THREE ESSAYS IN BEHAVIORAL AND CORPORATE FINANCE

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Abstract

This thesis examines topics in corporate finance and behavioral finance. First, I examine the effects of ownership structure on the amount of firm-specific information in stock prices, measured using synchronicity.[1] With a unique dataset of 6,184 firm-year observations for Canadian companies listed on the Toronto Stock Exchange during 2000-2012, I find evidence of a significant, non-linear relationship between the size of the largest shareholder and synchronicity. Using propensity score matching (PSM) to isolate the effect of family firms on synchronicity, I find no evidence of a significant difference in synchronicity for matched pairs of family and non-family firms. Finally, I find evidence of a negative relationship between firms with multiple large controlling shareholders and synchronicity.

Second, in a co-authored paper with Dr. Richard Deaves (McMaster University) and Dr. Brian Kluger (University of Cincinnati) we investigate the relationship between path-dependent behaviors (i.e., the disposition effect, house money effect and break-even effect) and investor characteristics (e.g., overconfidence and emotional stability) using experimental trading sessions. The majority of our subjects exhibit path-dependent biases and there are significant

[1] Synchronicity is defined to be the variation in stock prices that is driven by market and industry movements (so when synchronicity increases there is *less* firm-specific information in price changes).

correlations between these biases. The correlations hint at the possibility that a common underlying factor may be driving all path-dependent behaviors. We also find some evidence that the existence of psychological bias (overconfidence and negative affect) leads to more bias in financial decision-making.

Third, in co-authored work with Dr. Lucy Ackert (Kennesaw State University), Dr. Richard Deaves (McMaster University) and Dr. Quang Nguyen (Middlesex University) we report the results of an experiment designed to explore whether *both* cognitive ability (IQ) and emotional stability (EQ) impact risk preference and time preference in financial decision-making, finding evidence in support. Specifically, IQ impacts risk preferences and EQ impacts time preferences. Our results are primarily driven by our male participants. Most interestingly, EQ plays a role that is almost as meaningful as IQ when it comes to explaining preferences.

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Chapter One: *Introduction*

This thesis focuses on two main areas in finance: (i) corporate governance, specifically the intersection of ownership structure characteristics and firm-specific information in stock prices; and (ii) behavioral finance with a particular focus on exploring investor decision-making through experimental analysis.

In the first essay of this thesis, entitled *Ownership structure and stock price synchronicity in Canada: ownership concentration, family ownership and multiple large controlling shareholders,* I examine the effects of the size of a firm's largest shareholder (in terms of voting rights held), family ownership, and multiple large controlling shareholders on the amount of firm-specific information in stock prices, measured using synchronicity.[2] Ownership structure has been known to influence stock prices and the information environment of a firm (Boubaker, Mansali, & Rjibam, 2014; Brockman & Yan, 2009; Gul, Kim, & Qiu, 2010; Piotroski & Roulstone, 2004). Using a unique dataset that I have collected of 6,184 firm-year observations for Canadian companies listed on the Toronto Stock Exchange during 2000-2012, I find evidence of a significant, non-linear relationship between the size of the largest shareholder and the firm-specific information in stock prices.

[2] Synchronicity is defined to be the variation in stock prices that is driven by market and industry movements (so when synchronicity increases there is *less* firm-specific information in price changes).

Previous studies that link corporate governance to financial markets tend to consider large controlling shareholders as a homogenous entity. The dataset that I have constructed identifies the largest controlling shareholder of a firm and allows for the separation between family firms (i.e., a group of related individuals or an individual person is the largest controlling shareholder) and non-family firms (where the largest controlling shareholder is not classified as a family; this group includes government or government-controlled entities, pension funds, royalty trusts, income trusts, partnerships and other non-corporate entities). Family firms have many characteristics, incentives and motivations that differentiate them from their non-family counterparts, and this may affect the information environment of these firms (Anderson & Reeb, 2003; Classens, Djankov, Faccio, & Lang, 2002; La Porta, Lopez-De-Silanes, & Shliefer, 1999). Investigating the relationship between informativeness, as proxied by synchronicity, and family vs non-family control provides insight into the information environment of family firms and contributes to the understanding of how family owners may differ from other types of ownership. Interestingly, using propensity score matching (PSM) to isolate the effect of family firms on synchronicity, I find no evidence of a significant difference in synchronicity for matched pairs of family and non-family firms.

Finally, I consider first, whether or not the largest controlling shareholder in a firm is alone and second, whether multiple large controlling shareholders (i.e., there exists at least one shareholder, other than the controlling one, with at least 10% voting equity through a control chain that does not overlap with the controlling shareholder) vs. a single controlling shareholder are associated with informativeness. I find evidence of a positive relationship between firms with multiple large controlling and the level of firm-specific information in stock prices. The use of the unique dataset, together with the distinction between family and non-family firms, provides new insights into the effects of ownership structure on firms' stock price information.

This study is relevant to market participants at different levels. First, it informs investors and shareholders. Second, it provides insight that regulators can use to enhance the information environment of financial markets.[3] And finally, all stakeholders, including: managers, directors, capital providers, customers and employees, will benefit from the findings of this study, since they are each subject to contracts that depend on market prices.

This study also makes several contributions to the literature. First, the Canadian environment presents an opportunity to investigate a setting where ownership structure characteristics share similarities to studies that find evidence supporting entrenchment theory, such as concentrated ownership by family

[3] Even in a country like Canada, with regulations in place to provide minority shareholders with protection from dominant shareholders, there has been evidence of excessive active illegal insider trading and reporting violations, leaving room for regulatory improvements (Cheffins, 1999; McNally and Smith, 2003; Bris, 2005; Attig, Fong, Gadhoum and Lang, 2006).

members with divergence between cash flow rights and voting rights, while maintaining corporate governance mechanisms and strong shareholder protections that are in line with studies that support incentive alignment (Morck, 2005; Attig et al., 2006; Ben-Amar and André, 2006; Gul, Kim and Qiu, 2010). Second, I test the effect of family firms on stock price synchronicity, which to my knowledge has yet to be addressed by the literature. Finally, I consider whether the largest controlling shareholder in a firm is alone, contributing to the literature on multiple controlling shareholders, corporate governance and financial markets (Bond, Edmans, & Goldstein, 2012; Edmans, 2013).

I turn my focus to behavioral finance and investor decision-making in the second and third essays of this thesis. The second essay, entitled *An experimental analysis of path-dependent financial behaviors and investor characteristics,* is co-authored work with Dr. Richard Deaves (McMaster University) and Dr. Brian Kluger (University of Cincinnati). We investigate the relationship between path-dependent behaviors (i.e., the disposition effect, house money effect and break-even effect) and investor characteristics (e.g., overconfidence and emotional stability) using experimental trading sessions. There is abundant evidence that financial decision-makers are susceptible to path-dependent behavior that do not conform to what neo-classical economics would predict and have the potential to decrease shareholder wealth (Arkes & Blumer, 1985; Choi, Laibson, Madrian, & Metrick, 2009; DeFondhi & Pchiraju, 2010; Kaustia & Knüpfer, 2008; Malmendier

&Nagel, 2009). Path-dependent behaviors occur when a decision-making process is influenced by what has taken place in the past. Our experimental design involves a simple portfolio choice task featuring two risky assets and cash. The design of the experiment is unique in that it allows us to test for multiple path dependent effects in the same experiment, without cross-contamination.[4]

This study makes some important contributions. First, we investigate whether the tendency of an individual to exhibit one behavior makes it more or less likely that they will exhibit another behavior. This is important because it should allow researchers to more carefully model path-dependent behavior. Second, collecting psychometric and demographic makes it possible to explore to what extent investor characteristics are associated with path-dependent behaviors. This too could facilitate modelling: for example, if we find that overconfidence strongly correlates with disposition effect tendencies but not any wealth effects, then it is logical to believe that overconfidence should form part of the explanation of the former but not the latter. Third, these findings may also be of use in a practical sense: for example, investment advisors may be better able to debias clients once they know the investor characteristics that that may lead to increased susceptibility to bias. Suppose overconfidence correlates with disposition effect.

[4] The experimental environment also eliminates possible rational reasons for disposition effect behavior, for instance mean-reversion (our setup eliminates this possibility).

A financial planner, administering a questionnaire to clients containing an overconfidence metric should be able to intuit which clients are more likely to exhibit such behavior and undertake appropriate educational activity.

Our main finding is that the majority of our subjects exhibit path-dependent biases and there are significant correlations between these biases. Subjects prone to the disposition effect are more likely to also be prone to the breakeven effect, and less likely to display the house money effect. We also find that the house money effect is negatively correlated with the breakeven effect. These correlations hint at the possibility that a common underlying factor may be driving all path-dependent behaviors. In terms of psychometric variables, we find that the existence of psychological bias (overconfidence and negative affect) leads to more bias in financial decision-making.

The third essay, entitled *Cognitive Ability, Emotional Stability and Risk and Time Preferences: An Experimental Analysis,* is co-authored work with Dr. Lucy Ackert (Kennesaw State University), Dr. Richard Deaves (McMaster University) and Dr. Quang Nguyen (Middlesex University). In this essay, we report the results of an experiment designed to uniquely explore whether *both* cognitive ability (IQ) and emotional stability (EQ) impact risk preference and time preference in financial decision-making, finding solid evidence in support.

