Investor experiences and financial market dynamics

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Abstract

How do macrofinancial shocks affect investor behavior and market dynamics? Recent evidence on experience effects suggests a long-lasting influence of personally experienced outcomes on investor beliefs and investment but also significant differences across older and younger generations.We formalize experience-based learning in an overlapping generations (OLG) model, where different cross-cohort experiences generate persistent heterogeneity in beliefs, portfolio choices, and trade. The model allows us to characterize a novel link between investor demographics and the dependence of prices on past dividends while also generating known features of asset prices, such as excess volatility and return predictability. The model produces new implications for the cross-section of asset holdings, trade volume, and investors′ heterogeneous responses to crises, which we show to be in line with the data.

1. Introduction

Empirical evidence suggests a need for dynamic models that go beyond the rational-expectations hypothesis.

The existing theories assume homogeneous overweighing of realizations from the last year or couple of years, they miss two important empirical patterns: **first,** macroeconomic shocks appear to alter investment and consumption behavior for decades to come, as conveyed by the notion of "depression babies" or of the "deep scars" left by the 2008 financial crisis (Blanchard, 2012; Malmendier and Shen, 2018). In other words, the measurable impact of past realizations goes far beyond the timeframe of existing models. **Second**, there is significant and predictable cross-sectional heterogeneity. Younger cohorts tend to react significantly more strongly to a recent shock than older cohorts, both for positive and for negative realizations.

A growing empirical literature on experience effects shows both empirical patterns in numerous macrofinance contexts. **This literature emphasizes that the long-lasting neuropsychology effects of personal "experience" is the key mechanism at work**.

Our paper develops an equilibrium model of asset markets that formalizes experience-based learning and the resulting belief heterogeneity across investors. The model clarifies the channels through which past realizations affect future market outcomes by pinning down the effect on investors' own belief formation and the interaction with other generations' belief formation. We derive the aggregate implications of learning from experience and the implied cross-sectional differences in investor behavior. To our knowledge, this model is the first to tease out the tension between experience effects and recency bias. It aims to provide a guide for testing to what extent experience- based learning can enhance our understanding of market dynamics and of the long-term effect of demographic changes

Model features

Agents have constant absolute risk aversion (CARA) preferences.

Living for a finite number of periods.

They choose portfolios of a risky and a risk-free security.

Agents maximize their per-period payoffs.

The risky asset is in unit net supply and pays a random dividend every period.

The risk- free asset is in infinitely elastic supply and pays a fixed return.

Investors do not know the true mean of dividends but learn about it by observing the history of dividends.

We begin by characterizing the benchmark economy in which agents know the true mean of dividends. In this setting, there is no heterogeneity, and thus the demands of all active market participants are equal and constant over time. Furthermore, there is a unique no-bubble equilibrium with constant prices. We then introduce experience-based learning. The assumed belief formation process captures the two main empirical features of experience effects: first, agents over- weigh their lifetime experiences. Second, their beliefs exhibit recency bias. We identify two channels through which past dividends affect market outcomes.

The first channel is the belief formation process: shocks to dividends shape agents' beliefs about future dividends. Hence, individual demands depend on personal experiences, and the equilibrium price is a function of the history of dividends observed by the oldest market participant. **The second** channel is the generation of cross-sectional heterogeneity: different lifetime experiences generate persistent differences in beliefs.

The model captures an interesting tension between heterogeneity in personal experiences (which generates belief heterogeneity across cohorts) and recency bias (which reduces belief heterogeneity).When there is strong recency bias, all agents pay a lot of attention to the most recent dividends. Thus, their reactions to a recent shock are similar. Price volatility increases, while price autocorrelation and trade volume decrease.

We explore the connection between market demographics and the dependence of prices on past dividends by analyzing the effect of a one-time change in the fraction of young agents that participate in the market. We find that the demographic composition of markets significantly influences the dependence of prices on past dividends.

We then turn to several tests of the empirical implications of our model.

First, we show that the model accommodates several key asset pricing features identified in prior literature. We then turn to the predictions regarding trade volume and show that the detrended turnover ratio is strongly correlated with differences in lifetime market experiences across cohorts. That is, changes in the experience-based level of disagreement between cohorts predict higher abnormal trade volume, as predicted by the model.

Contribution

Our paper contributes to this literature in several respects.

First, we allow for recency bias in the belief formation process

Second, our agents are not Bayesian and do not update their posterior variance as they gain experience, and thus our results do not depend on heterogeneous posterior variances.

Third, our CARA- normal framework allows us to obtain closed-form solutions to clearly understand the link between demographics, experience, and recency.

Finally, we consider our empirical approach more comprehensive, as we test the model predictions about portfolio holdings, asset pricing features, and trade volume.

2. Model set-up

Consider an infinite-horizon economy with overlapping generations of a continuum of risk-averse agents. At each point in time $t \in \mathbb{Z}$, a new generation is born and lives for q periods, $q \in \{1, 2, 3, \ldots\}$. Hence, there are $q + 1$ generations alive at any t. The generation born at $t = n$ is called generation n. Agents have CARA preferences with risk aversion γ. They can transfer resources across time by investing in financial markets. Trading takes place at the beginning of each period. At the end of the last period of their lives, agents consume the wealth they have accumulated. We use n_q to indicate the last time at which generation n trades; $n_q = n + q - 1$. (If the generation is denoted by t, we use t_q.) Fig. 1 illustrates the timeline of this economy for two-period lived generations ($q = 2$).

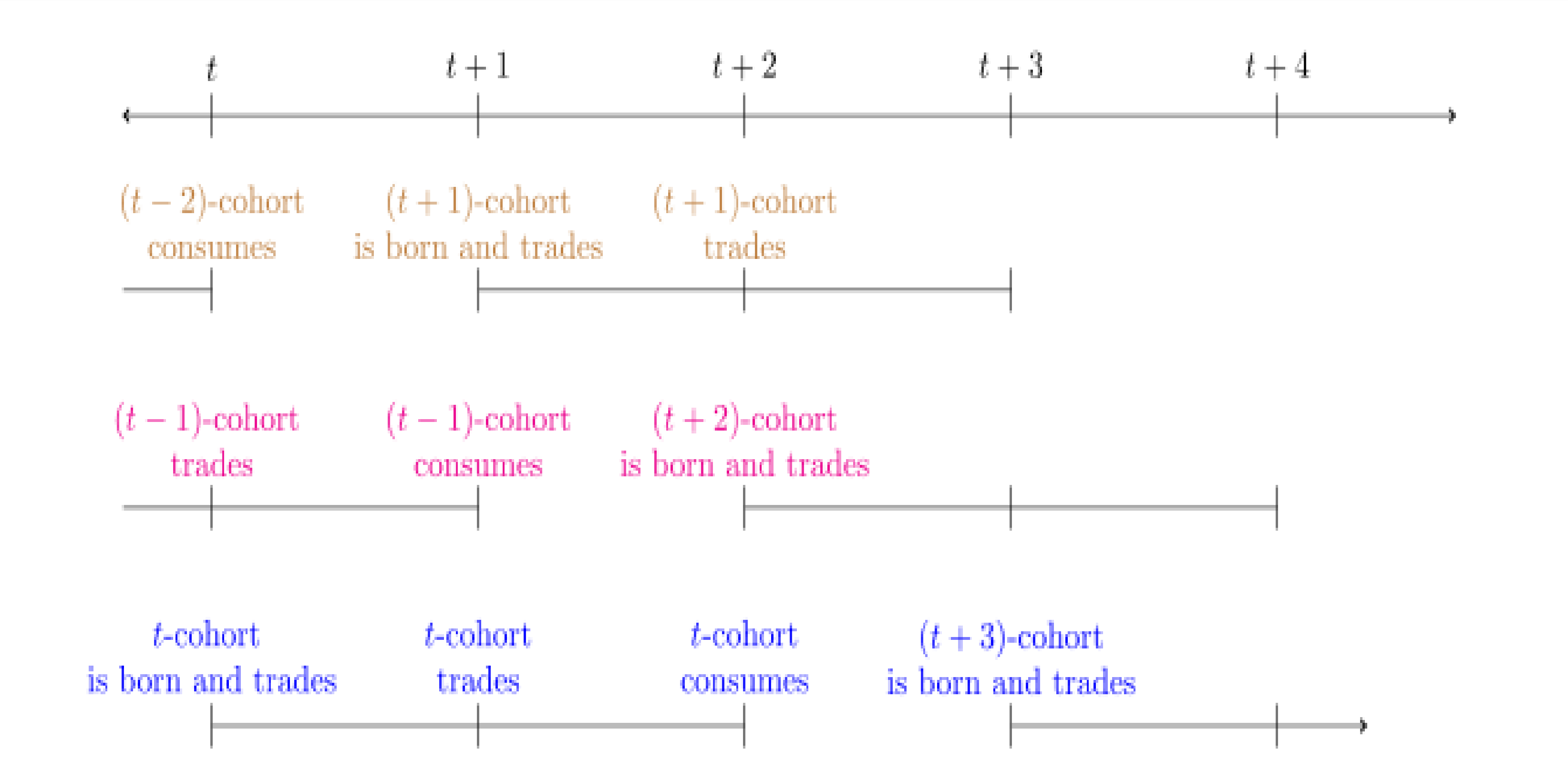


Fig. 1. A timeline for an economy with two-period lived generations, q = 2

There is a risk-free asset, which is in perfectly elastic supply and has a gross return of $R > 1$ at all times. And there is a single risky asset (a Lucas tree), which is in unit net supply and pays a random dividend $d_t \sim N(\theta, \sigma^2)$ at time t. To model uncertainty about fundamentals, we assume that agents do not know the true mean of dividends θ and use past observations to estimate it. To keep the model tractable, we assume that the variance of dividends σ^2 is known at all times. For each generation $n \in Z$, the budget constraint at any time $t \in \{n, \ldots, n+q\}$ is :

$$W_t^n = x_t^n p_t + a_t^n, \quad (1)$$

As a result, wealth next period is:

$$\begin{aligned} W_{t+1}^n &= x_t^n (p_{t+1} + d_{t+1}) + a_t^n R \\ &= x_t^n (p_{t+1} + d_{t+1} - p_t R) + W_t^n R. \end{aligned} \quad (2)$$

