that it is straightforward to restrict the above test to portfolios up to a specific size, S, by replacing the set $\mathcal{A}$ with $\mathcal{A}^S = \{\mathbf{v} \in \mathcal{A} : c_{\mathbf{v}} \leq S\}$. This allows us to draw additional inferences about whether potential non-randomness stems from elements with a low number of constituents or not. Of course, $\mathcal{A}^N = \mathcal{A}$.

For the portfolio data, we use the set of portfolios of households in different postal code areas, $\mathcal{A}_p = \{\mathbf{v}_h : h \in \mathcal{H}_p\}$, $p = 1, \ldots, P$. Our null hypothesis is that households' portfolios within a postal code are randomly selected from the total set of portfolios, $\mathcal{V} = \cup_p \mathcal{A}_p$. We compare the actual and expected total overlap across postal-code areas, controlling for portfolio size,

$$N^c_{TOT} = \sum_p o(\mathcal{A}^S_p) \qquad \text{with} \qquad \mathbb{E}\left[\tilde{N}^c_{TOT}\right] = \sum_p o^{\text{Exp}}(\mathcal{A}^S_p),$$

where we vary the portfolio size, S, between 1 and N.

The advantage of this approach, which is admittedly more complex than the simple test in the main paper, is that instead of assuming each household picks each stock with probability $\frac{1}{N}$, we use the empirical distribution of portfolios to test whether the actual portfolios observed within postal codes are consistent with a "random allocation" of these portfolios. This approach, therefore, is robust to some stocks being much more widely held than others. Note that our total test contains $P = 2,923$ postal codes, each with an average of 139 households. Thus, the overrepresentation of overlap of 43.6%–139% we report in Table 5 is strongly statistically significant.

A.2. Additional Tables

The stocks in our sample are shown in Table A.1. The remaining tables describe the results of the additional tests reported in Section II.D. The estimated sensitivity coefficient $\frac{1}{r}$ when excluding the Helsinki area is shown in Table A.2. The estimated sensitivity coefficient when controlling for employment effects by including only distant observations is shown in Table A.3. The estimated sensitivity coefficient when including investor year-of-birth and gender as additional controls is given in Table A.4.

