An Excessive-Demand Measure Outperforms Other Demand Proxies in Explaining Lab Asset-Market Price Changes: Toward a Brain Biomarker of Excessive Demand

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Abstract

Dynamic stochastic general equilibrium models have been criticized for failing to forecast the Global Financial Crisis. This and other flaws of neoclassical economics are proposed to arise partly from the failure of equilibrium-based models to capture *excessive demand*, which exceeds the balanced excess demand in general equilibrium theory. Excessive demand is defined as demand that promotes disequilibria in asset or goods markets and drives prices above fundamental values (e.g., an asset-price bubble). Neuroimaging studies are elucidating the neuroeconomics of asset-price bubbles. However, these studies have been limited in characterizing individual-level brain-behavior relationships due to the lack of a subject-level excessive-demand measure (EDM). The present study makes such a measure available. In a standard lab asset-market design, 9 experiments each included 9 subjects. Experiments consisted of 15 2.5-minute periods of trading cash and a risky asset. To capture excessive demand, the end of each Period 1-14 was followed by a survey that elicited each subject's number of asset shares that they want to hold at the end of the next period. This measure was designed to tap into anticipatory affect that may drive price bubbles. Two other predictive measures included excess bids and price-change momentum. A market-level EDM, which explained 34.5% of the variance in asset-price changes, outperformed the excess-bids and momentum measures, which each explained less than 10% of this variance. The EDM's outperformance in predicting price changes aligns with numerous other findings that underscore the predictive power of measures related to anticipatory affect. For example, neuroimaging-measured activity in nucleus accumbens, an area implicated in anticipatory affect, performed better than choice behavior in forecasting crowdfunding outcomes. Similarly, the survey-elicited EDM, which may reflect anticipatory affect, was a better price-change predictor than the behavioral excess-bids measure. Therefore, the presently introduced EDM may facilitate finding an excessive-demand biomarker with market-price predictive power.

Introduction

Excess demand is the amount of demand that exceeds supply. General equilibrium theory stipulates that supply and demand readily adjust, in directions signaled by price changes, to become equated in a balanced, equilibrating manner (Arrow, 1974; Debreu, 1984). Consistent with this scenario, lab-market studies found that price dynamics are driven by a market's excess demand (Plott, 2000; Anderson, Plott, Shimomura, & Granat, 2004; Crockett, Oprea, & Plott, 2011; Plott, Roy, & Tong, 2013). Excessive demand is presently defined as demand that promotes disequilibria in asset, goods, or services markets and drives prices above fundamental values (e.g., an asset-price bubble). Neuroimaging studies are elucidating the neuroeconomics of asset-price bubbles (Smith, Lohrenz, King, Montague, & Camerer, 2014). However, these studies have been limited in characterizing individual-level brain-behavior relationships due to the lack of a subject-level excessive-demand measure (EDM). The present study makes such a measure available to neuroimaging researchers.

Methods

In a standard, continuous double-auction lab asset-market design (Smith, Suchanek, & Williams, 1988), 9 experiments each included 9 undergraduate-student subjects. Each experiment consisted of 15 2.5-minute periods of trading cash and an asset with a commonly known fundamental value that declined across periods. Starting endowments were 1080 experimental currency units (ECU) and 3 asset shares for Subjects 1-3, 720 ECU and 4 shares for Subjects 4-6, and 360 ECU and 5 shares for Subjects 7-9. The 36 shares paid the same dividend in each period: 0, 8, 28, or 60 ECU with equal likelihood, so each period's expected dividend was 24 ECU per share (i.e., [0 + 8 + 28 + 60]/4 = 24). Therefore, a share's expected value at the start of an experiment was 360 ECU (i.e., 24 x 15 periods = 360). The shares' expected, or fundamental, value fell each period by 24 ECU, thereby becoming 0 after the last dividend was paid at the end of Period 15. A subject's cash and shares carried over from one period to the next. Instructions to subjects before the experiment explained the dividend process and the expected value calculation was shown on their computer screen during each period. In each period, subjects could submit an offer to sell a share or a bid to buy a share and/or accept a current offer to sell or a current bid to buy. The Summary and Survey Screen shown at the end of each period displayed information about the period that had just ended: average transaction price, total number of transactions in the market, and a subject's number of shares owned, cash balance before the dividend, and new cash balance after receiving dividends. The Summary and Survey Screen also asked each subject three questions at the end of Periods 1-14: 1) What do you think will be the total number of trades next period? 2) What do you think will be the average price of the asset next period? 3) How many shares do you plan on holding at the end of the next period (assuming that the price is what you forecasted)? Subjects earned money based on their accuracy in answering the first two questions. After each experiment, subjects were paid in cash according to their earnings, which consisted of forecast earnings and the final cash balance adjusted by the exchange rate of 200 ECU = 1 USD. The average earning per subject was $14.09, which was in addition to a $7.00 show-up fee.