There is abundant evidence that decision-making involves both cognitive and emotional processes (Benjamin et al., 2013; Sanfey, Rilling, Aronson, Nystrom,

& Cohen, 2003; Vastfjall & Slovic, 2013). Given the observation that individuals are experiencing increasingly crushing levels of credit card debt and insufficient levels of retirement savings, and that these behaviors may stem in part from both risk and time preferences, it is important to understand the characteristics driving these preferences (Angeletos, Laibson, Repetto, Tobacman, & Weinberg, 2001; Bar-Gill, 2004; Meier & Sprenger, 2010; Shamosh et al., 2008). While there has been work done that has established important associations between IQ and risk and time preferences (Barberis, Huang, & Thaler, 2006; Dohmen et al., 2010; Frederick, 2005; Read, Loewenstein, Rabin, Keren, & Laibson, 1999); EQ and risk preferences (Charupat et al., 2012) and EQ and time preferences (Manning et al., 2014; Walther, 2010), research investigating whether relationships exist for both IQ and EQ is rather limited.[5]

In this paper, we report the results of an experiment designed to explore, uniquely we believe, whether a relationship exists between proxies for both cognitive ability (IQ) and emotional stability (EQ) and the key parameters in risk preference and time-preference models. Specifically, we focus on cumulative

[5] In fact, to our knowledge there is one other study that is somewhat similar to ours. Hirsh, Morisano, and Peterson (2008) look at time preferences (delay discounting) and interactions between EQ (neuroticism) and IQ (cognitive ability). Using 97 undergraduate students at McGill University, they find that decreased EQ is associated with higher discounting rates, but only for individuals with higher IQ scores.

prospect theory and quasi-hyperbolic discounting, both of which nest models grounded in rationality.

We find that both IQ and EQ impact preferences. If we take expected utility theory as the hallmark of normative decision-making when facing risk, those with higher levels of IQ have preferences that are more rational than those with low levels of IQ. This operates almost entirely in the male subsample. EQ seems to matter for probability weighting in the case of women. As for time preference, again more consistent with rationality, high-EQ males are less subject to present (or future) bias. And high-EQ males are also more patient in that they tend to have lower rates of time preference.

What is perhaps novel here is that EQ plays a role that is about as meaningful as IQ when it comes to explaining preferences. While the recent spate of research on the impact of cognitive ability on preferences is commendable, our results suggest that more research on the role played by emotional stability is in order.

This thesis proceeds as follows. Chapter 2 examines the relationship between ownership structure and synchronicity in Canada, focusing on ownership concentration, family ownership and multiple large controlling shareholders. Chapter 3 is an experimental analysis of path-dependent financial behaviors and investor characteristics. Chapter 4 is an experimental analysis of cognitive ability, emotional stability and risk and time preferences. And Chapter 5 concludes with the overall findings and implications of the research conducted.

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Chapter Two: *Ownership structure and stock price synchronicity in Canada: Ownership concentration, family ownership and multiple large controlling shareholders*

2.1. Introduction

The degree of information available in share prices varies across firms and has important implications for all market participants. Investors, managers, capital providers and regulators have all been shown to use share prices as a source of information in their decision-making (Bond, Edmans, & Goldstein, 2012). Informative prices can help managers make better decisions about capital investment resulting in higher efficiency in capital allocation, and can reduce the risk for uninformed investors thereby decreasing the cost of capital for a firm (Chen, Goldstein, & Jiang, 2007; Durnev, Morck, & Yeung, 2004; Fernandes & Ferreira, 2009; Wurgler, 2000). Accordingly, investigating the informativeness of stock prices and its determinants is of importance.

In particular, one strand of the literature shows that ownership structure (i.e., the distribution of ownership claims by shareholders and the identities of the shareholders) plays a significant role in influencing share prices and the information environment of a firm. For example, Piotroski and Roulstone (2004) investigate the effect of informed market participants, including large shareholders, on the relative amount of market-, industry- and firm-specific information in prices. They find that large shareholders, particularly institutional investors, possess informational advantages that accelerate the incorporation of firm-specific information into share prices. This finding has motivated a growing body of research that corroborates the significant influence of ownership structure on the firm-specific information component in share prices (Boubaker, Mansali, and Rjiba, 2014; Brockman & Yan, 2009; Gul, Kim, & Qiu, 2010). The latter is measured using stock price synchronicity (hereafter 'synchronicity'), defined to be the variation in stock prices that is driven by market and industry movements (so when synchronicity increases there is *less* firm-specific information in price changes).[6] Examples of such studies are Brockman and Yan (2009) on the effect of block ownership; Gul, Kim and Qiu (2010) on the effect of foreign ownership; and Boubaker, Mansali and Rjibam (2014) on the effect of the separation of cash flows and voting rights.

The purpose of this paper is to examine the effects of ownership structure on stock price informativeness (hereafter 'informativeness'), as proxied by synchronicity, using a unique dataset of the largest controlling shareholders (where the controlling shareholder of a firm is defined to be the largest shareholder who controls at least 10% of its voting equity) of Canadian companies listed on the Toronto Stock Exchange (TSX) during 2000-2012. I first consider two important dimensions of ownership structure: the percentage of voting equity held by the

[6] More specifically, synchronicity is measured using the market model R^2 (Morck, 2000; Roll, 1998).

largest controlling shareholder, and whether or not the firm is a family firm.7 Previous studies that link corporate governance to financial markets tend to consider large controlling shareholders as a homogenous entity. The dataset that I have constructed identifies the largest controlling shareholder of a firm and allows for the separation between family firms (a firm with a group of related individuals or an individual person as the largest controlling shareholder); non-family firms (where the largest controlling shareholder is not classified as a family, and can be government or government-controlled entities, pension funds, royalty trusts, income trusts, partnerships and other non-corporate entities); and widely-held firms (where there is no controlling shareholder with at least 10% voting equity). In addition, I examine whether the presence of multiple large controlling shareholders (i.e., there exists at least one shareholder, other than the controlling one, with at least 10% voting equity through a control chain that does not overlap with the controlling shareholder) facilitates informativeness.

There are two competing theories used to explain the relationship between ownership structure and informativeness: entrenchment theory and incentive alignment theory. Under entrenchment (theory), controlling shareholders have incentives to withhold or selectively disclose information (Claessens, Djankov, Fan, & Lang, 2002; Fama & Jensen, 1985; Fan & Wong, 2002; Jin & Myers, 2006;

[7] A *family firm* refers to a firm in which a group of related individuals or an individual person is the largest controlling shareholder with at least 10% voting equity.

Morck, Yeung, & Yu, 2000). This increases the cost of acquiring firm-specific information, contributing to an opaque information environment and disrupting the flow of firm-specific information into share prices, thereby decreasing informativeness and increasing synchronicity.

On the other hand, incentive alignment (theory) posits that large controlling shareholders can facilitate the alignment of interests between controlling and minority shareholders (Grossman & Hart, 1980; Jensen & Meckling, 1976; Shleifer & Vishny, 1997). In this case, large shareholders closely monitor managers and constrain agency problems, leading to the disclosure of more and better firm-specific information. This decreases the cost of information and facilitates more informed trading, leading to more information being incorporated into share prices with a concomitant increase in informativeness and decrease in synchronicity (Grossman & Stiglitz, 1980).

Empirical support for the two theories is mixed. Evidence of incentive alignment exists for blockholders (Brockman & Yan, 2009) and foreign ownership (He, Li, Shen, & Zhang, 2013), but, when control rights exceed cash flow rights, Boubaker, Mansali and Rjiba (2014) have documented evidence supporting entrenchment. Previous corporate governance studies have found non-linear relationships that support both the entrenchment and alignment effects for different levels of share ownership, but the results of these studies are sometimes conflicting (Morck, Shleifer, & Vishny, 1988; Sánchez-Ballesta & García-Meca, 2007; Short & Keasey, 1999). As a result, this issue is still an open empirical question in need of further examination.

I choose to study the effects of family firms because they represent a significant portion of firms with large controlling shareholders (Anderson & Reeb, 2003; Claessens, Djankov, & Lang, 2000; Faccio & Lang, 2002; La Porta, Lopez-De-Silanes, & Shleifer, 1999). In my sample of Canadian publicly traded companies, 72% have one or more large shareholders (that is, a shareholder who owns at least 10% voting equity in the firm), of which 44% are family firms, and 28% are non-family firms. The remaining 28% are widely-held. Since family firms, in some markets, are a common ownership structure, it is important to investigate whether such firms have different incentives and behaviors than non-family firms.

The reputation and perception of the family within its social environment as well as the firm being a significant source of wealth are strong incentives for family owners to take a long-term perspective in the firm (Arregle, Hitt, Sirmon, & Very, 2007). This alignment of the interests of family owners and the long-term well-being of the firm should result in better information disclosure, increased informativeness and decreased synchronicity. On the other hand, others have argued that family owners are likely to be prone to entrenchment (Schulze, Lubatkin, & Dino, 2002; Fan & Wong, 2002). More specifically, Fan and Wong (2002), determine that the governance characteristics of family firms enables easy expropriation of non-family shareholders and demonstrate that the likelihood of earnings management is higher for firms in which ownership is mostly families. To my knowledge, whether family control (vs. non-family control) leads to more or less informativeness has yet to be empirically tested.

Finally, I consider whether or not the largest controlling shareholder in a firm is alone versus being the largest of several multiple large controlling shareholders is associated with informativeness. Gorton, Huang and Kang (2013) find a positive association between the existence of multiple large shareholders and informativeness. Edmans (2013) posits that multiple large shareholders will trade aggressively on private information and that this trading will incorporate more information into prices so that prices more closely reflect fundamental value and managers' actions. Gallagher, Gardner and Swan (2013) find that the trading behavior of large shareholders leads to subsequent increases in price efficiency and that these effects are stronger in the presence of multiple large shareholders. According to this work, having multiple large controlling shareholders should increase the firm-specific information component in prices (thereby decreasing synchronicity).