1	Bank of Aland Plc A	2	Pohjola Group Plc
3	Norvestia Plc	4	Kesko Corporation B
5	Stockmann Plc A	6	Stockmann Plc B
7	Tieto Corporation	8	Amer Sports Corporation
9	Fiskars Corporation	10	Fiskars Corporation K
11	Huhtamki Oyj	12	Instrumentarium
13	Kone Corporation B	14	Metsa Board Oyj A
15	Metsa Board Oyj B	16	Nokia Corporation
17	Tamro Oyj	18	Tamfelt Corp.
19	Tamfelt Corporation Ord. shares	20	Bank of Aland Plc B
21	Uponor Oyj	22	Outokumpu Oyj
23	Citycon Oyj	24	Polar Real Estate Corp.
25	Raisio Plc Vaihto-osake	26	Birka Line Abp B
27	Pohjola Bank A	28	Finnair Oyj
29	Sampo Plc A	30	Stromsdal Corporation
31	Apetit Plc	32	Rautaruukki Corporation
33	Finnlines Plc	34	Silja Oyj Abp
35	Wartsila Corporation A	36	Wartsila Corporation
37	Tiimari Plc	38	Kemira Oyj
39	Ponsse Oyj	40	Viking Line Abp
41	Nokian Tyres Plc	42	Biohit Oyj B
43	Konecranes Plc	44	Stora Enso Oyj A
45	Stora Enso Oyj R	46	UPM-Kymmene Corporation
47	HKScan Oyj A	48	PKC Group Oyj
49	Incap Corporation	50	Atria Plc A
51	Payry PLC	52	Sponda Plc
53	Technopolis Plc	54	Valoe Oyj
55	Alma Media Corporation 1	56	Alma Media Corporation 2
57	Ramirent Plc	58	Fortum Corporation
59	Bittium Corporation	60	Yomi Plc
61	Rapala VMC Corporation	62	Sonera Oyj
63	Eimo Oyj	64	Innofactor Plc
65	Marimekko Corporation	66	SanomaWSOY Corporation A
67	Sanoma Corporation	68	Teleste Corporation
69	Oral Hammaslakarit Plc	70	Perlos Corporation
71	Metso Corporation	72	Talentum Oyj
73	Kesko Corporation A	74	Aldata Solution Oyj
75	Digia Plc	76	Solteq Oyj
77	Ixonos Plc	78	Aspo Plc
79	Aspocomp Group Plc	80	Dovre Group Plc
81	Trainers House Plc	82	Comptel Corporation
83	SSH Communications Security Oyj	84	Basware Corporation
85	Wulff Group Plc	86	Saunalahti Group Oyj
87	Etteplan Oyj	88	QPR Software Plc
89	eQ Oyj	90	Tekla Corporation
91	Sievi Capital plc	92	Sentera Plc
93	Okmetic Oyj	94	CapMan Plc B
95	Vacon Plc	96	eQ Oyj
97	Evox Rifa Group Plc	98	Componenta Corporation
99	Glaston Corporation	100	Tecnotree Corporation
101	Lassila & Tikanoja Plc	102	Suominen Oyj
103	Revenio Group Corporation	104	Biotie Therapies Corp.
105	Ilkka-Yhtyma Oyj 2	106	Neo Industrial Oyj
107	Orion Corporation A	108	Orion Corporation B
109	Raisio Plc K	110	Saga Furs Oyj C
111	YIT Corporation	112	Stonesoft Corporation
113	F-Secure Corporation	114	Chips Corporation B
115	Efore Plc	116	Hackman Oyj Abp
117	Honkarakenne Oyj B	118	Lemminkainen Corporation
119	Evia Oyj	120	Martela Oyj A
121	Olvi Plc A	122	Cramo Oyj
123	Tulikivi Oyj A	124	Elecster Oyj A
125	Vaisala Corporation A		

TABLE A.1—STOCKS IN OUR SAMPLE

Notes. This table lists the 125 stocks issued by companies that are headquartered in Finland and are included in our sample. For companies with A- and B-shares, both shares are included in our sample.

	(1)	(2)	(3)	(4)
Panel A: Including all observations				
Estimate of $\frac{1}{r}$ (normalized units)	4.228***	3.868***	3.771***	3.771***
Standard error	0.069	0.071	0.073	0.630
Mean radius, r (miles)	188	206	211	211
Mean radius, r (km)	303	331	339	339
$g_p \equiv \ln(\gamma_p / W_p)$				
-average		−3.806	−3.771	
-max		−1.097	−1.073	
-min		−12.393	−12.355	
$s_n \equiv \ln(\mu_n / \sigma_n^2)$				
-average			0	
-max			5.418	
-min			−1.797	
R^2	0.051	0.308	0.487	0.487
Adj. R^2	0.051	0.283	0.469	0.469
$N = 69,368$				
Panel B: Excluding observations with $amt_{pn} = 0$				
Estimate of $\frac{1}{r}$ (normalized units)	1.824***	1.892***	2.754***	2.754***
Standard error of $\frac{1}{r}$	0.074	0.082	0.071	0.325
Mean radius, r (miles)	436	420	289	289
Mean radius, r (km)	702	676	465	465
$g_p \equiv \ln(\gamma_p / W_p)$				
-average		−8.072	−8.084	
-max		−2.681	−2.282	
-min		−12.392	−12.757	
$s_n \equiv \ln(\mu_n / \sigma_n^2)$				
-average			0	
-max			1.787	
-min			−3.197	
R^2	0.028	0.249	0.501	0.501
Adj. R^2	0.028	0.159	0.440	0.440
$N = 20,787$				