Results

As in many previous studies using this double-auction design (e.g., Smith et al., 1988), experiments typically showed an asset-price bubble in early trading periods followed by a price crash and convergence of the price toward fundamental value. The price crash may reflect cognitive uncertainty that deters people from options that are difficult to evaluate (i.e., uncertainty about whether an asset's price will continue to rise even higher above fundamental value; Enke and Graeber, 2023; Enke, 2024). Regression results (observations = 117 [i.e., 9 experiments x 13 periods, besides Periods 1 and 15, with data required for the regression analysis]) of models were tested for an ability to explain asset-price changes. Each model's independent variable was a demand proxy and the dependent variable was the change in average asset price from one period to the next. Answers to the third survey question yielded subject-level EDMs (i.e., desired holding [DH] responses in Equation 1) at the end of Periods 1-14. Following the Introduction's terminology, "excessive demand" is used here because asset prices often exceed fundamental value in this experimental setting (e.g., Smith et al., 1988). Equation 1 calculates the market-level EDM (i.e., from summed subjects' DH responses; EDM_t was reduced by one so that its sign would be negative for instances of excess supply) for each period t.

(1) $EDM_t = [(\sum_{i=1}^{n} DH_{i,t})/36] - 1$

Equation 2 examines the relationship between the previous period's market-level EDM and price change, with the latter calculated as in Equation 3.

(2) $\Delta \text{ave}P_t = b_0 + b_1(EDM_{t\text{-}1})$

(3) $\Delta \text{ave}P_t = (\text{ave}P_t - \text{ave}P_{t\text{-}1})/\text{ave}P_{t\text{-}1}$, where $\text{ave}P_t$ is the average transaction price of the asset during period t.

Equation 4 modifies the excess bids calculation of Smith et al. (1988) that was based on the previous period's number of bids ($B_{t\text{-}1}$) and offers ($O_{t\text{-}1}$). The modification yields excess bids as a proportion of total bids and offers.

(4) $\Delta \text{ave}P_t = b_0 + b_1[(B_{t\text{-}1} - O_{t\text{-}1})/(B_{t\text{-}1} + O_{t\text{-}1})]$

Equation 5 models price-change momentum based on the previous interperiod change in asset price.

(5) $\Delta \text{ave}P_t = b_0 + b_1(\Delta \text{ave}P_{t\text{-}1})$

The market-level EDM (Equation 1), which explained 34.5% of the variance in asset-price changes, outperformed the excess-bids (Equation 4) and momentum (Equation 5) measures, which each explained less than 10% of this variance. Smith et al. (1988, p. 1141) viewed their excess-bids measure as a surrogate or proxy for excess demand (i.e., "…a measure of the revealed excess demand for shares…"). Although their excess-demand measure reportedly predicted asset-price changes, the present market-level EDM showed greater predictive power, perhaps because the EDM is better able to account for anticipatory affect (i.e., the "animal spirits" or "irrational exuberance" that are proposed to play a role in the formation of asset-price bubbles).

Conclusions

The market-level EDM's outperformance in predicting asset-price changes aligns with numerous other findings that underscore the predictive power of measures related to anticipatory affect. For example, functional magnetic resonance imaging-measured activity in nucleus accumbens, an area implicated in anticipatory affect, performed better than choice behavior in forecasting crowdfunding outcomes (Genevsky, Yoon, & Knutson, 2017). Similarly, the survey-elicited EDM, which may reflect anticipatory affect, was a better price-change predictor than the behavioral excess-bids measure. Therefore, the presently introduced market-level EDM may facilitate finding an excessive-demand biomarker with market-price predictive power. Biomarkers for neuroforecasting market-level outcomes (Genevsky et al., 2017; Knutson & Genevsky, 2018; Tong, Acikalin, Genevsky, Shiv, & Knutson, 2020; van Brussel, Boksem, Dietvorst, & Smidts, 2024; Genevsky, Tong, & Knutson, 2025) in luxury-goods or -services markets (e.g., top-line cars, flights, etc.) may elucidate the neuroeconomics of worsening, anthropogenic global warming (Haracz & Zakaria, 2024). Haracz (2022) further exemplified the usefulness of the excessive demand concept by applying it in a proposed learning-to-neuroforecast framework.

The presently introduced subject- and market-level EDMs may be useful for studying the neuroeconomics of excessive demand that drives disequilibria in asset, goods, and services markets.

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