The dataset employed here comprises 6,184 firm-year observations for Canadian companies listed on the Toronto Stock Exchange during 2000-2012. To preview, my empirical findings support the hypothesis that ownership structure is significantly related to informativeness, as proxied by synchronicity. More specifically, I find a non-linear relationship that indicates incentive alignment for low and high levels of ownership, and entrenchment for ownership levels in the mid-range (in my sample between approximately 25-60%). Further, using propensity score matching (PSM) to isolate the effect of family firms on synchronicity, I find that there is no significant difference in synchronicity for family firms compared to non-family firms. Finally, I find evidence of a negative relationship between firms with multiple large controlling shareholders and synchronicity, which is consistent with the notion that stock price efficiency is facilitated by the existence of multiple large controlling shareholders.

This study makes several contributions to the literature. First, the Canadian environment presents an opportunity to look at the impact of ownership concentration on the information environment of a firm in a setting where ownership structure characteristics share similarities to studies that find evidence supporting entrenchment theory, such as high levels of family ownership along with divergence between cash flow rights and voting rights, while maintaining the corporate governance mechanisms and strong shareholder protections that are in line with studies that support incentive alignment (Attig et al., 2006; Ben-Amar & André, 2006; Gul et al., 2010; Morck, 2005). Second, I test the effect of family firms on informativeness, as proxied by synchronicity, which to my knowledge has yet to be addressed by the literature on ownership structure and informativeness. Finally, I consider whether or not the largest controlling shareholder in a firm is alone impacts informativeness, contributing to the literature on multiple controlling owners, corporate governance and financial markets (Bond, Edmans, & Goldstein, 2012; Edmans, 2013).

This study is also relevant to market participants at different levels. First, it is useful for investors and shareholders to know the extent to which stock prices contain firm-specific information (Bond, Edmans, & Goldstein, 2012). Second, investigating ownership structure and synchronicity provides insights that regulators can use to enhance the information environment of financial markets. The financial crisis of 2008 emphasized the significance of corporate governance and the importance of mechanisms that ensure that managers act in the interest of shareholders. Even in a country like Canada, with regulations in place to provide minority shareholders with protection from dominant shareholders, there has been evidence of illegal insider trading and reporting violations, leaving room for regulatory improvements (Attig, Fong, Gadhoum, & Lang, 2006; Bris, 2005; Cheffins, 1999; McNally & Smith, 2003). And finally, all stakeholders, including managers, directors, capital providers, customers and employees, will benefit from the findings of this study since they are each subject to contracts that depend on market prices (Edmans, 2013).

The remainder of the chapter proceeds as follows. Section 2.2 develops the research hypotheses. Section 2.3 describes the data and analysis methods used to test the research hypotheses. Section 2.4 presents the empirical results. Section 2.5 includes some additional tests. And section 2.6 concludes.

2.2. Hypothesis development

2.2.1. Ownership concentration and synchronicity.

Previous studies provide evidence of a significant relationship between ownership concentration (the size of the largest controlling shareholder) and synchronicity (Boubaker, Mansali, & Rjiba, 2014; Brockman & Yan, 2009; Gul, Kim, & Qiu, 2010; He, Li, Shen, & Zhang, 2013). This relationship can be explained by entrenchment, incentive alignment, or a combination of the two theories.

There is a large body of literature that finds evidence supporting entrenchment and the incentives that concentrated owners have to hide self-serving behaviors, limit the release of unfavorable information, and opportunistically time the release of value-relevant private information to the market (Fan & Wong, 2002; Gul, Lynn, & Tsui, 2002, 2010; Jin & Myers, 2006; Shleifer & Vishny, 1989). Empirical evidence for entrenchment (i.e., the positive relationship between ownership and synchronicity) has been found in emerging markets with highly concentrated ownership, and in markets where control rights exceeds cash flow rights (Boubaker, Mansali, & Rjiba, 2014; Gul, Kim, & Qiu, 2010).[8]

Gomes (2000), on the other hand, finds that a high concentration of ownership signals a commitment made by controlling shareholders to not

[8] Dual-class shares allow for the separation of control rights from cash flow rights.

expropriate the interests of minority shareholders. This alignment of interests between concentrated owners and all other shareholders creates incentives to closely monitor managers and constrains agency problems, leading to the disclosure of more and better firm-specific information.[9]

Support for incentive alignment (i.e., the negative relationship between ownership and synchronicity) is strongest in developed economies with strong investor protections and a transparent information environment. Brockman and Yan (2009) find evidence in the U.S. that the existence of both inside and outside concentrated owners increase the probability of informed trading and decrease synchronicity of a firm. He, Li, Shen and Zhang (2013) conduct a study that includes 40 countries, including both emerging and developed markets, and find that large foreign ownership concentration is related to a decrease in synchronicity, and that the effect is stronger for firms in developed economies with strong investor protections.

The conflicting empirical evidence leads us to believe that both effects are likely to be at play at the same time. Specifically, researchers have found non-linear

[9] There is also evidence that the absence of concentrated ownership (widely-held firms) increases the separation of ownership and control, which can lead to agency conflicts between managers and outside shareholders. This creates incentives for managers to report financial information that deviates from the underlying economic transactions of a firm in order to maximize private benefits at the cost of shareholders or creditors, disrupting the flow of private information to financial markets (Leuz, Nanda, & Wysocki, 2003; Warfield, Wild, & Wild, 1995).

relationships that support both entrenchment and incentive alignment effects for different intervals of ownership concentration (Gul, Kim, & Qiu, 2010; Morck, Shleifer, & Vishny, 1988; Sánchez-Ballesta & García-Meca, 2007; Short & Keasey, 1999). For example, Gul, Kim and Qiu (2010), find for China, that synchronicity is a concave function of ownership concentration, providing evidence of entrenchment for low levels of ownership concentration and incentive alignment for ownership concentration levels greater than 50%.

Whether entrenchment, incentive alignment, or a role for both, dominates in the Canadian market is an open empirical question. Since the Canadian environment has characteristics that support both entrenchment (such as family ownership and divergence between cash flow rights and voting rights) and incentive alignment (such as corporate governance mechanisms and strong shareholder protections), it would not be surprising to find evidence supporting both.

Therefore, I anticipate a concave non-linear relationship between ownership concentration and synchronicity, with decreased synchronicity for low and high levels of ownership concentration. As suggested by La Porta, Lopez-De-Silanes and Shleifer (1999), at very low levels of concentration, below 20%, the largest shareholders do not yet have sufficient voting power to influence the management of the company, which could result in incentive alignment type behavior and decreased synchronicity at low levels of ownership concentration.

Gul, Kim and Qiu (2010) report decreased synchronicity (incentive alignment behavior) at high levels of concentration, above 50%. High levels of ownership concentration may be related to a decrease in incentives for entrenchment. Morck, Shleifer and Vishny (1988) explain that while increased ownership concentration may lead to deeper entrenchment, diminishing returns might set in at a certain ownership concentration level decreasing the incentive for entrenchment. This leads to the first hypothesis to be tested.

H_1. *There is a concave non-linear relationship between ownership concentration and synchronicity.*

2.2.2. Family firms and synchronicity

The dataset collected for this study identifies the largest controlling shareholder of a firm. This makes it feasible to ask whether the identity of the largest concentrated owner matters. Firms with different concentrated owners can have different forms of governance, be affected by firm characteristics in different ways, and have different incentives and motivations that will affect the information environment of the firm (Isakov & Weisskopf, 2014). Specifically, I focus on family firms since they have been shown to have different incentives than non-family firms

(Anderson & Reeb, 2003; Claessens et al., 2000; Faccio & Lang, 2002; La Porta et al., 1999).

Jensen and Meckling (1976) argue for the uniqueness of family firms. In their view, family firms are exempt from the agency problem that other concentrated owners face because they have an altruistic, intra-familial element not present in non-family firms. More recently, in Canada, the notion that family firms are governed by significantly different criteria than other firms has lead to the Family Firm Board Effectiveness Index created by the Clarkson Centre for Board Effectiveness (CCBE) (Fullbrook, 2015).[10] This index, created by CCBE, is designed to measure the unique corporate governance characteristics of family firms. More specifically, this index recognizes that family firms have share structures, director independence, CEO/Chair split, and compensation peer group disclosure ratings that differ significantly from other firms on the S&P/TSX Composite Index, while being more inclined to avoid short-term gains in favor of long-term interests.

There are three strong incentives for family owners to take a long-term perspective in the well-being of a firm. First, the reputation of the family may be closely associated with the performance of the firm (Arregle, Hitt, Sirmon, & Very,

[10] The CCBE is a corporate governance research centre at the Rotman School of Management, University of Toronto. Its mandate is to "monitor Canadian corporate governance trends and provide insight to firms looking to improve their board effectiveness and disclosure." *http://www.rotman.utoronto.ca/FacultyAndResearch/ResearchCentres/ClarksonCentreforBoardEffectiveness.aspx*

2007). Second, family firms tend to hold poorly diversified portfolios linking the wealth of the family to the welfare of the firm (Demsetz & Lehn, 1985). And third, family firms tend to have multiple generations of owners. This encourages the family to view the firm as an asset to pass on to their descendants rather than wealth to consume during their lifetimes, supporting the notion that family firms are concerned with wealth transfer to the next generation (Chami, 2001).