We denote the excess payoff received in t + 1 from investing at time t in one unit of the risky asset, relative to the riskless asset, as

$$S_{t+1} \equiv P_{t+1} + d_{t+1} - P_t R$$

This is analogous to the equity premium in our CARA model. Using this notation:

$$W_{t+1}^{n} = x_t^n s_{t+1} + W_t^{n} R$$

For a given initial wealth level w , the problem of a generation n at each time t ∈ { n, . . . , n q } is to choose x :

$$x_t^n \in \arg\max_{x \in \mathbb{R}} E_t^n[-\exp(-\gamma x s_{t+1})], \qquad (3)$$

2.1. Experience-based learning

In this framework, experience-based learning (EBL) means that agents overweigh realizations observed during their lifetimes when forecasting dividends and they may tilt the excess weights toward the most recent observations. For simplicity, we assume that agents only use observations realized during their lifetimes. That is, even though they observe the entire history of dividends, they choose to disregard earlier observations. EBL differs from reinforcement learning-type models in two ways. ***First***, as already discussed, EBL agents understand the model and know all the primitives except the mean of the dividend process. Hence, they do not learn about the equilibrium; they learn in equilibrium. **Second**, EBL is a passive learning problem in the sense that players′ actions do not affect the information they receive. This would be different if we had, say, a participation decision that links an action (participate or not) to the type of data obtained for learning. We consider this to be an interesting line to explore in the future

Let m denote the prior belief about the mean of dividends that agents are born with and where we restrict m to be Gaussian with mean θ for tractability. With this, we construct the subjective mean of dividends of generation n at time t following the empirical evidence on Malmendier and Nagel (2011) as follows:

$$\theta_t^n \equiv (1-\omega_{age}) \cdot m + \omega_{age} \cdot \sum_{k=0}^{age} w(k, \lambda, age) d_{t-k}, \tag{4}$$

where $age = t - n$, and where, for all $k \leq age$,

$$w(k, \lambda, age) = \frac{(age + 1 - k)^{\lambda}}{\sum_{k'=0}^{age} (age + 1 - k')^{\lambda}} \tag{5}$$

$$W_{age} = \frac{age + 1}{\tau + age + 1}$$

The denominator in Eq. (5) is a normalizing constant that depends only on age and on the parameter that regulates the recency bias, λ. For $\lambda > 0$, more re- cent observations receive relatively more weight, whereas for $\lambda < 0$, the opposite holds.

Observe that by construction, $\theta_t^n \sim N\{\theta, \sigma^2 \sum_{k=0}^{age} (w(k, \lambda, age))^2\}$

Hence, θn t does not necessarily converge to the truth as $t \to \infty$; it depends on whether sum $\to 0$. This in turn depends on how fast the weights for "old" observations decay to zero (i. e., how small λ is). When agents have finite lives, convergence will not occur.

2.2. Comparison to Bayesian learning

To better understand the experience-effect mechanism, we compare the subjective mean of EBL agents to the posterior mean of agents who update their beliefs using Bayes rule. We consider two cases: full Bayesian learning (FBL), wherein agents use all the available observations to form their beliefs; and Bayesian learning from experience (BLE), where agents only use data realized during their lifetimes

2.2.1. Full Bayesian learners

We denote the prior of FBL agents as N(m, σ2 m)

$$\hat{\theta}_t = \frac{\sigma_m^{-2}}{\sigma_m^{-2} + \sigma^{-2}t} m + \frac{\sigma^{-2}t}{\sigma_m^{-2} + \sigma^{-2}t} \left(\frac{1}{t} \sum_{k=0}^{t} d_k \right).$$

The belief of an FBL agent is a convex combination of the prior m and the average of all observations d k realized since time 0. The key difference to EBL agents is that differences in personal experiences do not play a role: there is no heterogeneity in beliefs, and all generations alive in any given period have the same belief about the mean of dividends. In addition, beliefs of FBL agents are nonstationary (i. e., they depend on the time period). As $t \rightarrow \infty$, the posterior mean converges (almost surely) to the true mean. That is, with FBL the implications of learning vanish as time goes to infinity. With EBL, this is not true. Since agents have finite lives and learn from their own experiences, our model generates learning dynamics even as time diverges.

2.2.2. Bayesian learners from experience

The belief of a BLE generation is a convex combination of the prior m and the average of (only) the lifetime observations d k available to date.

$$\tilde{\theta}_t^n = \frac{\sigma_m^{-2}}{\sigma_m^{-2} + \sigma^{-2}(age+1)} m + \frac{\sigma^{-2}(age+1)}{\sigma_m^{-2} + \sigma^{-2}(age+1)} \left(\frac{1}{age+1} \sum_{k=n}^{t} d_k \right).$$

2.3. Equilibrium definition

Linear equilibrium: A linear equilibrium is an equilibrium wherein prices are an affine function of dividends. That is, there exists a K ∈ N , α ∈ R , and βk ∈ R for all k ∈ { 0 , . . . , K} such that

$$p_t = \alpha + \sum_{k=0}^{K} \beta_k d_{t-k}. \quad (6)$$

For the sake of benchmarking our results for EBL agents, we characterize equilibria in an economy where the mean of dividends, θ, is known by all agents ($E_t^n[d_t] = \theta$).

In this scenario, there are no disagreements across cohorts, and the demand of any cohort trading at time t is

$$x_t^n \in \arg\max_{x \in \mathbb{R}} E[-\exp(-\gamma x s_{t+1})]. \quad (7)$$

The solution to this problem is standard and given by

$$x_t^n = \frac{E[s_{t+1}]}{\gamma V[s_{t+1}]} \quad (8)$$

Since there is no heterogeneity in cohorts′ demands and there is a unit supply of the risky asset, in any equilibrium, x n t = 1 for all n ∈ { t − q + 1 , . . . , t} , and zero otherwise. Furthermore, there exists a unique bubble-free equilibrium with constant prices

$$P = \frac{\theta - \gamma\sigma^2}{R - 1}$$

3. Toy model

To illustrate the mechanics of the model, we first high- light the main results of the paper in a simple environ- ment, namely, for q = 2 . We will solve the model for any q > 1 in the next section. In the toy model with q = 2 . At time t , the problem of generations n ∈ { t, t − 1 } is given by Eq. (3) . It is easy to show that their demands for the risky asset are

$$x_t^n = \frac{E_t^n[s_{t+1}]}{\gamma V_t^n[s_{t+1}]}.$$

As one of our first key results in Section 4 , we will show that (i) prices depend on the history of dividends and (ii) this price predictability is limited to the past dividends observed (experienced) by the oldest generation trading in the market. In other words, we show that K = q − 1 in Eq. (6) . Anticipating this result here for q = 2 , we have

$$p_t = \alpha + \beta_0 d_t + \beta_1 d_{t-1}. \tag{9}$$

Given the functional form for prices, we can rewrite the demands of both cohorts that are actively trading as

$$x_t^t = \frac{\alpha + (1+\beta_0)E_t^t[d_{t+1}] + \beta_1 d_t - p_t R}{\gamma(1+\beta_0)^2\sigma^2}$$

$$x_t^{t-1} = \frac{\alpha + (1+\beta_0)E_t^{t-1}[d_{t+1}] + \beta_1 d_t - p_t R}{\gamma(1+\beta_0)^2\sigma^2}.$$

The difference between cohorts′ demand arises from their different beliefs about future dividends.

$$E_t^t[d_{t+1}] = d_t,$$

$$E_t^{t-1}[d_{t+1}] = \underbrace{\left(\frac{2^\lambda}{1+2^\lambda}\right)}_{w(0,\lambda,1)} d_t + \underbrace{\left(\frac{1}{1+2^\lambda}\right)}_{w(1,\lambda,1)} d_{t-1}.$$

These formulas illustrate the mechanics of EBL and the cause of heterogeneity among agents. In the simplified setting, the younger generation has only experienced the dividend d t and expects the dividends to be identical in the next period. The older generation has more experience and incorporates the previous dividend in their weighing scheme. An implication of these formulas is that the younger generations react more optimistically than older generations to positive changes in recent dividends and more pessimistically to negative changes.