TABLE A.2—ESTIMATE OF r EXCLUDING THE HELSINKI AREA

Notes. This table, using only firms and households outside of the Helsinki area (with 5-digit postal codes), estimates the sensitivity coefficient $\frac{1}{r}$ from equation (22) based on normalized units of distance. Note that $g_p \equiv \ln(\gamma_p / W_p)$ denotes the log of risk aversion scaled by wealth and $s_n \equiv \ln(\mu_n / \sigma_n^2)$ denotes the log of expected excess return scaled by return variance. Panel A includes observations with $\text{amt}_{pn} = 0$ replaced with an investment of one Finnish mark, corresponding to about USD 0.17. Panel B excludes observations with $\text{amt}_{pn} = 0$. Univariate regression in Column (1), including risk aversion in Column (2), including risk aversion and expected excess stock returns scaled by variance of returns in Column (3), panel regression with postal code and stock fixed effects and robust standard errors double-clustered at the postal code and firm level in Column (4). Statistical significance levels: * = 0.01, ** = 0.001, *** = 0.0001.

	(1)	(2)	(3)	(4)
Panel A: Including only postal code/firm observations at distances larger than 8 miles				
Estimate of $\frac{1}{r}$ (normalized units)	1.772***	1.844***	2.397***	2.397***
Standard error of $\frac{1}{r}$	0.036	0.063	0.048	0.392
Mean radius, r (miles)	449	431	332	332
Mean radius, r (km)	722	694	534	534
$g_p \equiv \ln(\gamma_p/W_p)$				
-average		−8.480	−7.899	
-max		−4.543	−2.282	
-min		−12.415	−12.609	
$s_n \equiv \ln\left(\mu_n/\sigma_n^2\right)$				
-average			0	
-max			4.142	
-min			−3.952	
R^2	0.018	0.186	0.614	0.614
Adj R^2	0.018	0.168	0.605	0.605
$N = 129,802$				
Panel B: Including only postal code/firm observations at distances larger than 24 miles				
Estimate of $\frac{1}{r}$ (normalized units)	0.931***	0.991***	1.662***	1.662***
Standard error of $\frac{1}{r}$	0.039	0.070	0.053	0.326
Mean radius, r (miles)	854	802	478	478
Mean radius, r (km)	1374	1291	770	770
$g_p \equiv \ln(\gamma_p/W_p)$				
-average		−8.187	−7.680	
-max		−4.000	−2.561	
-min		−11.798	−12.117	
$s_n \equiv \ln\left(\mu_n/\sigma_n^2\right)$				
-average			0	
-max			4.067	
-min			−3.977	
R^2	0.005	0.160	0.599	0.599
Adj. R^2	0.005	0.139	0.589	0.589
$N = 119,874$				

TABLE A.3—ESTIMATE OF r CONTROLLING FOR EMPLOYMENT EFFECTS

Notes. This table estimates the sensitivity coefficient $\frac{1}{r}$ from equation (22) while controlling for employment effects. It does this by including only postal code/firm observations at distances larger than d_0, and excluding $\text{amt}_{pn} = 0$ observations. Panel A sets d_0 to 0.01, corresponding to a minimum distance between the postal codes of the account holder and firm headquarters of about 8 miles (12.8 km), whereas in Panel B $d_0 = 0.03$, corresponding to a minimal distance of about 24 miles (39 km). Note that $g_p \equiv \ln(\gamma_p/W_p)$ denotes the log of risk aversion scaled by wealth and $s_n \equiv \ln\left(\mu_n/\sigma_n^2\right)$ denotes the log of expected excess return scaled by return variance. Univariate regression in Column (1), including risk aversion in Column (2), including risk aversion and expected excess stock returns scaled by variance of returns in Column (3), panel regression with postal code and stock fixed effects and robust standard errors double-clustered at the postal code and firm level in Column (4). Statistical significance levels: * = 0.01, ** = 0.001, *** = 0.0001.