Their long-term interest in the firm encourages family owners to monitor managers and mitigate managerial expropriation. Moreover, the historical presence of a large undiversified equity position and control of senior management positions place families in a position to influence and monitor the firm (Demsetz & Lehn, 1985). Anderson and Reeb (2003) find that family firms exhibit significantly better accounting and market performance than non-family firms, indicating that family ownership mitigates managerial opportunism. Non-family firms, on the other hand, may not have the same vested interest. For example, an individual representing a pension plan that owns a large block of shares in a firm may not have as high of an incentive to monitor managers as a family (Isakov & Weisskopf, 2014).

Perhaps families arguably are long-term value-maximization advocates and, in fact, family firms tend to be more profitable and have higher market valuation than their non-family counterparts. Ben-Amar and André (2006) find that positive abnormal returns are greater for family firms, and when there is separation of ownership and control for family firms it does not result in a negative impact on performance. In a more recent study, during 1998-2012, the returns of Canadian publicly-listed family firms outperformed other companies found on the S&P/TSX Composite Index (TSX Index) with total difference in returns of 1.59% (Spizzirri and Fullbrook, 2013).[11]

While the long-term perspective of their governance structure is likely to predispose family firms to behave according to incentive alignment theory, there is also evidence supporting the entrenchment effect among family firms. For example, it has been shown that family firms may be more exposed to agency costs since the governance characteristics of family firms can lead to shareholder expropriation (Schulze, Lubatkin, & Dino, 2002). Along these lines, Fan and Wong (2002) demonstrate that the likelihood of earnings management is higher for firms in which ownership is mostly families.

Investigating the relationship between informativeness, as proxied by synchronicity, and family vs non-family control provides insight into the information environment of family firms and contributes to the understanding of how family owners may differ from other types of ownership. Since the majority of the evidence in the Canadian environment favors incentive alignment, I am expecting to find that family firms are positively related to informativeness

[11] The cumulative average growth rate during 1998-2012 was 7.70% for family firms, and 6.11% for non-family firms.

(negatively related to synchronicity). I am also expecting the effect of family firms on informativeness to be significantly different, and stronger, than that of non-family firms.

***H_{2a}*.** *Family firms exhibit less synchronicity (i.e., their stock prices carry a higher proportion of firm-specific information).*

***H_{2b}*.** *The relation of family firms to synchronicity is stronger than non-family firms.*

2.2.3 Multiple large shareholders and synchronicity

If there is more than one controlling shareholder, then both the monitoring of management and the other controlling shareholders should be enhanced, reducing the agency costs between management and shareholders. This can be done through "voice" (direct intervention in the activities of management), or through "exit" (trading strategies based on private information that are meant to pressure management decisions). An increase in monitoring should increase the transparency of the information environment of a firm and decrease the acquisition cost of information, leading to more informed trading, which should in turn decrease synchronicity.

Large controlling shareholders are considered to be informed traders and their trading behavior is associated with increases in price efficiency, an effect that is stronger when there are multiple large controlling shareholders (Gallagher, Gardner, & Swan, 2013; Gorton, Huang, & Kang, 2013). There is evidence that trading by multiple large controlling shareholders has a permanent effect on stock prices, suggesting that the price changes are due to information rather than liquidity (Sias, Starks, & Titman, 2006). Edmans (2013) explains that when there are multiple controlling shareholders of a firm, they may be encouraged to trade aggressively on private information, leading to an increase in the amount of firm-specific information in prices and lower synchronicity. This leads to the final hypothesis.

***H_3*.** *Synchronicity is lower (informativeness is higher) for firms with multiple large shareholders.*

2.3. Research methodology

2.3.1. Largest controlling shareholder dataset

The dataset created for this study is based on the intersection of Canadian publicly traded companies available from the Toronto Stock Exchange – Canadian Financial Markets Research Center (CFMRC) and COMPUSTAT for 2000-2012.

Monthly and daily stock return data for domestic common stocks is obtained from CFMRC. These are combined with annual financial reporting data available from COMPUSTAT. The resultant dataset is comprised of 6,184 firm year observations with 1,258 unique firms.

The primary source for controlling shareholder information is the Inter-Corporate Ownership (ICO) database from Statistics Canada. The ICO database provides information on major shareholders based on voting equity for Canadian Corporations. Unfortunately, the ICO database determines control at 50.1% voting equity, which is much higher than the threshold typically adopted by previous studies. In this study, for comparability with the rest of the literature, I use a cut-off of 10% voting equity to define a controlling shareholder. This requires the use of Financial Post (FP) Historical Reports, SEDAR and SEDI filings to extend the ICO data where necessary.

The construction of the largest controlling shareholder dataset is based on the methodology of La Porta, Lopez-De-Silanes and Shleifer (1999). The general process is to determine whether a company has principal shareholders who control at least 10% of voting equity. If the principal shareholders are corporate entities then the principal shareholders of the corporate entities is determined. This process continues until the ultimate controller of the votes is determined. The ultimate controller of votes is referred to as the largest controlling shareholder. If a foreign corporation is detected in the process of determining the largest controlling shareholder, to maintain tractability, then the process is halted. These companies are classified as foreign-controlled and are not included in the final dataset of 6,184 firm year observations.

The final dataset used in this study includes the continuous variable *Concentration. Concentration* is the percentage of voting equity controlled by the largest concentrated shareholder. I use the weakest link in the ownership chain to determine concentration, similar to the method used by Ben-Amar & Andre (2006).[12]

The following indicator variables are also employed: *Family*, *NonFamily*, *Multiple,* and *WidelyHeld*. *Family* is set to one for a company in which the largest share of voting equity is controlled by a group of related individuals or an individual person. *NonFamily* is set to one if the largest share of voting equity is not held by a family (where this includes pension funds, royalty trusts, mutual funds, hedge funds, partnerships, government or other non-corporate entities). *Multiple* is set to one if the firm has a shareholder, other than the largest controlling shareholder, with at least 10% of votes through a control chain that does not overlap with that of the controlling shareholder, it is zero otherwise. If a company has no shareholder with at least 10% voting equity then *WidelyHeld* is set to one.[13]

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[12] For example: Assume that a family controls 15% of firm A. And firm A controls 23% of firm B. Then the controlling shareholder of firm B is the family and concentration of ownership is 15%.
[13] If the company is widely-held then the concentration of ownership is 0.

2.3.2. Measurement of synchronicity

Synchronicity, the amount of non-firm-specific information in prices, is measured using the market model R^2 and thus represents the variation in stock prices that is driven by market and industry movements (Morck, 2000; Roll, 1998). When synchronicity is high this means that, prices move more with the market and the industry sector, implying there is less firm-specific information in prices. The construction of synchronicity is based on the following market model estimation:

(1) $RET_{i,t} = \alpha_0 + \alpha_1 MKTRET_t + \alpha_2 MKTRET_{t-1} + \alpha_3 INDRET_t + \alpha_4 INDRET_{t-1} + \varepsilon_{i,t}$,

where daily returns (*RET*) are regressed on market (*MKTRET*) and industry (*INDRET*) returns for each firm i, for each year in the sample; the market return is the daily value-weighted market return available from CFMRC; the daily S&P/TSX Sector Indices from CFMRC are used for industry returns. Once the market model has been estimated synchronicity is measured as follows:

(2) $Synchronicity_{i,t} = log\left(\frac{R^2}{1-R^2}\right)$,

where R^2 is the coefficient of determination from equation (1) for each firm i, for each year in the sample. Synchronicity uses a log transformation to replace a bounded variable, R^2, with an unbounded continuous variable.

2.3.3. Synchronicity and ownership characteristics

Equation (3) is estimated in order to test $\mathbf{H_1}$, $\mathbf{H_2}$, and $\mathbf{H_3}$, the effect of ownership concentration, family firms and multiple controlling shareholders, respectively, on synchronicity:

(3) $Synchronicity_{i,t+1} = \alpha_1 + \alpha_2 Concentration_{i,t} + \alpha_3 Family_{i,t} + \alpha_4 NonFamily_{i,t} + \alpha_5 Multiple_{i,t} + \sum_{k=1}^{N} \delta_k \times Controls_{i,t}^{k} + Industry\ Dummy + Year\ Dummy + \varepsilon_{i,t}$.[14]

Note that to address reverse causality concerns (i.e., the possibility that synchronicity causes ownership structure, instead of ownership structure causing synchronicity) I use lagged ownership and control variables. That is to say, the synchronicity variable for fiscal year *t+1* is regressed on ownership and control variables from fiscal year *t*. All variables used in the analysis have been winsorized at the first and ninety-ninth percentiles.[15]

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[14] There are three mutually exclusive dummy variables used to categorize firms: Family, NonFamily, Widely-Held.

[15] The data has been winsorized to reduce the effect of outliers. Tests were also run with non-winsorized data and the results are similar.

Synchronicity is measured as described in section 2.3.2. The ownership variables (i.e., *Concentration, Family, NonFamily* and *Multiple*) are as described in section 2.3.1. *Controls* is a vector of variables (*Size*, *Growth*, *Leverage*, *VolROA*, *Turnover*, *Bid-Ask*, *Analysts*, *CrossListed* and *Herfindahl*) that have been used in related research to proxy for information (Chan & Hameed, 2006; Ferreira & Laux, 2007; Jin & Myers, 2006; Morck, Yeung, & Yu, 2000; Piotroski & Roulstone, 2004). Industry and year dummies are included to control for fixed effects.