We now impose the market clearing condition, $\frac{1}{2}(x_t^t + x_t^{t-1}) = 1$, to derive the equilibrium price given these demands. We use the method of undetermined coefficients to solve for { α, β0 , β1 }. Setting the constants and the terms that multiply d t and d t−1 to zero, we obtain a system of equations whose solution determines the price constant and the loadings of prices on present and past dividends,

$$\alpha = -\frac{\gamma(1+\beta_0)^2\sigma^2}{R-1}, \tag{10}$$

$$\beta_0 = \frac{2R^2}{(R-1)\left(1+2R-\frac{2^\lambda}{1+2^\lambda}\right)} - 1, \tag{11}$$

$$\beta_1 = \frac{R\left(1-\frac{2^\lambda}{1+2^\lambda}\right)}{(R-1)\left(1+2R-\frac{2^\lambda}{1+2^\lambda}\right)}. \tag{12}$$

These solutions illustrate how the price loadings on past dividends depend on the demographics of the economy and on the magnitude of the recency bias.

The variance of prices is increasing in the recency bias λ, while the price autocorrelation is decreasing in the recency bias. The intuition is straightforward: as the recency bias increases, prices become more responsive to the most recent dividend, $\partial\beta0/\partial\lambda > 0$, increasing price volatility, and less responsive to past dividends, $\partial\beta1/\partial\lambda < 0$, decreasing price autocorrelation.

4. General model

Proposition 4.1 .

Suppose $P_t = \partial + \sum_{k=0}^{K} \beta_k d_{t-k}$ Then, for any generation n ∈ Z trading in period t ∈ { n, . . . , n q } , demands for the risky asset are given by

$$x_t^n = \frac{E_t^n[s_{t+1}]}{\gamma V[s_{t+1}]} = \frac{E_t^n[s_{t+1}]}{\gamma(1+\beta_0)^2\sigma^2}. \tag{13}$$

It is easy to see, then, that beliefs about future dividends are linear functions of the dividends observed by each generation participating in the market, and thus prices depend on the history of dividends observed by the oldest generation in the marke.

Proposition 4.2 .

The price in any linear equilibrium is affine in the history of dividends observed by the oldest generation participating in the market.

$$p_t = \alpha + \sum_{k=0}^{q-1} \beta_k d_{t-k}, \text{ with} \tag{14}$$

$$\alpha = -\frac{1}{\left(1 - \sum_{j=0}^{q-1} \frac{w_j}{R^{j+1}}\right)^2} \frac{\gamma\sigma^2}{R-1} \tag{15}$$

$$\beta_k = \frac{\sum_{j=0}^{q-1-k} \frac{w_{k+j}}{R^{j+1}}}{1 - \sum_{j=0}^{q-1} \frac{w_j}{R^{j+1}}} \qquad k \in \{0, \ldots, q-1\}, \tag{16}$$

where $w_k \equiv \frac{1}{q} \sum_{age=0}^{q-1} w(k, \lambda, age)$.

4.2 establishes a novel link between the factors influencing asset prices and demographic composition. For each $k = \{0, 1, \ldots, q-1\}$, one can interpret w_k as the average weight placed on the dividend observed at time $t-k$ by all generations trading at time t. As the formula also reveals, the relative magnitudes of the weights on past dividends, β_k, depend on the number of cohorts in the market, q, on the fraction of each cohort in the market, $1/q$, and on the extent of agents' recency bias, λ.

Note that $\partial\beta_k/\partial R < 0$ and $\partial\alpha/\partial R > 0$ for any λ. That is, if the interest rate is higher, the equilibrium price of the risky asset responds less strongly to past dividends. Furthermore, higher risk aversion γ decreases the equilibrium price by lowering α.

Proposition 4.3 .

For $\lambda > 0$, more recent dividends affect prices more than less recent dividends (i. e., $0 < \beta_{q-1} < \ldots < \beta_1 < \beta_0$).

Lemma 4.1 .

The effect of the most recent dividend realization on prices, β0 , is increasing in λ, with $\lim_{\lambda\to\infty}\beta_0(\lambda)=1/(R-1)$ and $\lim_{\lambda\to\infty}\beta_K(\lambda)=0$ .So under extreme recency bias (λ → ∞), only the current dividend affects prices in equilibrium, while the weights on all past dividends vanish.

4.2. Cross-section of asset holdings

Proposition 4.4 . For any t ∈ Z and any generations n ≤ m trading at t, there is a threshold time lag k 0 ≤ t − m − 1 such that for dividends that date back up to k 0 periods, the risky- asset demand of the younger generation (born at m) responds more strongly to changes than the demand of the older generation (born at n), while, for dividends that date back more than k 0 periods, the opposite holds. That is,

1. $\frac{\partial x_t^m}{\partial d_{t-k}} \geq \frac{\partial x_t^n}{\partial d_{t-k}}$ for $0 \leq k \leq k_0$ and
2. $\frac{\partial x_t^m}{\partial d_{t-k}} \leq \frac{\partial x_t^n}{\partial d_{t-k}}$ for $k_0 < k \leq q-1$.

For any two cohorts of investors, there is a threshold time lag up to which past dividends are weighted more by the younger generation and beyond which past dividend realizations are weighted more by the older generation.

Proposition 4.5 . Suppose $\lambda > 0$. Consider two points in time $t_0 \le t_1$ such that dividends are nondecreasing from t_0 up to t_1 . Then for any two generations $n \le n + k$ born between t_0 and t_1 , the demand of the older generation for the risky asset (x_t^n) is lower than the demand of the younger generation (x_t^{n+k}) at any point $n \le t \le t_1$; i. e., $\xi(n, k, t) \le 0$. On the other hand, if dividends are nonincreasing, then $\xi(n, k, t) \ge 0$.

The proposition illustrates that, while boom times tend to make all cohorts growing up in such times more optimistic, the effect is particularly strong for the younger generations. This induces them to be overrepresented in the market for the risky asset. The opposite holds during times of downturn.

$$\xi(n,k,t) = \frac{E_t^n[\theta] - E_t^{n+k}[\theta]}{\gamma(1+\beta_0)\sigma^2}$$
$$\forall k = \{0, \ldots, t-n\}, n = \{t-q+1, \ldots, t\}. \qquad (17)$$

4.3. Trade volume

We now study how learning and disagreements affect the volume of trade observed in the market. We consider the following definition of the total volume of trade in the economy:

$$TV_t = \left(\frac{1}{q} \sum_{n=t-q}^{t} \left(x_t^n - x_{t-1}^n \right)^2 \right)^{\frac{1}{2}}, \qquad (18)$$

Proposition 4.6 The trade volume defined in Eq. (18) can be expressed as

$$TV_t = \left(\frac{\chi^2}{q} \sum_{n=t-q}^{t} \left(\left(\theta_t^n - \theta_{t-1}^n \right) - \frac{1}{q} \sum_{\tilde{n}=t-q}^{t} \left(\theta_t^{\tilde{n}} - \theta_{t-1}^{\tilde{n}} \right) \right)^2 + \frac{1}{q} \left(x_t^t \right)^2 + \frac{1}{q} \left(x_{t-1}^{t-q} \right)^2 \right)^{\frac{1}{2}}, \qquad (19)$$

where $\chi = \frac{1}{\gamma \sigma^2 (1+\beta_0)}$, $\theta_{t-1}^t = \theta_t^{t-q} = 0$.

More specifically, when the change in a cohort’s beliefs is different from the average change in beliefs, trade volume increases. That is, trade volume increases in the dispersion of changes in beliefs.

5. Market participation

The results derived so far illustrate a key feature of EBL: the demographic structure of an economy, and in particular the cross-sectional composition of investors, affect equilibrium prices, demand, and trade volume in a predictable direction. In this section, we explore the link between market demographics and financial market outcomes by considering an unexpected increase in the fraction of young market participants (e. g., due to a baby boom or a generation- specific event drawing a certain generation into the stock market). The goal of this exercise is to understand how a larger fraction of young market participants affects market dynamics.