	(1)	(2)	(3)	(4)
Panel A: Including all postal code/firm observations				
Estimate of $\frac{1}{r}$ (normalized units)	2.298***	2.056***	2.658***	2.658***
Standard error, $\frac{1}{r}$	0.034	0.060	0.046	0.398
Mean radius, r (miles)	346	387	299	299
Mean radius, r (km)	557	622	481	481
Year of birth coefficient, YOB	−0.031***	−0.040***	−0.013***	−0.013***
Standard error	0.001	0.001	0.001	0.001
Gender coefficient, GEN	0.597***	0.445***	−0.157***	−0.157***
Standard error	0.019	0.018	0.013	0.033
R^2	0.065	0.249	0.630	0.630
Adj. R^2	0.065	0.233	0.622	0.622
$N = 134,825$				
Panel B: Including only postal code/firm observations at distances larger than 40 miles				
Estimate of $\frac{1}{r}$	0.809***	0.704***	1.377***	1.377***
Standard error, $\frac{1}{r}$	0.040	0.073	0.056	0.263
Mean radius, r (miles)	983	1130	577	577
Mean radius, r (km)	1582	1818	929	929
Year of birth coefficient, YOB	−0.031***	−0.037***	−0.012***	−0.012***
Standard error	0.001	0.001	0.001	0.001
Gender coefficient, GEN	0.461***	0.345***	−0.169***	−0.169***
Standard error	0.019	0.019	0.014	0.033
R^2	0.039	0.200	0.606	0.606
Adj. R^2	0.039	0.180	0.596	0.596
$N = 115,256$				

TABLE A.4—ESTIMATE OF r WITH ADDITIONAL CONTROLS FOR HEDGING EFFECTS

Notes. This table estimates the sensitivity coefficient $\frac{1}{r}$ from equation (22) when including investor year-of-birth (YOB) and gender (GEN) as additional controls for hedging effects. Panel A sets $d_0 = 0$, whereas Panel B sets $d_0 = 0.05$, corresponding to a threshold distance of about 40 miles (64 km). No fixed effects in Column (1), including risk aversion in Column (2), including risk aversion and expected excess stock returns scaled by variance of returns in Column (3), panel regression with postal code and stock fixed effects and robust standard errors double-clustered at the postal code and firm level in Column (4). Statistical significance levels: * = 0.01, ** = 0.001, *** = 0.0001.

REFERENCES

Adam, Klaus, Dmitry Matveev, and Stefan Nagel, 2021, Do survey expectations of stock returns reflect risk adjustments?, *Journal of Monetary Economics* 117, 723–740.

Adam, Klaus, and Stefan Nagel, 2023, Expectations data in asset pricing, in *Handbook of Economic Expectations*, 477–506 (Elsevier).

Afrouzi, Hassan, Spencer Y. Kwon, Augustin Landier, Yueran Ma, and David Thesmar, 2023, Overreaction in expectations: Evidence and theory, *Quarterly Journal of Economics* 138, 1713–1764.

Badarinza, Cristian, Tarun Ramadorai, and Chihiro Shimizu, 2022, Gravity, counterparties, and foreign investment, *Journal of Financial Economics* 145, 132–152.

Bailey, Michael, Ruiqing Cao, Theresa Kuchler, and Johannes Stroebel, 2018, The economic effects of social networks: Evidence from the housing market, *Journal of Political Economy* 126, 2224–2276.

Barberis, Nicholas C., 2018, Psychology-based models of asset prices and trading volume, in *Handbook of Behavioral Economics: Applications and Foundations 1*, volume 1, 79–175 (Elsevier).

Barberis, Nicholas C., and Lawrence J. Jin, 2023, Model-free and model-based learning as joint drivers of investor behavior, NBER Working Paper.

Barberis, Nicholas C., Lawrence J. Jin, and Baolian Wang, 2021, Prospect theory and stock market anomalies, *Journal of Finance* 76, 2639–2687.

Barberis, Nicholas C., Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307–343.

