

ESSAYS ON EXPERIMENTAL AND
BEHAVIOURAL ECONOMICS AND FINANCE

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Abstract

Three essays of this thesis combine research projects devoted to markets, prices, and expectations. The first chapter provides results on an experimental test of a model with interacting boundedly rational agents. Adaptive switching between forecasting heuristics by heterogeneous agents brings instability to the price dynamics and generates bubbles and crashes. In the second chapter of this thesis, behavioural models of channelling attention to adaptive choice are empirically tested on data generated from laboratory experiments. According to the identified self-tuning model, subjects scale their attention to the task given the stakes. Computational analysis and simulations demonstrate the importance of this self-tuning model for generating price dynamics that balances on the edge of stability. The third chapter is an experimental investigation of the role of forecasting horizon length in generating excess price volatility. In markets with initially unstable prices with an increase in horizon length price dynamics stabilises. This finding can be partly explained by dis-coordination of subject on non-fundamental expectations in markets with longer horizons.

Certificate of Original Authorship

I, Aleksei Chernulich, declare that this thesis, is submitted in fulfilment of the requirements for the award of PhD in Economics, in the UTS Business School at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. This document has not been submitted for qualifications at any other academic institution. This research is supported by the Australian Government Research Training Program.

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*To my mom, Elena—my main advisor throughout life—and to my dad,
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