For ease of illustration, we focus again on our $q = 2$ economy. We denote the mass of young agents at any time t by y_t and the total mass of agents at t by $m_t = y_t + y_{t-1}$. We consider a one-time unexpected (exogenous) shock to the mass of young agents in the market at time τ. For all $t < \tau$ and $t > \tau + 1$, instead, $y_t = y$ and thus $m_t = 2y = m$.

$$p_\tau = a_\tau + b_{0,\tau} d_\tau + b_{1,\tau} d_{\tau-1}, \tag{21}$$

$$p_{\tau+1} = a_{\tau+1} + b_{0,\tau+1} d_{\tau+1} + b_{1,\tau+1} d_\tau. \tag{22}$$

We solve the problem by backward induction. Note that the form of agents' demands remains unchanged. By im- posing market clearing in $\tau + 1$, with mass y of young agents and y_τ of old agents, and using the method of undetermined coefficients, we obtain

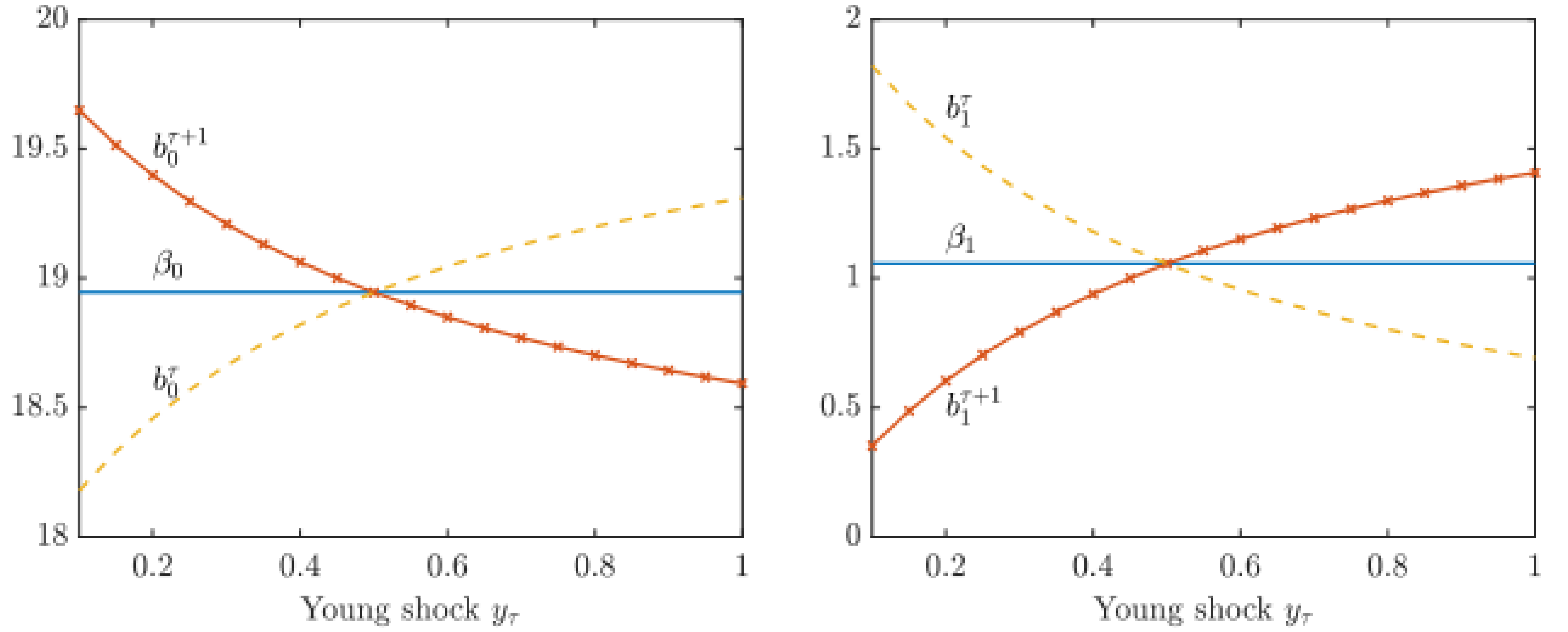
$$a_{\tau+1} = \alpha \frac{1}{R}\left[1 + \frac{R-1}{m_\tau}\right],$$

$$b_{0,\tau+1} = \beta_0\left[1 + \frac{1}{R}\left(\frac{m_\tau - y_\tau}{m_\tau} + \frac{y_\tau}{m_\tau}\omega - \frac{y}{m}(1+\omega)\right)\right]$$

$$+ \frac{1}{R}\left(\frac{m_\tau - y_\tau}{m_\tau} + \frac{y_\tau}{m_\tau}\omega - \frac{y}{m}(1+\omega)\right),$$

$$b_{1,\tau+1} = \beta_1 \frac{y_\tau}{m_\tau}\frac{m}{y},$$

Fig. 2 shows how the reliance of prices on past dividends changes with the fraction of young agents in the market at time τ.



(a) Price loading on d_t (b) Price loading on d_{t-1}

6. Empirical implications

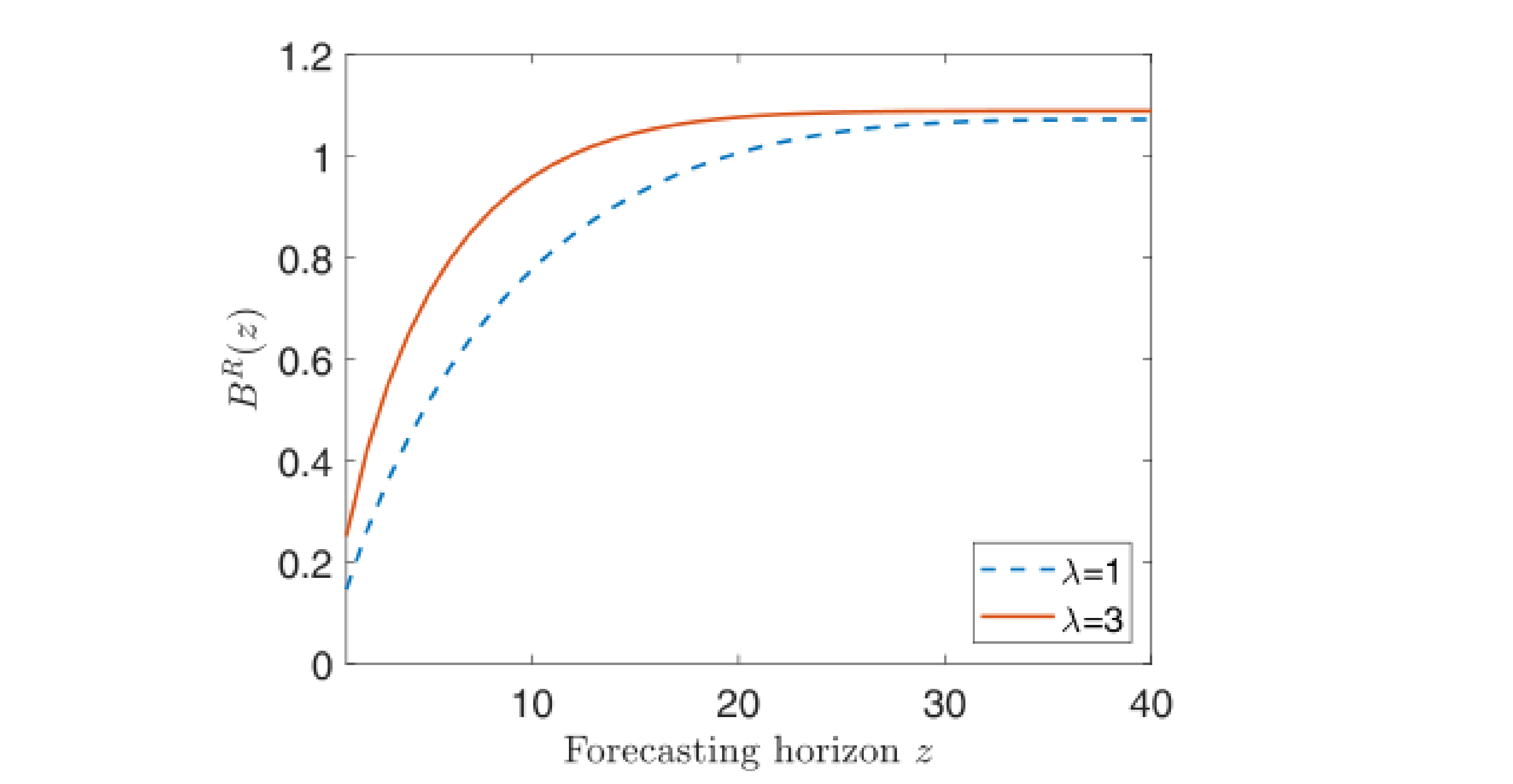
6.1. Quantitative implications for asset pricing moments

In this papers, we define quantities in terms of differences, rather than ratios, since variables in the model proxy for the log of their values in the data. We use capital letters P and D to denote prices and dividends, while small letters denote their logs, p = log (P) and d = log (D) . For example, instead of stock returns, we measure price changes ?p and, instead of the price-dividend ratio P / D , we study the difference p − d.