Barberis, Nicholas C., and Richard H. Thaler, 2003, A survey of behavioral finance, in George M. Constantinides, Milton Harris, and René M. Stulz, (eds.) *Handbook of the Economics of Finance* (Elsevier, Amsterdam).

Beutel, Johannes, and Michael Weber, 2023, Beliefs and portfolios: Causal evidence, chicago Booth Research Paper.

Bhamra, Harjoat S, and Raman Uppal, 2019, Does household finance matter? small financial errors with large social costs, *American Economic Review* 109, 1116–1154.

Bhandari, Anmol, Jaroslav Borovička, and Paul Ho, 2019, Survey data and subjective beliefs in business cycle models, University of Minnesota Working Paper.

Bodnaruk, Andriy, 2009, Proximity always matters: Local bias when the set of local companies changes, *Review of Finance* 13, 629–656.

Bordalo, Pedro, Nicola Gennaioli, Yueran Ma, and Andrei Shleifer, 2020a, Overreaction in macroeconomic expectations, *American Economic Review* 110, 2748–82.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2018, Diagnostic expectations and credit cycles, *Journal of Finance* 73, 199–227.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2020b, Memory, attention, and choice, *Quarterly Journal of Economics* 135, 1399–1442.

Branikas, Ioannis, Harrison Hong, and Jiangmin Xu, 2020, Location choice, portfolio choice, *Journal of Financial Economics* 138, 74–94.

Cabrales, Antonio, Olivier Gossner, and Roberto Serrano, 2013, Entropy and the value of information for investors, *American Economic Review* 103, 360–77.

Camerer, Colin, 1995, Individual decision making, in J. Kagel and A. Roth, (eds.) *Handbook of Experimental Economics* (Princeton University Press, Princeton, NJ).

Camerer, Colin, 1998, Bounded rationality in individual decision making, *Experimental Economics* 1, 163–183.

Campbell, John Y., and Samuel B. Thompson, 2008, Predicting excess stock returns out of sample: Can anything beat the historical average?, *Review of Financial Studies* 21, 1509–1531.

Chaney, Thomas, 2018, The gravity equation in international trade: An explanation, *Journal of Political Economy* 126, 150–177.

Chiang, Yao-Min, David Hirshleifer, Yiming Qian, and Ann E. Sherman, 2011, Do investors learn from experience? Evidence from frequent IPO investors, *Review of Financial Studies* 24, 1560–1589.

Coibion, Olivier, and Yuriy Gorodnichenko, 2012, What can survey forecasts tell us about information rigidities?, *Journal of Political Economy* 120, 116–159.

Coibion, Olivier, and Yuriy Gorodnichenko, 2015, Information rigidity and the expectations formation process: A simple framework and new facts, *American Economic Review* 105, 2644–78.

Coval, J., and T. Moskovitz, 1999a, The geography of investment: Informed trading and asset prices, *Journal of Political Economy* 109, 811–841.

Coval, J., and T. Moskovitz, 1999b, Home bias at home: Local equity preference in domestic portfolios, *Journal of Finance* 54, 2045–2073.

D'Acunto, Francesco, Marcel Prokopczuk, and Michael Weber, 2019, Historical antisemitism, ethnic specialization, and financial development, *Review of Economic Studies* 86, 1170–1206.

Das, Sreyoshi, Camelia M. Kuhnen, and Stefan Nagel, 2020, Socioeconomic status and macroeconomic expectations, *Review of Financial Studies* 33, 395–432.

Föllmer, Hans, and Alexander Schied, 2011, *Stochastic finance: An introduction in discrete time* (Walter de Gruyter, Berlin).

French, K., and J. Poterba, 1991, Investor diversification and international equity markets, *American Economic Review* 81, 222–226.

Gabaix, Xavier, 1999, Zipf's law for cities: An explanation, *Quarterly Journal of Economics* 114, 739–767.

Gabaix, Xavier, 2009, Power laws in economics and finance, *Annual Review of Economic* 1, 255–294.