Size is measured as the log market value of equity at fiscal year-end. Firm size is an important indicator of the information environment of a firm. Larger firms have more publicly available information and a tendency to signal macro-economic trends. This gives the stock prices of large firms the ability to dominate market movements, resulting in a positive association between synchronicity and the size of a company (Chan & Hameed, 2006; Easley, Hvidkjaer, & O'Hara, 2002; Piotroski & Roulstone, 2004).

Leverage is measured as short-term plus long-term debt divided by market value at fiscal year-end. Leverage is related to stock return volatility and synchronicity: increased leverage will shift risk to debt holders resulting in higher idiosyncratic volatility and in turn decreased synchronicity (Hutton, Marcus, & Tehranian, 2009).

VolROA represents asset return volatility and is measured using the standard deviation of return on assets over the previous five years. *VolROA* is included to control for operating efficiency (Piotroski & Roulstone, 2004).

Turnover the average monthly turnover over for the fiscal year, is included as a measure of trading activity. A firm that is traded actively is more likely to have market- and firm-specific information in prices (Piotroski & Roulstone, 2004).

The liquidity of a stock is measured by *Bid-Ask*, the average bid-ask spread. An increase in *Bid-Ask* should be related to a decrease in the amount of firm-specific information included in stock prices (Chordia, Roll, & Subrahmanyam, 2008).

Analysts, the number of analysts following a firm, can impact the information environment of a firm (Piotroski & Roulstone, 2004). It is not clear whether the number of analysts should have a positive or negative effect on synchronicity. The role of analysts is to distribute information about the firm to investors, but unique firm-specific information can be costly to collect and so a good deal of information being released through analysts may be market- and industry-related (Chan & Hameed, 2006).

When a firm is cross-listed in the U.S. market, more public information is available, leading to less firm-specific information and increased synchronicity for these firms. *CrossListed* is an indicator variable that is set to one if the firm is cross-listed in the U.S. market.

The information environment of a firm can also be influenced by industry-level information. To account for this, *Herfindahl* is the Herfindahl index, which measures industry concentration as the sum of squared market share (sales/total industry sales). Further details on the construction of the control variables are available in Table 2.1.

2.3.4 Synchronicity and ownership structure - non-linear relationships

Previous corporate governance studies have found non-linear relationships that support both the entrenchment and alignment effects for different intervals of ownership concentration (Morck, Shleifer, &Vishny, 1988; Short & Keasey, 1999; Yeo, Tan, Ho, &Chen, 2002). I test for a possible non-linear relationship between synchronicity and ownership concentration by estimating the following regressions:

(4) $Synchronicity_{i,t+1} = \alpha_1 + \alpha_2 Concentration_{i,t} + \alpha_3 Concentration\,_{i,t}^{2} + \alpha_4 Family_{i,t} + \alpha_5 NonFamily_{i,t} + \alpha_6 Multiple_{i,t} + \sum_{k=1}^{N} \delta_k \times Controls_{i,t}^{k} + Industry\ Dummy + Year\ Dummy + \varepsilon_{i,t}$

(5) $Synchronicity_{i,t+1} = \alpha_1 + \alpha_2 Concentration_{i,t} + \alpha_3 Concentration\,_{i,t}^{2} + + \alpha_4 Concentration\,_{i,t}^{3} + \alpha_5 Family_{i,t} + \alpha_6 NonFamily_{i,t} + \alpha_7 Multiple_{i,t} + \sum_{k=1}^{N} \delta_k \times Controls_{i,t}^{k} + Industry\ Dummy + Year\ Dummy + \varepsilon_{i,t}.$

2.3.5. Propensity score matching

The distribution of family firms for different levels of *Concentration* and other control variables is different than that of non-family firms. For example, Figure 2.1 shows the cross-sectional average number of *Family* and *NonFamily* firms based on *Concentration*. The majority of non-family firms have *Concentration* between 10-20%, while family firms are distributed across all levels of *Concentration*. In order to isolate the effect of family ownership on synchronicity from *Concentration* and other control variables propensity score matching is used. [16]

Each family firm (treated) is matched with a non-family firm (control) based on *Concentration, Size, Turnover, Bid-Ask, VolROA, and Herfindahl*. Each matched set of firms must be from the same fiscal year. The control variables used to match firms have been chosen based on the control variables that prove to be significantly related to synchronicity in the regression analysis in section 2.4.2. Due to the limited size of my dataset and the number of characteristics that are being matched on, an exact match for family firms and non-family firms in every category of the control variables is not always available. The propensity score matching procedure, proposed by Rosenbaum and Rubin (1983), determines matches by a function of characteristics rather than by an exact match of each characteristic. A

[16] I also use propensity score matching to isolate the effect of multiple large shareholders from firm that have only one controlling shareholder on synchronicity. The process followed is the same as described in section 2.3.5, and the results are provided in section 2.4.3.2.

propensity score is the probability that a firm is a family firm (treated) based on observed firm characteristics. Propensity scores are estimated using the following logistic regression in equation (Austin, 2011; Dehejia & Wahba, 2002; Rosenbaum & Rubin, 1983):

$$(6)\ \ln\left(\frac{\Pr\,(Y = 1|\,\mathrm{x})}{1-\Pr\,(\mathrm{Y} = 1|\,\mathrm{x})}\right) = \alpha + \beta'\mathrm{x}\,,$$

where Y=1 for a family firm; x is a vector of i characteristics (*Concentration, Size, Turnover, Bid-Ask, VolROA,* and *Herfindahl*); and β = $(\beta_1, \beta_2, \ldots \beta_i\,)'$ is the vector of i slope parameters.

Firms' propensity scores are matched using a 1:1 caliper matching estimator with replacement which means that each treated firm is matched to one control firm and that treated firms are compared to all control firms within a propensity score radius ("caliper") in order to find a match (Dehejia & Wahba, 2002). Matching with replacement means that each treatment firm can be matched to the nearest control firm, even if the control firm is matched more than once. Matching with replacement minimizes the distance of propensity scores between treated and control firms (Dehejia & Wahba, 2002). Any unmatched treated and control firms are discarded from the analysis.

2.4. Empirical results

2.4.1. Descriptive statistics

As mentioned above, the largest controlling shareholder dataset created for this study is based on the intersection of CFMRC, COMPUSTAT and the Inter-Corporate Ownership (ICO) database during 2000-2012 (with Financial Post (FP) Historical Reports, SEDAR and SEDI filings used to extend the ICO data where necessary). Recall the final largest controlling shareholder dataset is comprised of 6,184 firm year observations with 1,258 unique firms.

Details on the composition of the largest controlling shareholder dataset are available in Table 2.2. Of the total sample, 44% are *Family*, 28% are *NonFamily* and 28% are *WidelyHeld*. Average *Concentration* for the total sample is 25%: 41% for *Family* and 25% for *NonFamily*.[17] Firms with more-than-one controlling shareholder, indicated as *Multiple,* make up 23% of the total sample: 35% of *Family* firms are also *Multiple* and 19% of *NonFamily* firms.

Synchronicity and the control variables previously described were calculated from several sources including: CFMRC, COMPUSTAT, Institutional Brokers' Estimate System (I/B/E/S) and Bloomberg. Descriptive statistics for these for the total sample period are given in Table 2.3. The sample distribution and descriptive statistics for each fiscal year are given in Table 2.4. The sample

[17] Recall, *Concentration* for *WidelyHeld* is zero.

distributions, *Concentration,* and average *Synchronicity* values for each industry group are given in Table 2.5. The time series average of cross-sectional sample size and *Synchronicity* for each level of *Concentration* is given in Figure 2.2.

Pearson pair-wise correlations between variables are given in Table 2.6. It is apparent that *Synchronicity* is negatively correlated with *Concentration, Family,* and *NonFamily* and is positively correlated with *WidelyHeld*. This suggests that firms with concentrated ownership have more firm-specific information in prices. *Family* is more negatively correlated with *Synchronicity* than *NonFamily,* suggesting that there may be a difference between the two groups of firms when it comes to *Synchronicity*. Finally, *Multiple* is negatively correlated with *Synchronicity*, suggesting firms with multiple controlling shareholders have more firm-specific information in prices, consistent with the prediction made by hypothesis 3 in section 2.2.3.

2.4.2. Ownership and synchronicity regression results

Table 2.7 reports the panel data regression results where *Synchronicity* is regressed on ownership and control variables. Columns 1, 2, 3, and 4 report the results of equation (3) testing the linear relationship between *Concentration* and *Synchronicity*. The coefficient on *Concentration* is negative and significant (at 1%), supporting incentive alignment. The implication of *Concentration* being negatively related to *Synchronicity* is that increases in ownership concentration are related to more firm-specific information being incorporated into stock prices. This result is similar to Brockman and Yan (2009), who find the concentrated ownership of large shareholders plays a significant role incorporating firm-specific information into stock prices, and to He, Li, Shen and Zhang (2013) who find a high level of foreign ownership is positively related to price informativeness (i.e., negatively related to synchronicity).

As stated above, previous studies have found non-linear relationships that support both the entrenchment and incentive alignment effects for different levels of *Concentration*. Therefore equations (4) and (5) are estimated for quadratic and cubic terms on *Concentration* respectively (Morck, Shleifer and Vishny, 1988; Short and Keasey, 1999; Yeo, Tan, Ho and Chen, 2002; Gul et al., 2010; Sánchez- Ballesta and García- Meca, 2007).