6.1.1. Predictability of excess returns

$$B^R(z) \equiv \frac{Cov(d_t - p_t, p_{t+z} - p_t)}{Var(d_t - p_t)}. \qquad (23)$$

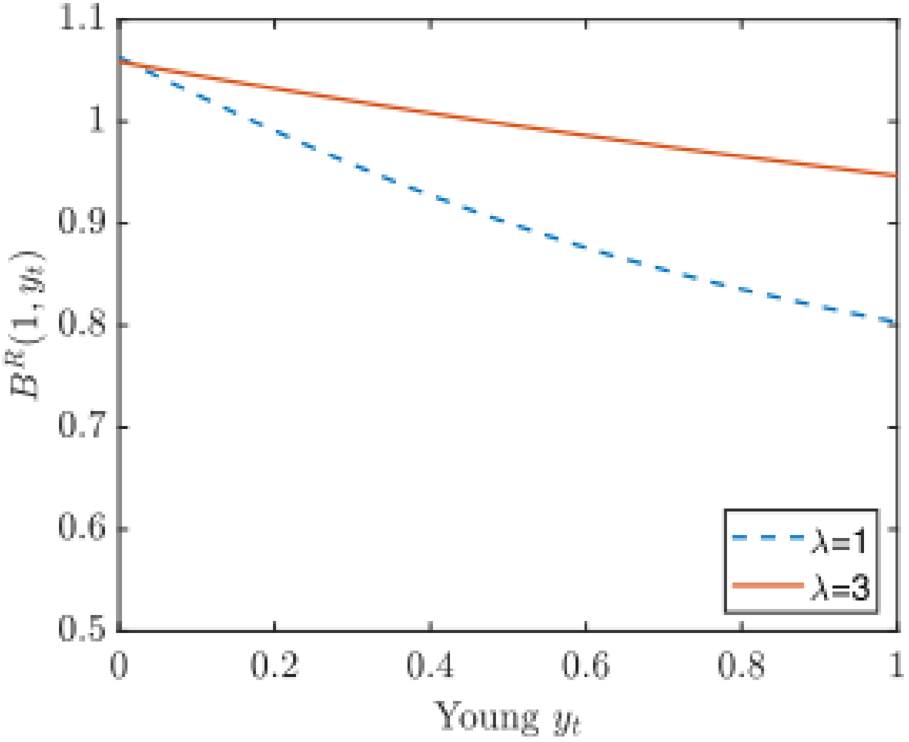
As the figure shows, the EBL model generates a positive (and strong) relation between the dividend-price ratio and returns, which increases with the return horizon.**Fig. 3.**



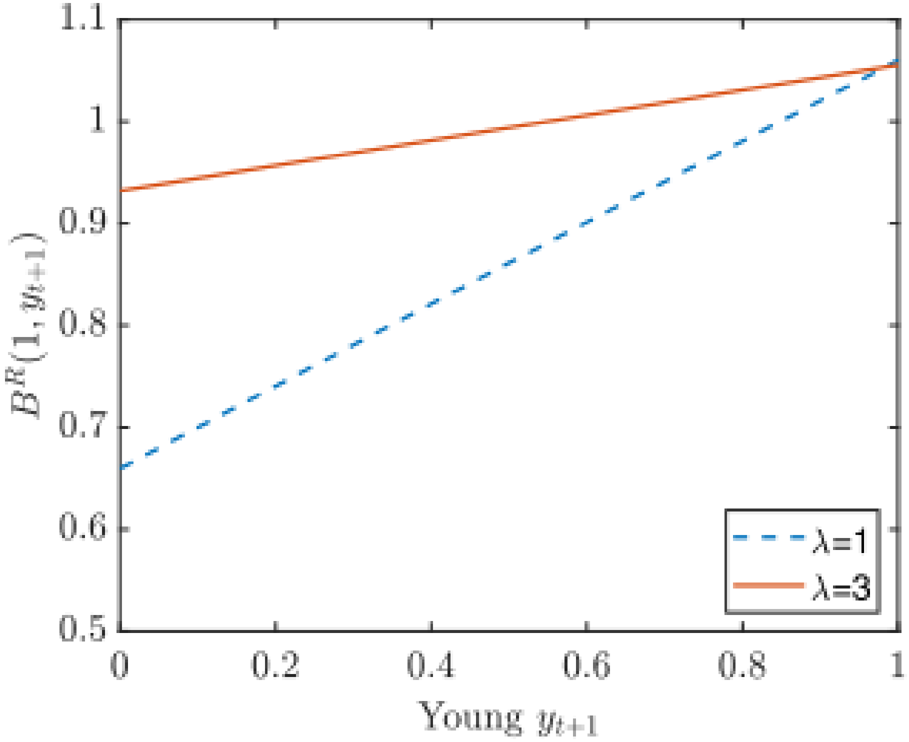
Predictability of d t − p t for p t+ z − p t Notes. This figure plots the coefficient B R (z) over varying horizons z for two levels of recency bias, λ ∈ {1, 3}, in a q = 40 economy with R = 1 .05 .

Fig. 4 (a) plots $BR(1, y_t)$ as a function of the fraction of young agents at time t, y_t. As the plot shows, the predictability of next period' s return decreases in the fraction of young market participants in the current period. The increase in the fraction of young market participants at time t increases the covariance between $d_t - p_t$ and returns $p_{t+1} - p_t$, as the new mass of young agents increases the sensitivity of price p_t to dividends at time t . However, this also increases the variances of $d_t - p_t$. These two effects go in opposite directions, and the latter effect dominates.

Fig. 4 (b). In this case, the predictability measure increases with the fraction of young agents. As before, the increase in the fraction of young market participants at time $t + 1$ increases the covariance between $d_t - p_t$ and $p_{t+1} - p_t$ as the new mass of young agents increases the sensitivity of price p_{t+1} to dividends at time $t + 1$. However, the variance of $p_t - d_t$ is not affected by y_{t+1}, and thus the "covariance effect" dominates.



(a) $B^R(1, y_t)$



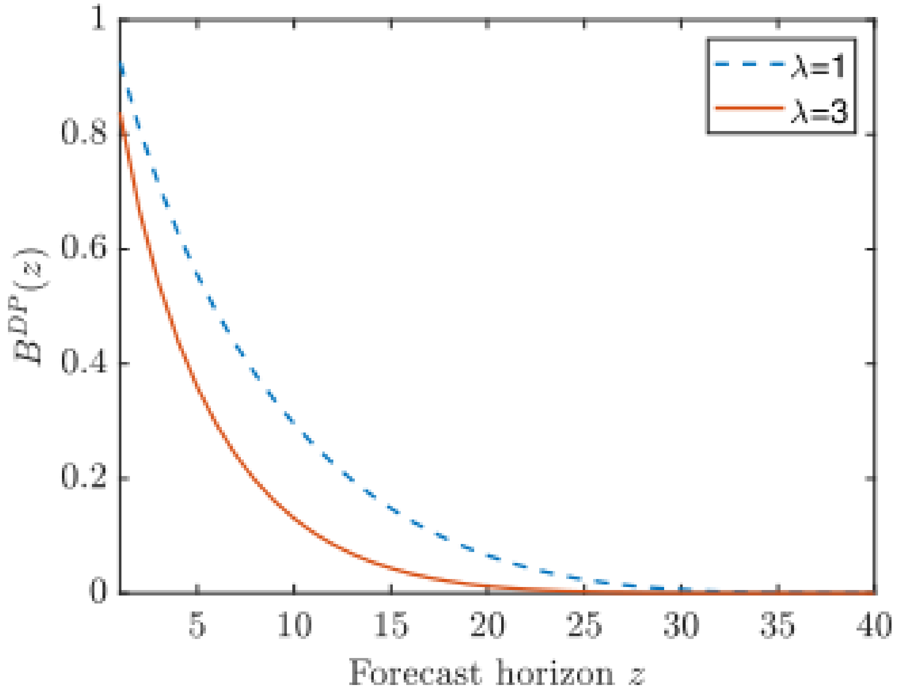
(b) $B^R(1, y_{t+1})$

6.1.2. Predictability of price-dividend ratio

In addition to the predictability of returns, we can also compute the predictability of the price-dividend (P/D) ratio implied by the model. That is, we relate past P/D ratios to future P/D realizations and analyze the persistence of the P/D ratio. In particular, we study how this predictability of P/D ratios varies with the investment horizon and with the fraction of young people in the market. Our measure of predictability is constructed as follows:

$$B^{PD}(z) = \frac{cov(p_{t+z} - d_{t+z}, p_t - d_t)}{var(p_t - d_t)} \qquad (24)$$

Fig. 5.



(a) $B^{DP}(z)$ with $q = 40$ (b) $B^{DP}(1, y_t)$ with $q = 2$

6.2. Demographics and price-dividend predictability

We want to test whether the predictive power of the lagged P/D ratios for the current one depends on the relative representation of younger versus older generations in the market in the manner predicted by the model. EBL predicts that the correlation between future and current lags is higher when the current share of young market participants is large. Moreover, the model generates the heuristic that young people put little weight on observations of the "distant" past (cf. Proposition 4.4). To test these predictions, we regress the log of the P/D ratio onto lags of itself interacted with a dummy variable that indicates a larger presence of young people in the market. To model the dynamics of the P/D process, we depart from the standard linear AR models and postulate a Markov-switching regime (MSR) model, which allows us to capture richer nonlinear dynamics in a tractable way. The regression model is thus given by

$$p_{t+1} - d_{t+1} = \mu(S_{t+1}) + \sum_{j=1}^{3}(p_{t+1-j} - d_{t+1-j})(\beta_j + \delta_j \times Y_{t+1}) + \sigma\epsilon_{t+1}, \qquad (25)$$

The theoretical prediction of our model is that the correlation between future and current lags should be higher when the current share of young market participants is large.