Gabaix, Xavier, 2016, Power laws in economics: An introduction, *Journal of Economic Perspectives* 30, 185–206.

Gabaix, Xavier, and Augustin Landier, 2008, Why has CEO pay increased so much?, *Quarterly Journal of Economics* 123, 49–100.

Gârleanu, Nicolae, and Lasse Heje Pedersen, 2022, Active and passive investing: Understanding Samuelson's dictum, *Review of Asset Pricing Studies* 12, 389–446.

Gennaioli, Nicola, and Andrei Shleifer, 2018, *A Crisis of Beliefs: Investor Psychology and Financial Fragility* (Princeton University Press).

Gennaioli, Nicola, Andrei Shleifer, and Robert Vishny, 2015, Neglected risks: The psychology of financial crises, *American Economic Review* 105, 310–14.

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Stephen Utkus, 2021, Five facts about beliefs and portfolios, *American Economic Review* 111, 1481–1522.

Greenwood, Robin, and Stefan Nagel, 2009, Inexperienced investors and bubbles, *Journal of Financial Economics* 93, 239–258.

Greenwood, Robin, and Andrei Shleifer, 2014, Expectations of returns and expected returns, *Review of Financial Studies* 27, 714–746.

Grinblatt, Mark, and Matti Keloharju, 2000, The investment behavior and performance of various investor types: A study of Finland's unique data set, *Journal of Financial Economics* 55, 43–57.

Grinblatt, Mark, and Matti Keloharju, 2001, How distance, language, and culture influence stockholdings and trades, *Journal of Finance* 56, 1053–1073.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2006, Does culture affect economic outcomes?, *Journal of Economic Perspectives* 20, 23–48.

Head, Keith, and Thierry Mayer, 2014, Gravity equations: Workhorse, toolkit, and cookbook, in *Handbook of International Economics*, volume 4, 131–195 (Elsevier).

Hirshleifer, David, 2001, Investor psychology and asset pricing, *Journal of Finance* 56, 1533–1597.

Hirshleifer, David, 2015, Behavioral finance, *Annual Review of Financial Economics* 7, 133–159.

Hirshleifer, David, 2020, Presidential address: Social transmission bias in economics and finance, *Journal of Finance* 75, 1779–1831.

Huberman, Gur, 2001, Familiarity breeds investment, *Review of Financial Studies* 14, 659–680.

Hvide, Hans K, Tom G. Meling, Magne Mogstad, and Ola L. Vestad, 2024, Broadband internet and the stock market investments of individual investors, *Journal of Finance* 79, 2163–2194.

Jaynes, Edwin T., 1957, Information theory and statistical mechanics, *Physical Review* 106, 620–630.

Jaynes, Edwin T., 1986, Monkeys, kangaroos, and N, in J. Justice, (ed.) *Maximum Entropy and Bayesian Methods in Applied Statistics: Proceedings of the Fourth Maximum Entropy Workshop University of Calgary*, 26–58 (Cambridge University Press).

Kaustia, Markku, and Samuli Knüpfer, 2008, Do investors overweight personal experience? Evidence from IPO subscriptions, *Journal of Finance* 63, 2679–2702.

Kaustia, Markku, and Samuli Knüpfer, 2012, Peer performance and stock market entry, *Journal of Financial Economics* 104, 321–338.

Knüpfer, Samuli, Elias Rantapuska, and Matti Sarvimäki, 2017, Formative experiences and portfolio choice: Evidence from the Finnish Great Depression, *Journal of Finance* 72, 133–166.

Kuchler, Theresa, and Basit Zafar, 2019, Personal experiences and expectations about aggregate outcomes, *Journal of Finance* 74, 2491–2542.

Laudenbach, Christine, Ulrike Malmendier, and Alexandra Niessen-Ruenzi, 2018, The long-lasting effects of propaganda on financial risk-taking, Working Paper.