The results of the cubic regression are reported in columns 1a, 2a, 3a and 4a in Panel B of Table 2.7.[18] It is apparent that there is a negative and significant coefficient on *Concentration*, a positive and significant coefficient on *Concentration*^{2} and a negative and significant coefficient on *Concentration*^{3} (all at 1% significance). This suggests incentive alignment for low and high levels of *Concentration*, and

[18] Quadratic regressions were also run but the cubic regression is a better fit. The concentration variable changes sign across the quadratic model. In Figure 2 the relationship between ownership concentration and synchronicity is consistent with a cubic relationship. Panel C of Table 7 reports the results of the test of the null hypothesis of linearity against the alternative that the regression is cubic. The hypothesis that the regression is linear is rejected at the 1% significance level for all of the cubic regressions estimated.

entrenchment for mid-levels of *Concentration*. The *Synchronicity* minimum/maximum levels of *Concentration* are denoted *Concentration**.[19] The final row of Table 2.7, Panel B reports the minimum and maximum *Concentration** for each of the non-linear regressions.

I focus on Column 4a for the discussion of the minimum and maximum *Concentration** since it reports the results of a non-linear regression that includes the variables *Family*, *NonFamily,* and *Multiple* along with *Concentration*. *Concentration** is at a local minimum at approximately 26% and at a local maximum at approximately 62%.[20] *Synchronicity* is decreasing as *Concentration* is increasing until approximately 26%, indicating incentive alignment. When *Concentration* is between 26% and 62%, *Synchronicity* is increases with *Concentration* indicating entrenchment. Beyond 62%, *Synchronicity* is decreases with *Concentration* increases, indicating incentive alignment. This significant non-linearity is consistent with the prediction made by hypothesis 1 in section 2.2.1.

[19] To be more specific, the synchronicity minimum/maximum levels of Concentration, are reached when $\frac{\partial Synchronicity}{\partial Concentration} = \alpha_1 + 2\alpha_2 Concentration + 3\alpha_3 Concentration^2 = 0$, or when $Concentration^* = \frac{-2\alpha_2 \pm \sqrt{2\alpha_2{}^2 - 12\alpha_3\alpha_1}}{6\alpha_3}$.

[20] $\frac{\partial^2 Synchronicity}{\partial Concentration^2} = 2\alpha_2 Concentration + 6\alpha_3 Concentration < 0$ the *Concentration** is local minimum and $\frac{\partial^2 Synchronicity}{\partial Concentration^2} = 2\alpha_2 Concentration + 6\alpha_3 Concentration > 0$ then *Concentration** is local maximum.

Incentive alignment at 10-26% *Concentration* can be explained by voting equity not being high enough to meet the conditions necessary for entrenchment. La Porta, Lopez-De-Silanes and Shleifer (1999) report that a threshold of 20% is required to exert control. These relatively small concentrated owners may not have sufficient voting equity to influence the firm internally, but they still may be able to influence the firm-specific information in prices through exit (Admati and Pfleiderer, 2009; Edmans, 2009). When these informed concentrated owners trade on private information it increases the firm-specific information in prices and decreases synchronicity. The levels of ownership are also large enough to make an impact on stock prices while still small enough to be liquid and feasible to trade. The majority of non-family firms have ownership concentration between 10-20%, implying this group of concentrated owners is less prone to incentives related to entrenchment and more likely to participate in informed trading.[21]

When voting equity is between 26-62% I find evidence of entrenchment. This is somewhat similar to what was found by Gul, Kim and Qiu (2010), who find that synchronicity is a concave function of ownership. Their findings indicate entrenchment for lower levels of ownership concentration, which is eventually dominated by incentive alignment at around 50% ownership concentration. While my results support the finding that entrenchment is dominated by alignment at

[21] Figure 2.1 shows the number of family and non-family firms for levels of ownership concentration.

higher levels of ownership concentration, the principal differences between Gul, Kim and Qiu (2010) and my study are that they do not investigate a possible cubic relationship between ownership concentration and synchronicity, and that I find a shift from entrenchment to incentive alignment occurs at a somewhat higher level of ownership concentration (62%). It is also important to recognize that for this range of ownership concentration the majority of firms are family-firms with inside owners. Inside ownership along with the significant level of ownership concentration contribute to an environment that supports entrenchment.

When *Concentration* is greater than 62%, incentive alignment dominates. Gul, Kim and Qiu (2010) explain that entrenchment effects can be mitigated when concentration exceeds a certain level and the firm takes on characteristics of a "private" company. High levels of ownership concentration may be related to a decrease in incentives for entrenchment. Morck, Shleifer and Vishny (1988) explain that while increased ownership concentration may lead to deeper entrenchment, diminishing returns might set in at a certain ownership concentration level decreasing the incentive for entrenchment. For high levels of ownership concentration it appears that incentive alignment prevails. If these concentrated owners misreport information they will only be "tricking" themselves. Also, the majority of these concentrated owners are family firms. Family firms have been known to take a long-term perspective, which means they are less likely to damage the long-run well-being and reputation of the firm by withholding or misreporting firm-specific information.

The linear regression results reported in columns 2 and 4 of Table 2.7, Panel A indicate that family firms and non-family firms have significant and negative coefficients. This suggests that both family and non-family firms are positively related to firm-specific information in prices. But, once a non-linear equation is estimated the significant negative coefficient on family and non-family firms disappears. This suggests that *Family* is not significantly related to informativeness, this is contrary to the prediction made by hypothesis 2 in section 2.2.2. This may be the result of the confounding effect between family/non-family firms and ownership concentration. Figure 2.1 illustrates that the majority of non-family firms have ownership concentration between 10-20% whereas family firms are distributed across all levels of ownership concentration. The results of the propensity score matching test, in section 2.4.3.1, isolate the effect of family firms from non-family firms on synchronicity to get a better comparison of these two groups of firms.

The results in Table 2.7, Panel A, columns 3, 4, and Panel B columns 3a and 4a show that in both linear and non-linear regressions firms with multiple controlling shareholders have more informative prices. This is in support of the prediction made in hypothesis 3 in section 2.2.3.

2.4.3. Propensity score matching

Propensity score matching (PSM) is performed to isolate not only the effect of family ownership on synchronicity from ownership concentration and other control variables but also the effect of having multiple controlling shareholders on synchronicity from ownership concentration and other control variables.

2.4.3.1. Family and non-family firms

Propensity scores for 2307 family firms and 1453 non-family firms are calculated following the methodology outlined in section 2.3.5.[22] A total of 1939 matches were made. It is important to note that matches can only be made for firms that have between 10 and 50% ownership concentration. There are not enough non-family firms with greater than 50% ownership concentration to match on all of the variables used to create propensity scores. The analysis in this section therefore is restricted to firms with 10-50% ownership concentration.

Table 2.8 presents the results of a signed rank test to determine whether synchronicity is significantly different for matched pairs of family and non-family firms. The results reported in the first column of Table 2.8, 'Total Sample,' suggest that there is no significant difference in synchronicity for family and non-family firms. The remaining columns present the results for each year in the sample. Only results for 2001 and 2002 indicate that there may be a difference between family

[22] See Appendix 2.A for more details on the propensity score tests performed.

and non-family firms. The results are consistent with the regression results reported in section 2.4.2., and fail to support hypothesis 2b, that the relation of family firms to synchronicity is stronger than non-family firms, this may be due to the reduced range of ownership concentration that could be used to create matches. The results may be different if we could match on corporations that had non-family ownership at greater than 50% concentration.

2.4.3.2. Multiple controlling shareholders

This section uses PSM to compare synchronicity between firms categorized as having multiple controlling shareholders (*Multiple)* and firms with only one controlling shareholder (*OnlyOne).* [23] Propensity scores were calculated for 1247 *Multiple* and 2151 *OnlyOne* firms, with a total of 1194 matches being made. The analysis in this section is restricted to firms with 10-75% ownership concentration.[24]

Table 2.9 presents results of a signed rank test to determine whether synchronicity is significantly different for matched pairs of *Multiple* and *OnlyOne* firms. The results for the total sample suggest that there is a significant negative difference in synchronicity for *Multiple* and *OnlyOne* firms. This finding supports

[23] *OnlyOne* firms refer to any firm that has only one shareholder with at least 10% voting equity.
[24] It is important to note that matches can only be made for firms that have between 10 and 75% ownership concentration. There are not enough matches for firms with greater than 75% ownership concentration to match on all of the variables.

the regression results in section 2.4.2 as well as hypothesis 3, implying that synchronicity is lower (informativeness is higher) for firms with multiple large shareholders.

2.5. Additional tests

2.5.1. Synchronicity and earnings informativeness

In this section I test the validity of synchronicity as a measure of firm-specific information in stock prices. Corporate earnings are important, value-relevant, firm-specific information. If synchronicity is a valid measure then the return-earnings association should be weaker for firms with high synchronicity than for firms with low synchronicity (Gul, Kim and Qiu, 2010).

I follow Gul, Kim and Qiu (2010) and estimate the following for each firm *i* and year *t*:

$$(8)\quad R_{it} = \alpha_0 + \alpha_1 NI_{it} + \alpha_2 NI_{it} * SYNCHdr_{it} + \sum_{k=1}^{N} \alpha_k NI_{it} * CONTROL_{it}^{k} + Industry\ Dummies + Year\ Dummies + \varepsilon,$$

where R_{it} is the market-adjusted monthly return compounded over the 12-month period ending in the third month after the ends of a firm's fiscal year; *NI* is net income (earnings before extraordinary items) adjusted by the market value of equity at the beginning of the fiscal year; *CONTROL* is a vector of control variables that includes *Size*, *Growth* (B/M), *Leverage*, *Risk* (beta) and *VolROA* (asset return volatility).