	Dependent variable: $p_t - d_t$	
	(1) Y_t age-based	(2) Y_t age/wealth-based
δ_1	0.701**	0.475*
	(0.154)	(0.252)
δ_2	−0.013	−0.115
	(0.146)	(0.366)
δ_3	−0.745**	−0.329
	(0.115)	(0.232)
β_1	0.377**	0.622**
	(0.120)	(0.159)
β_2	−0.216**	−0.074
	(0.088)	(0.136)
β_3	0.714**	0.249**
	(0.093)	(0.099)
$\mu(S_1)$	5.089**	5.741**
	(1.554)	(1.812)
$\mu(S_2)$	19.450**	18.350**
	(3.070)	(4.768)
σ	3.812	4.343
	(0.388)	(0.600)
Q_{11}	0.956	0.978
	(0.026)	(0.017)
Q_{21}	0.365	0.206
	(0.204)	(0.154)
N	51	51

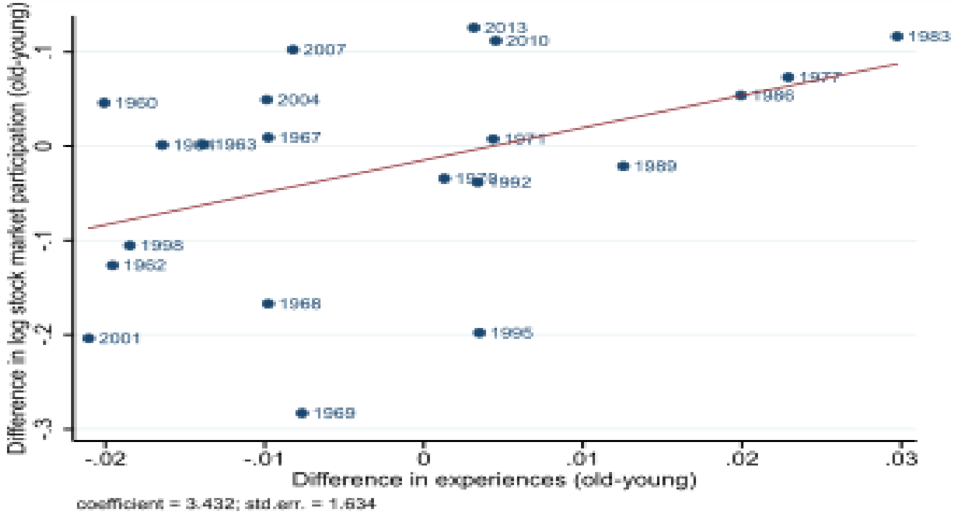
6.3. Cross-section of asset holdings and trade volume

We now turn to the novel empirical predictions of the EBL model about the cross-section of equity holdings and stock turnover. We investigate two sets of predictions that are directly testable and jointly hard to generate by alternative models. The first prediction is that cross-sectional differences in the demand for risky securities reflect cross-sectional differences in lifetime experiences of risky payoffs. That is, cohorts with more positive lifetime experiences are predicted to invest more in the risky asset than cohorts with less positive experiences (Proposition 4.1). We test this both in terms of stock market participation (extensive mar- gin) and in terms of the amount of liquid assets invested in the stock market (intensive margin). The second prediction is that changes in the cross-section of experience-based beliefs generate trade (Proposition 4.6).

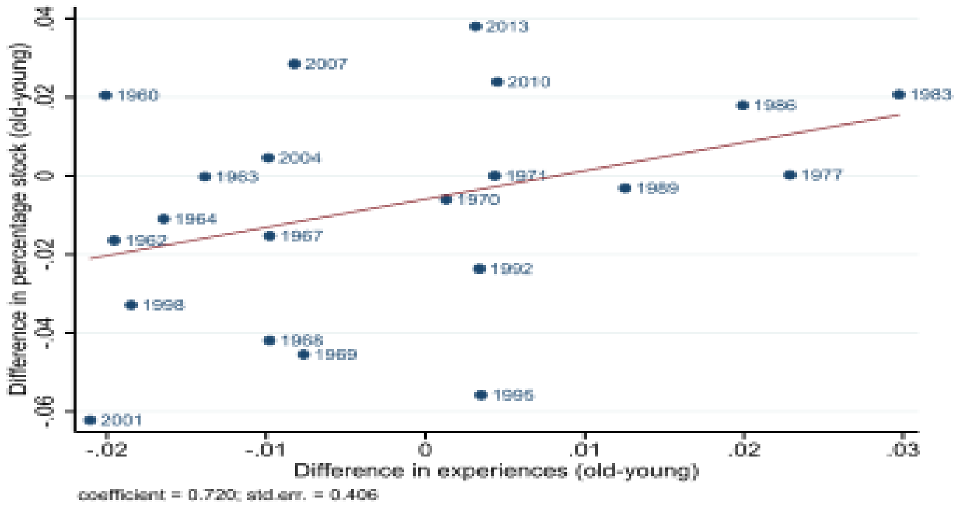
6.3.1. Stock market participation

Fig. 6 , we see that the older age group is more likely to hold stock, compared to the younger age group.

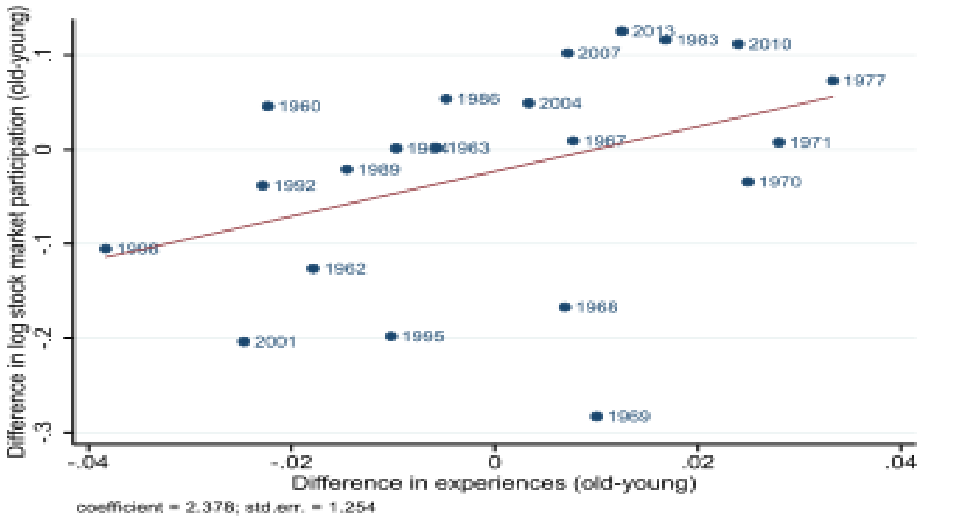
Both graph (b) and graph (d) indicate that older generations invest a higher share of the their liquid assets in stock, compared to the younger generations, when their experienced returns have been higher than those of the younger age group over their respective lifespans so far, and vice versa when they have experienced lower returns than the younger cohorts



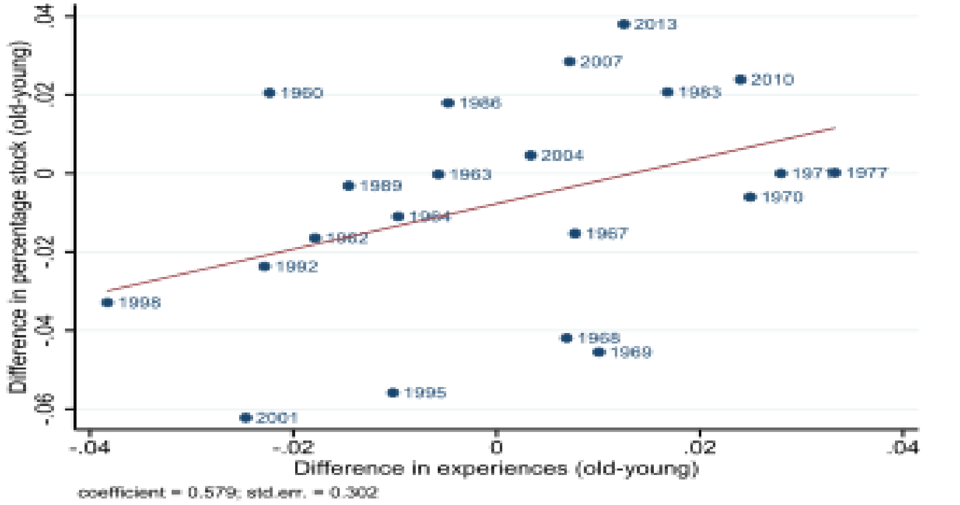
(a) Stock market participation ($\lambda = 1$)



(b) Fraction invested in stock ($\lambda = 1$)