Lucas, Jr., Robert E., 1976, Econometric policy evaluation: A critique, in Karl Brunner and Allan H. Meltzer, (eds.) *The Phillips Curve and Labor Markets: Carnegie-Rochester Conference Series on Public Policy*, volume 1, 19–46 (North-Holland).

Malmendier, Ulrike, 2021, FBBVA lecture 2020: Exposure, experience, and expertise: Why personal histories matter in economics, *Journal of the European Economic Association* 19, 2857–2894.

Malmendier, Ulrike, and Stefan Nagel, 2011, Depression babies: Do macroeconomic experiences affect risk taking?, *Quarterly Journal of Economics* 126, 373–416.

Malmendier, Ulrike, and Stefan Nagel, 2015, Learning from inflation experiences, *Quarterly Journal of Economics* 131, 53–87.

Mandelbrot, Benoît, 1953, An informational theory of the statistical structure of language, *Communication theory* 84, 486–502.

Manski, Charles F., 2004, Measuring expectations, *Econometrica* 72, 1329–1376.

Manski, Charles F., 2018, Survey measurement of probabilistic macroeconomic expectations: Progress and promise, *NBER Macroeconomics Annual* 32, 411–471.

Marschak, Jacob, 1959, Remarks on the economics of information, in *Contributions to Scientific Research in Management*, 79–98 (Western Data Processing Center, University of California, Los Angeles).

Merton, Robert C., 1980, On estimating the expected return on the market: An exploratory investigation, *Journal of Financial Economics* 8, 323–361.

Merton, Robert C., 1987, A simple model of capital market equilibrium with incomplete information, *Journal of Finance* 42, 483–510.

Muth, John F., 1961, Rational expectations and the theory of price movements, *Econometrica* 29, 315–335.

Nagel, Stefan, and Zhengyang Xu, 2022, Asset pricing with fading memory, *Review of Financial Studies* 35, 2190–2245.

Pavlov, Ivan P., 1927, *Conditioned Reflexes* (Oxford University Press, London).

Pedersen, Lasse Heje, 2022, Game on: Social networks and markets, *Journal of Financial Economics* 146, 1097–1119.

Shefrin, Hersh, 2007, *Beyond Greed and Fear: Understanding Behavioral Finance and the Psychology of Investing* (Oxford University Press).

Shefrin, Hersh, 2010, Behavioralizing finance, *Foundations and Trends in Finance* 4, 1–184.

Shepard, Roger N., 1987, Toward a universal law of generalization for psychological science, *Science* 237, 1317–1323.

Shive, Sophie, 2010, An epidemic model of investor behavior, *Journal of Financial and Quantitative Analysis* 45, 169–198.

Shleifer, Andrei, 2000, *Inefficient Markets: An Introduction to Behavioral Finance* (Oxford University Press, Oxford).

Statman, Meir, 2010, What is behavioral finance, in A. Wood, (ed.) *Behavioral Finance and Investment Management* (Research Foundation of CFA Institute).

Statman, Meir, 2011, *What Investors Really Want* (McGraw-Hill).

Tinbergen, Jan, 1962, *Shaping the world economy: Suggestions for an International Economic Policy* (Twentieth Century Fund, New York, NY).

Trope, Yaacov, and Nira Liberman, 2010, Construal-level theory of psychological distance, *Psychological Review* 117, 440–463.

Van Nieuwerburgh, Stijn, and Laura L. Veldkamp, 2009, Information immobility and the home bias puzzle, *Journal of Finance* 64, 1187–1215.

Van Nieuwerburgh, Stijn, and Laura L. Veldkamp, 2010, Information acquisition and portfolio under-diversification, *Review of Economic Studies* 77, 779–805.

Veldkamp, Laura L., 2011, *Information choice in macroeconomics and finance* (Princeton University Press).

Walden, Johan, 2019, Trading, profits, and volatility in a dynamic information network model, *Review of Economic Studies* 86, 2248–2283.

Weber, Michael, 2022, Subjective inflation expectations of households, *Business Economics* 57, 217–221.