Subjective Learning of Trading Talent  
Theory and Evidence from Individual Investors in the U.S.  
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Overview

▶ Research Question: How do individual investors learn about their trading talent?
▶ Quantitative Result: Learning about trading talent is about 7 times more sensitive to new signals than learning about stocks.
▶ Qualitative Result: A unifying framework that explains Bayesain learning about two subjects with constant-gain updating (Nageland Xu, 2019).

Abstract

Recent studies show evidence that investors learn about their trading abilities. This paper focuses on understanding how investors learn about their talent and proposes a unifying framework that explains Bayesian learning about two subjects with constant-gain updating. This framework also accounts for the performance-contingent trading intensity, investment in stocks, and the current stock-to-cover the fixed cost, which strongly predicts disposition effect in stock because switching requires a sufficiently large wedge between expected returns of the replacement stock and the expected return of the next replacement stock. This framework also accounts for the performance contingent trading intensity and attribution, and explains why a negative shock leads to attrition when an investor has several years of experience, which is inconsistent with the decreasing-gain updating under standard Bayesian learning.

Key Feature: Two Types of Learning

Bayesian learning about two subjects with constant-gain updating (Nagel and Xu, 2019).

Trading

Learning about ex-ante distribution of a draw of the subjective mean return \( \mu_{i,x} \) of the current stock \( x \) and variance \( \nu_{i,y} \) of trading talent.

Why two types of learning?

Attrition takes place when learning about more than stock.

Why only learn about mean?

Under-diversified portfolio + relatively long horizon (not day traders) + simplify + demonstrate the mechanism.

Belief dynamics

Weighted average of prior and new signal \( \mu_{i,x,t+1} = (1 - p) \mu_{i,x,t} + p \bar{y}_{i,x,t} \)

Memory decay parameter \( p \) and \( \bar{y}_{i,x,t} \). Calibrated to individual holdings data. \( \bar{y} = 0.144, \quad \sigma^2 = 0.02 \).

Figure 1. Estimation of Decay Parameters

Theory: Settings

▶ Discrete time portfolio choice

An investor chooses from a pool of stocks.

- Stock \( i \) log return \( r_{i,t+1} = \ln R_{i,t+1} \) follows normal distribution \( \ln R_{i,t+1} = \mu_i + \varepsilon_{i,t+1} \)

- \( \varepsilon_{i,t+1} \sim N(0, \sigma^2) \) i.d. (i.e. \( \sigma^2 \) is a known constant)

- \( \mu_i \) is unknown, constant, not random, key parameter to learn, equivalently draw of \( \mu_i \)

- Can only hold one stock at a time.

- Two decisions each period: (1) current vs. replacement; (2) investment consumption.

▶ Timing: Within each period,

- Realized stock return \( r_{i,t} \) is observed

- Two subjective beliefs are updated

- Decisions on consumption, investment, and stock choice (replace or not) are made

Preferences: Epstein-Zin utility function, i.e.,

\[
U_t = \left[ 1 - (1 - \delta) \phi_t \right]^{-\beta} \left[ \beta + \rho \bar{y}_{i,x,t} \right] \]

Theory: Result


- Log-linearization of Euler equation, budget constraint and portfolio turn.

- Guess-and-verify method (Re-derived for the unit root state variable in my settings)

▶ Optimal investment and consumption:

\[
\begin{align*}
\sigma_t^2 &= \theta_{t} + \theta_{i} \bar{y}_{i,x,t} + \theta_{y} \nu_{i,y,t} + \theta_{\beta} U_t \beta_t + \theta_{\varepsilon} \varepsilon_{i,t+1} \\
V_t^* &= \exp \left( \frac{B_t}{1 - \rho} \left( 1 - \beta \right) + B_t \lambda_t \right)
\end{align*}
\]

- Optimal switching rule: Compare

\[
U_t (y,t) = W_t \exp \left( \frac{B_t}{1 - \rho} \left( 1 - \beta \right) + B_t \lambda_t \right)
\]

- and switch to the new stock \( y \) if \( U_t (y,t) > U_t (x,t) \)

Properties: Monotonicity (\( A_{i,x} > 0 \)) and Convexity (\( B_{i,x} > 0 \))

Figure 2. Value Function

Evidence: Data

▶ Trading records data of individual investors in the U.S. between February 1991 and November 1996

Filter:

- Long-only investors that start trading after February 1991

- Quit at most once

- Have records of at least 3 consecutive months

- All stocks in holding matched to CRSP monthly database

- Total number of accounts: 7817

Evidence: Regressions

▶ Timing of stock switching

- Regressions: \( \text{stock switch}_{i,t} = \beta_0 + \beta_2 \times \bar{y}_{i,x,t} + \beta_3 \times \nu_{i,y,t} + \beta_4 \times \beta_t + \varepsilon_{i,t+1} \)

- \( \bar{y}_{i,x} \), \( \nu_{i,y} \), and \( \beta_t \) are generated in the model

- Takeaway: As implied by the model, stock switching is more likely to happen when the wedge between the subjective beliefs about trading talent and current stock is large enough to cover the transaction cost.

- Attribution and performance

- Regressions: \( U_t = \beta_0 + \beta_2 \times \bar{y}_{i,x,t} + \beta_3 \times \nu_{i,y,t} + \beta_4 \times \text{stock switch}_{i,t} + \varepsilon_{i,t} \)

- Takeaway: Higher subjective mean of talent distribution pushes the investor further away from dropping out of the market as implied by the model.

- More frequent stock switching hurts investment performance (Barber and Odean, 2000).

References


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