SYNCHdr is a decile rank for synchronicity. This is done, as in Gul, Kim and Qiu (2010), to alleviate concerns that the results for equation (8) are influenced by a small number of outlying synchronicity observations and/or that synchronicity is measured with error. Synchronicity is classified into deciles for each year in the sample and the decile ranks are scaled to range between zero and one.

Table 2.10 reports the results of regressing returns on net income, a decile rank for synchronicity and controls. The coefficient on $NI_{it} * SYNCHdr_{it}$ is significantly negative at 5% significance. This implies that the market attaches a lower value to earnings of high-synchronicity firms and that corporate earnings information is capitalized into stock prices to a lesser extent for these firms. Synchronicity is supported as a valid (inverse) measure of firm-specific information incorporated into stock prices.

2.5.2. Ownership structure and earnings informativeness

As an additional test, I examine whether dimensions of ownership structure are related to stock prices that contain more information about future operating performance measured by earnings. This is a narrower test of price informativeness than using synchronicity. Reported earnings are an important source of information used to determine firm value. Earnings informativeness describes the share price response to earnings.

The following regressions test whether stock prices contain more information about earnings for different ownership structure variables:

$$(9)\ R_{j,t} = \alpha_0 + \alpha_1 NI_{j,t} + \alpha_2 NI_{j,t} * OC_{j,t} + \sum_{k=1}^{N} \beta_k NI_{j,t} * CONTROL_{j,t}^{k} + \varepsilon_{j,t},$$

$$(10)\ \mathrm{R_{j,t}} = \alpha_0 + \alpha_1 \mathrm{NI_{j,t}} + \alpha_2 \mathrm{NI_{j,t}} * \mathrm{OC_{j,t}} + \alpha_3 \Delta \mathrm{NI_{j,t}} + \alpha_4 \Delta \mathrm{NI_{j,t}} * \mathrm{OC_{j,t}}\ ,$$

where $R_{i,t}$ is the market adjusted monthly returns compounded over the 12-month period ending in the third month after the end of a firm's fiscal year end; $NI_{j,t}$ is net income (earnings before extraordinary items) deflated by the market value of equity at the beginning of the fiscal year; $\Delta NI_{j,t}$ is the change in earnings between year *t*-1 and *t* scaled by the market value of equity at the end of fiscal year *t*-1; $OC_{j,t}$ is a vector of ownership characteristics including *Concentration*, *Family NonFamily*, and *Multiple*; and *CONTROL* is a vector of control variables that includes *Size, Growth* (B/M), *Leverage, Risk* (beta) and *VolROA* (asset return volatility).

If the coefficients on *NI* and Δ*NI* are significantly positive, then it suggests that prices contain information about earnings. If an ownership structure characteristic is positively associated with the pricing of earnings information, then the coefficients on the interaction terms $NI_{j,t} * OC_{j,t}$ and $\Delta NI_{j,t} * OC_{j,t}$ should be positive and significant.

The results for the panel regressions of returns on earnings ownership characteristics are reported in Table 2.11. Columns 1 and 2 indicate that the interaction of ownership concentration and the information content of earnings does not have a significant effect on returns. Column 5 includes interaction terms for *Family, NonFamily* and *Multiple*. The coefficient on *NonFamily* is negative and significant with a t-value of 1.71. This indicates the interaction of non-family firms and the information content of earnings is negatively related to returns. Most of the non-family firms in this study have voting equity between 10-20% and are considered outsiders. These characteristics are likely to prevent these shareholders from using direct intervention to monitor the financial reporting decisions of managers.

The coefficient on *Multiple* is positive and significant at 1%. This indicates that the interaction of having more-than-one controlling shareholder and the information content of earnings is positive. This supports the monitoring role played by multiple controlling shareholders, and is evidence of possible internal direct intervention in a firm's operations, more specifically financial reporting.

2.6. Summary and Conclusions

The purpose of this paper was to examine the effects of various dimensions of ownership structure on synchronicity using a unique dataset of the largest controlling shareholders of Canadian companies listed on the Toronto Stock Exchange during 2000-2012. Two important dimensions of ownership structure: the concentration of ownership of the largest controlling shareholder and whether the largest shareholder is a family firm. My empirical findings supported the hypothesis that ownership structure is significantly related to informativeness, as proxied by synchronicity, and that there was no a significant difference between family and non-family firms.

The empirical evidence here supports a non-linear relationship between ownership concentration and synchronicity. Synchronicity is decreasing as concentration is increasing until approximately 26% ownership concentration indicating incentive alignment. Between 26% and 62% ownership concentration synchronicity is increasing as concentration is increasing indicating entrenchment and after 62% ownership concentration synchronicity is decreasing as concentration is increasing indicating incentive alignment. In linear regressions both family firms and firms and non-family firms are negatively related to stock price. But, once a non-linear equation is estimated the significant negative coefficient on family and non-family firms disappears. Propensity score matching (PSM) is performed to isolate the effect of family ownership on synchronicity from ownership concentration and other control variables. For firms with ownership concentration between 10% and 50% there is no significant difference between levels of synchronicity for family firms and non-family firms.

The evidence also supports the hypothesis that the presence of multiple large controlling shareholders is negatively associated with synchronicity. In both linear and non-linear regressions firms with more than one controlling shareholder are negatively related to synchronicity. This suggests a positive relationship between firms with multiple controlling shareholders and firm-specific information in stock prices. Matched pairs of firms with multiple controlling shareholders with firms that have only one controlling shareholder are analyzed using PSM to see whether synchronicity is different for firms with more-than-one owner. For firms with ownership concentration between 10% and 75% there is a significant difference between levels of synchronicity for firms with multiple concentrated owners and firms with only one controlling shareholder. Having multiple large shareholders has a significant positive effect on the firm-specific information in prices.

This study makes several contributions to the literature. First, the Canadian environment presents an opportunity to look at the impact of ownership concentration on the information environment of a firm. Second, I test the effect of family firms on informativeness, as proxied by synchronicity, which to my knowledge has yet to be addressed by the literature on ownership structure and informativeness. Finally, I consider whether or not the largest controlling shareholder in a firm is alone impacts informativeness, contributing to the literature on multiple controlling owners, corporate governance and financial markets.

This study is also relevant to market participants at different levels. First, it is useful for investors and shareholders to know the extent to which stock prices contain firm-specific information. Second, investigating ownership structure and synchronicity provides insights that regulators can use to enhance the information environment of financial markets. And finally, all stakeholders, including managers, directors, capital providers, customers and employees, will benefit from the findings of this study since they are each subject to contracts that depend on information available in market prices.

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Tables

Table 2.1
Control Variables

This table provides details on the construction of the of the control variables used. The control variables that that have been used to proxy for information are based on those chosen in previous related research (Morck, Yeung, and Yu, 2000; Heflin, and Shaw, 2000; Piotroski, and Roulstone, 2004; Chan, and Hameed, 2006; Jin, and Myers, 2006; Ferreira, and Laux, 2007). CFMRC refers to the Toronto Stock Exchange – Canadian Financial Markets Research Center. I/B/E/S refers to the Institutional Brokers' Estimate System.

Variable	Description	Source
Size	Log market value of equity at fiscal year end	CFMRC - Monthly
Growth	Log book value of equity minus log market value of equity at fiscal year-end.	CFMRC - Monthly, Compustat-Annual
Leverage	Short-term plus long-term debt divided by market value equity at fiscal year-end.	CFMRC - Monthly, Compustat- Annual
VolROA	Asset return volatility. Standard deviation of ROA over 5 years. ROA is income before extraordinary items divided by average total assets.	Compustat-Annual
Turnover	Average monthly turnover from month -12 to month -1.	CFMRC - Monthly
Bid-Ask	Average Bid-Ask Spread. Daily (Close Bid – Close Ask)/Close Ask averaged over fiscal year.	CFMRC - Daily
Analysts	The number of analysts covering a firm. I/B/E/S number of estimates for fiscal month/year end.	I/B/E/S
CrossListed	A dummy variable that equals 1 if a firm is cross-listed on a U.S. exchange and 0 otherwise.	Bloomberg
Herfindahl	Herfindahl Index. Sum of squared market share (sales/total industry sales).	Compustat-Annual

Table 2.2
Ownership Characteristics

This table presents the sample distribution across ownership types. The sample period is from 2000-2012. The largest controlling shareholder is defined as the ultimate controlling shareholder with at least 10% voting equity. *Family* refers to a group of related individuals or an individual person. *NonFamily* refers to government or government controlled entity; pension fund; royalty trust; income trust; partnership; other non-corporate entity. *WidelyHeld* refers to the case where there is no controlling shareholder with at least 10% voting equity. The number of firms (N) and the percentage of the total sample (%) are shown in the table below. *Multiple* refers to firms with more than one shareholders that owns at least 10% voting equity. The number of firms (N) with *Multiple* shareholders and the percentage of the total sample (%) are shown in the table below. Average *Concentration* is the average percentage of voting equity held by the largest controlling shareholder.