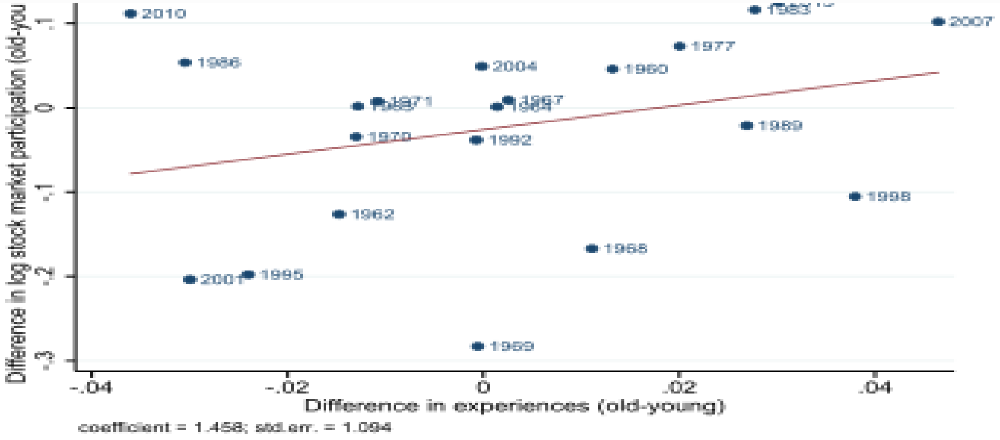


(c) Stock market participation ($\lambda = 3$)

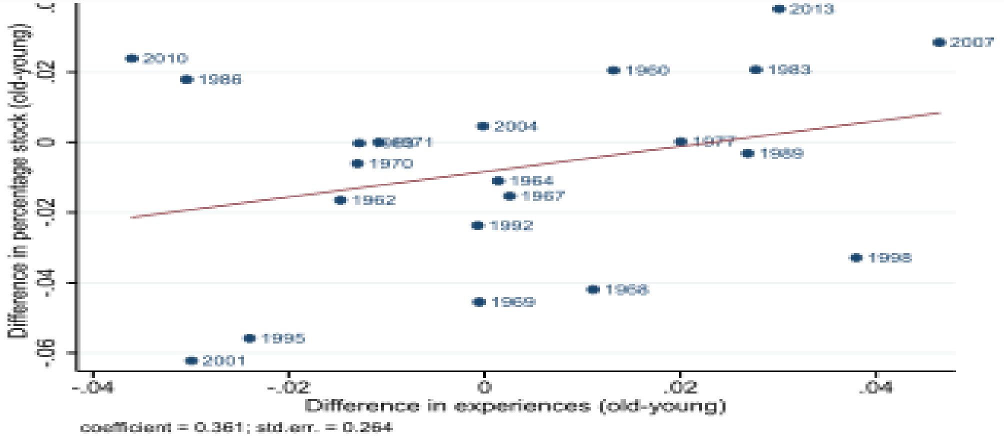


(d) Fraction invested in stock ($\lambda = 3$)

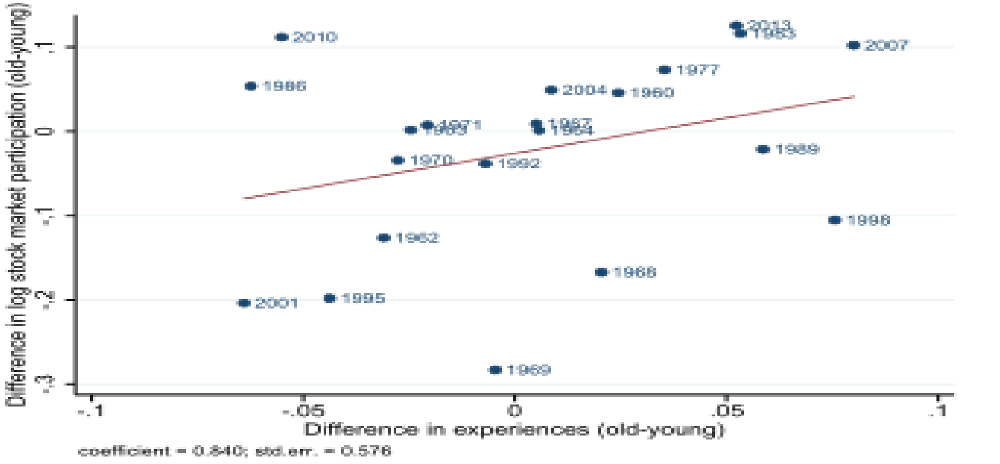
Figs. 7 to 9 present the corresponding results for experienced dividends, earnings, and GDP.**Figs. 7**



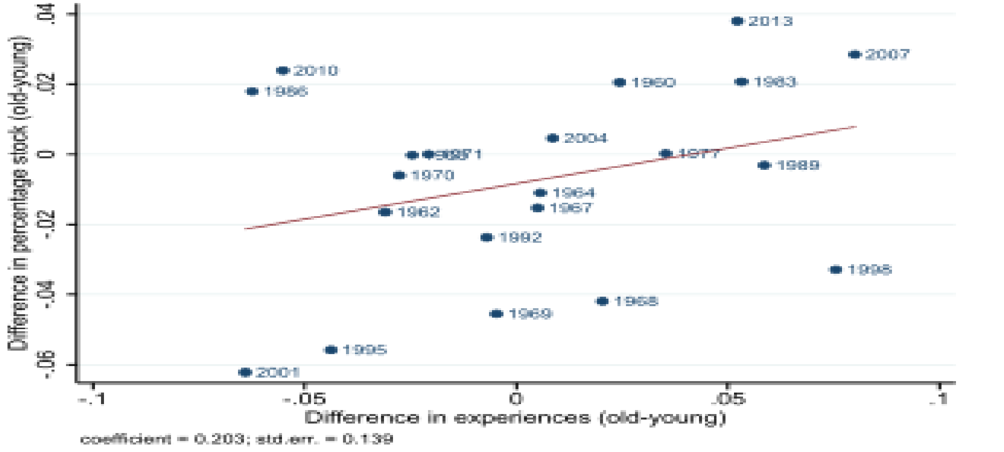
(a) Stock market participation ($\lambda = 1$)



(b) Fraction invested in stock ($\lambda = 1$)

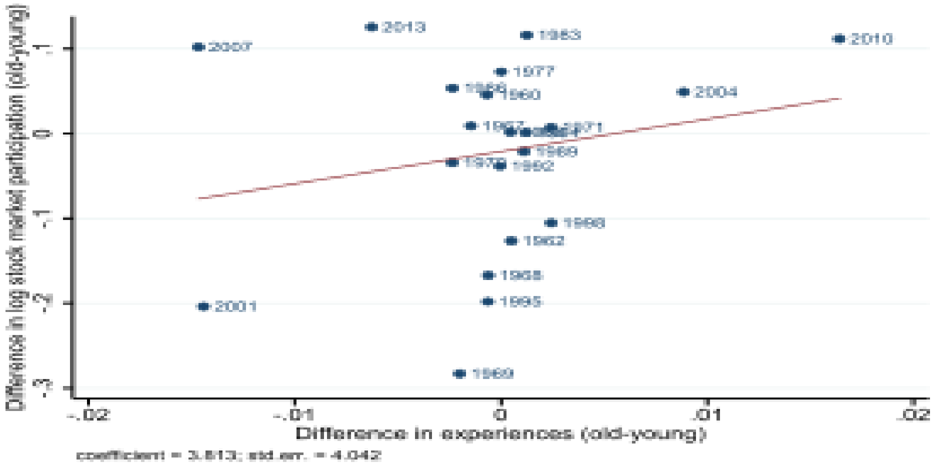


(c) Stock market participation ($\lambda = 3$)

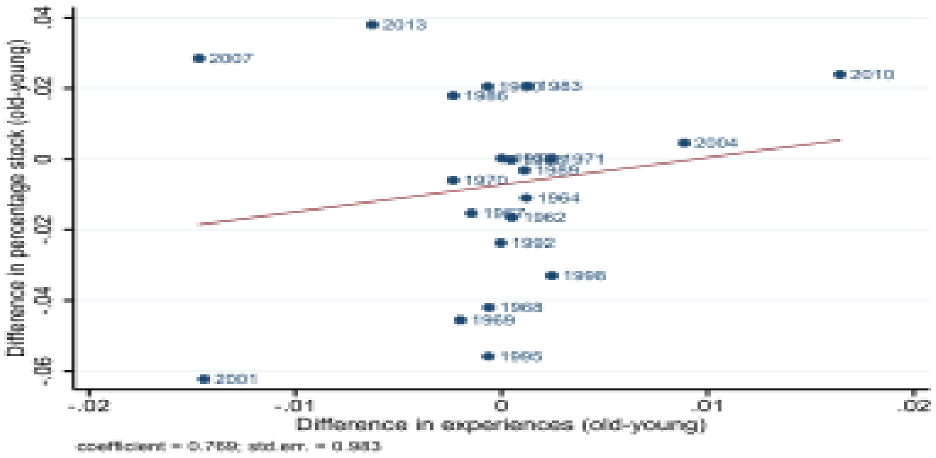


(d) Fraction invested in stock ($\lambda = 3$)

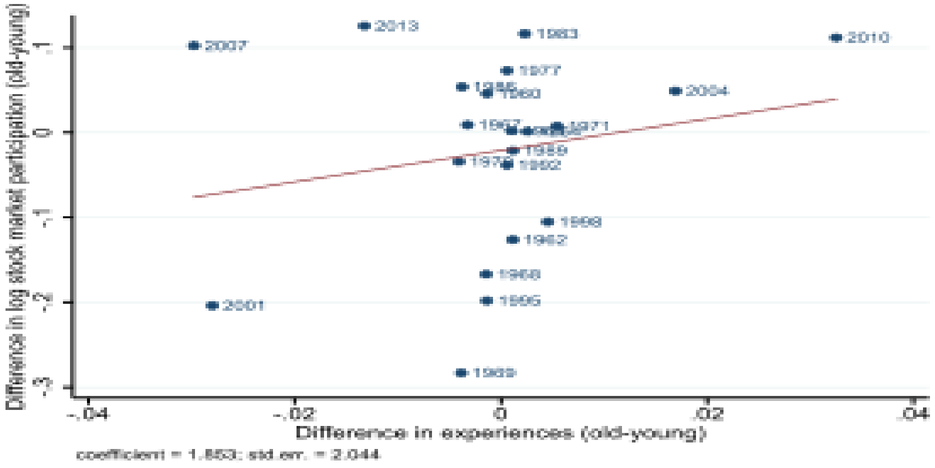
Figs. 8



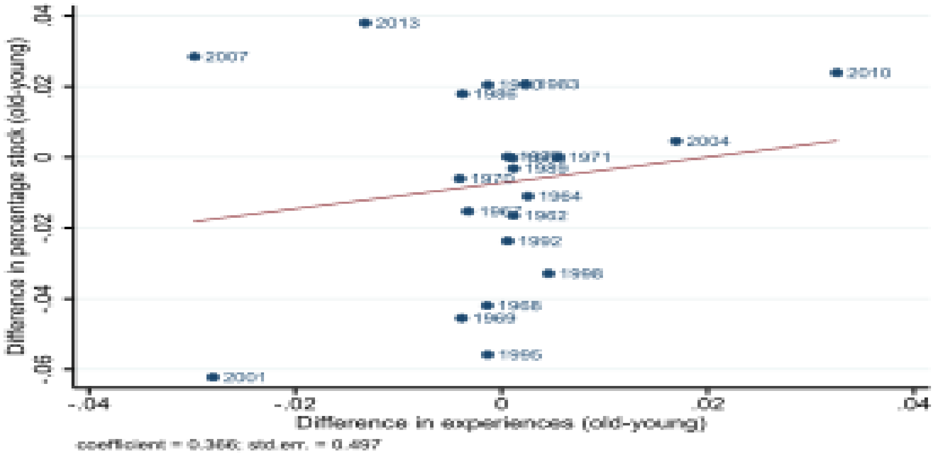
(a) Stock market participation ($\lambda = 1$)



(b) Fraction invested in stock ($\lambda = 1$)

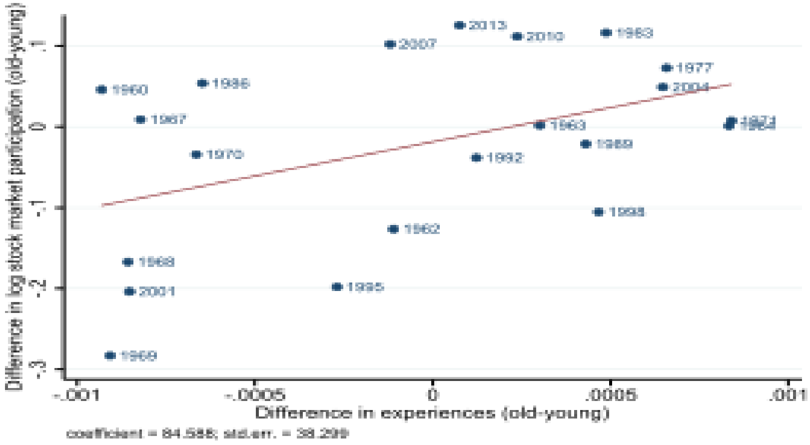


(c) Stock market participation ($\lambda = 3$)

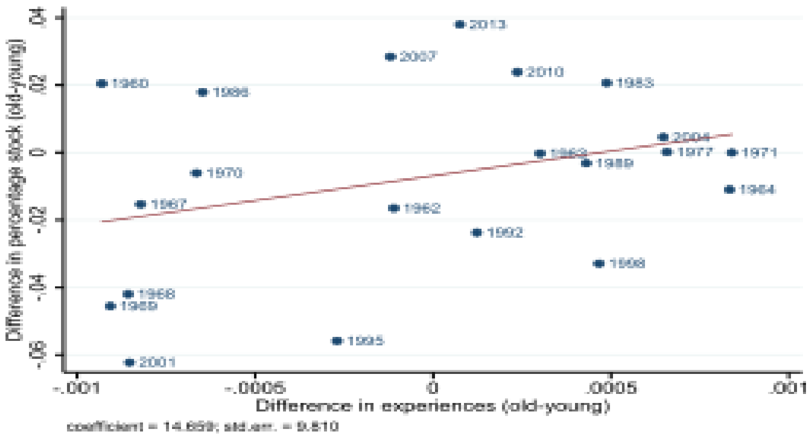


(d) Fraction invested in stock ($\lambda = 3$)

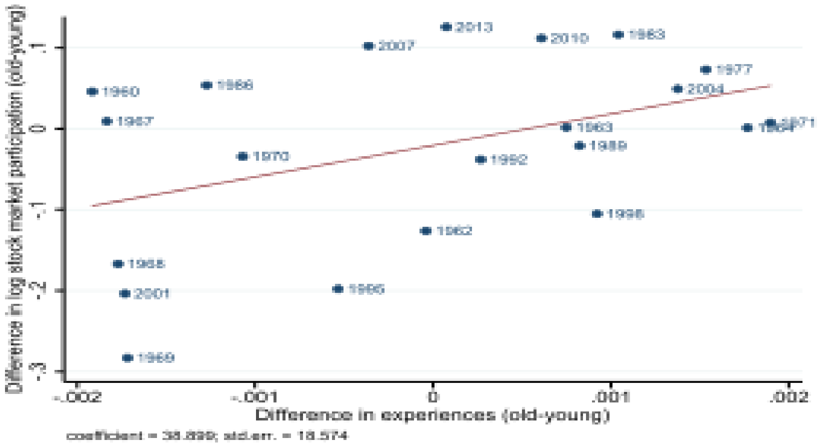
Figs. 9



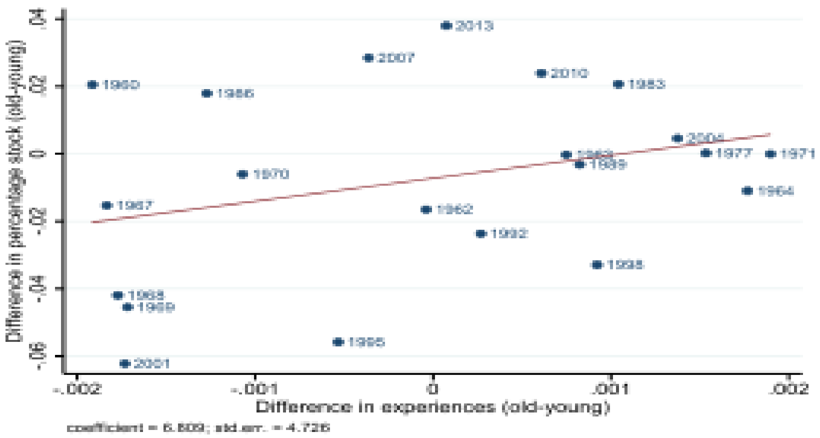
(a) Stock market participation ($\lambda = 1$)



(b) Fraction invested in stock ($\lambda = 1$)



(c) Stock market participation ($\lambda = 3$)



(d) Fraction invested in stock ($\lambda = 3$)

7. Conclusion

In this paper, we propose an OLG equilibrium framework to study the effect of personal experiences on market dynamics and how the demographic composition of an economy can have important implications for the extent to which prices depend on fundamentals. We incorporate the two main empirical features of experience effects, the overweighing of lifetime experiences and recency bias, into the belief formation process of agents. By doing so, we generate what we think are two important channels through which shocks have long-lasting effects on market outcomes. The first is the belief formation process: all agents update their beliefs about the future after experiencing a given shock. The second is the cross-sectional heterogeneity in the population: different experiences generate belief heterogeneity. We show that EBL not only generates several well- known asset pricing puzzles that have been observed in the data, but it also produces new testable predictions about the relation between demographics, prices, trading behavior, and the cross-section of asset holdings, which are in line with the data.