	Family	*NonFamily*	*WidelyHeld*	Total
Firms (N)	2724	1736	1724	6184
(%)	44%	28%	28%	
Multiple (N)	946	496	0	1442
(%)	15%	8%	0%	23%
Average *Concentration*	41%	25%	0%	25%

Table 2.3
Control Variable Descriptive Statistics

This table presents descriptive statistics for *Synchronicity* and control variables. The sample period is from 2000-2012. The sample includes Canadian firms listed on the Toronto Stock Exchange. *Size* is the log market value of equity at fiscal year-end (CFMRC). *Growth* is the log book value of equity (COMPUSTAT) – log market value of equity (CFMRC) at fiscal year-end. *Leverage* is short-term plus long term debt (COMPUSTAT) divided by market value of equity (CFMRC) at fiscal year-end. *VolROA* is the asset return volatility and is measured as the standard deviation of ROA over the previous five years (COMPUSTAT). *Turnover* is the average monthly turnover from fiscal year end month -12 to month -1 (CFMRC). *Bid-Ask* is the average bid-ask spread and is calculated daily then averaged over the fiscal year (CFMRC). *Analysts* is the number of estimates for fiscal year end (I/B/E/S). *Crosslisted* is a dummy variable that indicates whether a firm is also listed on a U.S. exchange (Bloomberg). *Herfindahl* is the Herfindahl Index measured as the sum of squared market share (sales/total industry sales) (COMPUSTAT). *Synchronicity* is log (R^2/1-R^2) from the market model estimated in equation (1) using CFMRC data.

	Total Sample			***Family***			***NonFamily***			***WidelyHeld***		
	MEAN	**N**	**STD**	**MEAN**	**N**	**STD**	**MEAN**	**N**	**STD**	**MEAN**	**N**	**STD**
Size	19.67	5909	2.10	19.32	2641	1.99	19.43	1639	1.94	20.49	1629	2.22
Growth	-0.45	5113	0.83	-0.39	2295	0.83	-0.41	1466	0.85	-0.6	1352	0.78
Leverage	1.19	5232	24.50	1.72	2364	35.52	0.98	1496	10.16	0.50	1372	1.53
VolROA	0.08	5290	0.12	0.07	2369	0.12	0.09	1523	0.11	0.09	1398	0.13
Turnover	0.05	5838	0.05	0.03	2594	0.04	0.05	1619	0.06	0.07	1625	0.05
Bid-Ask	0.03	5456	0.04	0.03	2533	0.05	0.03	1516	0.04	0.02	1407	0.03
Analysts	4.12	6184	5.20	3.23	2724	4.39	3.78	1736	4.71	5.89	1724	6.29
Crosslisted	0.32	6184	0.47	0.22	2724	0.41	0.33	1736	0.47	0.47	1724	0.50
Herfindahl	0.15	6122	0.19	0.14	2696	0.18	0.14	1725	0.17	0.16	1701	0.21
Synchronicity	-2.20	5002	1.59	-2.67	2280	1.42	-2.31	1337	1.50	-1.33	1385	1.57

Table 2.4
Sample Distribution and Descriptive Statistics by Fiscal Year

This table presents sample distribution and descriptive statistics for control variables for each year in the sample. The sample period is from 2000-2012. The sample includes Canadian firms listed on the Toronto Stock Exchange. *Size* is the log market value of equity at fiscal year-end (CFMRC). *Growth* is the log book value of equity (COMPUSTAT) – log market value of equity (CFMRC) at fiscal year-end. *Leverage* is short-term plus long term debt (COMPUSTAT) divided by market value of equity (CFMRC) at fiscal year-end. *VolROA* is the asset return volatility and is measured as the standard deviation of ROA over the previous five years (COMPUSTAT). *Turnover* is the average monthly turnover from fiscal year end month -12 to month -1 (CFMRC). *Bid-Ask* is the average bid-ask spread and is calculated daily then averaged over the fiscal year (CFMRC). *Analysts* is the number of estimates for fiscal year end (I/B/E/S). *Crosslisted* is a dummy variable that indicates whether a firm is also listed on a U.S. exchange (Bloomberg). *Herfindahl* is the Herfindahl Index measured as the sum of squared market share (sales/total industry sales) (COMPUSTAT). *Synchronicity* is log ($R^2/1-R^2$) from the market model estimated using equation (1).

	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**Total**
Number of Firms	575	540	520	506	501	513	394	396	427	433	441	473	465	6184
% of Total Sample	9.3%	8.7%	8.4%	8.2%	8.1%	8.3%	6.4%	6.4%	6.9%	7.0%	7.1%	7.6%	7.5%	100%
Avg. *Concentration* (%)	27%	27%	27%	27%	26%	25%	25%	25%	24%	24%	23%	22%	22%	25%
Family (N)	265	262	263	260	240	231	171	169	172	178	173	172	168	2724
Avg. *Concentration* (%)	41%	41%	40%	41%	42%	42%	42%	42%	41%	40%	41%	42%	41%	41%
NonFamily (N)	174	147	134	125	117	128	105	118	125	134	129	148	152	1736
Avg. *Concentration (%)*	26%	26%	25%	25%	25%	26%	26%	25%	24%	25%	24%	22%	23%	25%
Size	18.812	18.863	18.912	19.209	19.565	19.712	20.412	20.375	19.612	19.997	20.395	20.299	20.314	19.670
Growth	-0.366	-0.316	-0.340	-0.543	-0.698	-0.744	-0.678	-0.617	0.092	-0.242	-0.534	-0.450	-0.388	-0.450
VolROA	0.083	0.091	0.096	0.091	0.084	0.077	0.054	0.060	0.070	0.083	0.084	0.078	0.076	0.090
Turnover	0.043	0.038	0.039	0.042	0.048	0.048	0.056	0.058	0.060	0.060	0.050	0.049	0.043	0.050
Leverage	0.754	0.866	0.941	0.635	0.438	0.405	0.389	0.525	1.534	0.852	0.484	0.584	0.606	1.190
Bid-Ask	0.043	0.044	0.042	0.035	0.025	0.024	0.015	0.015	0.024	0.027	0.014	0.013	0.013	0.030
Analysts	3.405	3.246	3.415	3.925	3.826	4.142	4.482	4.091	3.745	3.910	4.721	5.461	5.688	4.120
Herfindahl	0.208	0.249	0.216	0.189	0.099	0.166	0.111	0.107	0.096	0.103	0.104	0.092	0.090	0.150
Synchronicity	-2.624	-2.487	-2.686	-2.694	-2.641	-2.430	-2.010	-1.373	-1.719	-1.949	-1.448	-1.892	-2.105	-2.200

Table 2.5
Sample Distribution and Characteristics by Industry

Industry is determined by GICS Code. This is done so that the industry classifications correspond to the daily S&P/TSX Sector Indices from CFMRC that are used for industry returns in equation (1) to calculate synchronicity. To correspond to the S&P/TSC Sector Indices Real Estate is excluded from Financials and Oil & Gas Refining &Marketing, Oil & Gas Storage & Transportation, and Coal & Consumable Fuels are excluded from Energy. If a GICS code cannot be determined for a firm, then it is excluded.

	Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	Information Technology	Telecom Sevices	Utilities
Sample Distribution										
Total Sample (N)	920	1205	755	767	379	226	296	514	98	161
Total Sample (%)	17%	23%	14%	14%	7%	4%	6%	10%	2%	3%
Family (N)	201	390	399	584	273	83	165	205	23	57
Family (%)	8%	16%	17%	25%	11%	3%	7%	9%	1%	2%
NonFamily (N)	282	411	210	136	63	99	83	174	41	35
NonFamily (%)	18%	27%	14%	9%	4%	6%	5%	11%	3%	2%
WidelyHeld (N)	437	404	146	47	43	44	48	135	34	69
WidelyHeld (%)	31%	29%	10%	3%	3%	3%	3%	10%	2%	5%
Multiple	1816	411	210	136	63	99	83	174	41	35
Multiple (%)	59%	13%	7%	4%	2%	3%	3%	6%	1%	1%
Concentration										
Family Concentration (%)	28%	34%	39%	49%	42%	39%	36%	39%	70%	50%
Non-Family Concentration (%)	23%	21%	22%	25%	21%	19%	35%	21%	36%	24%
Synchronicity										
Total Sample	-1.39	-1.81	-2.67	-2.8	-2.69	-2.94	-2.69	-2.96	-1.52	-1.89
Family	-1.913	-2.682	-2.914	-2.783	-2.705	-3.108	-2.859	-3.047	-1.003	-1.966
NonFamily	-1.772	-1.525	-2.923	-3.125	-2.809	-2.779	-2.416	-3.089	-2.639	-2.864
Widely-Held	-0.913	-1.273	-1.726	-2.094	-2.382	-2.961	-2.501	-2.671	-0.552	-1.324

Table 2.6
Correlation Matrix

This table presents the Pearson correlation matrix for the ownership and control variables in the sample. The sample period is from 2000-2012. The first number in each cell is the correlation coefficient and below the correlation coefficient is its p-value.

	Concentration	*Family*	*NonFamily*	*WidelyHeld*	*Multiple*	*Size*	*Growth*	*Leverage*	*VolROA*	*Turnover*	*Bid-Ask*	*Analysts*	*Crosslisted*	*Herfindahl*	*Synchronicity*
Concentration	**1.000**														
	--														
Family	**0.540**	**1.000**													
	<.0001	--													
NonFamily	**-0.011**	**-0.554**	**1.000**												
	0.3681	<.0001	--												
WidelyHeld	**-0.586**	**-0.552**	**-0.388**	**1.000**											
	<.0001	<.0001	<.0001	--											
Multiple	**0.067**	**0.239**	**0.078**	**-0.343**	**1.000**										
	<.0001	<.0001	<.0001	<.0001	--										
Size	**-0.077**	**-0.152**	**-0.071**	**0.240**	**-0.198**	**1.000**									
	<.0001	<.0001	<.0001	<.0001	<.0001	--									
Growth	**0.099**	**0.069**	**0.030**	**-0.109**	**0.068**	**-0.371**	**1.000**								
	<.0001	<.0001	0.0309	<.0001	<.0001	<.0001	--								
Leverage	**0.019**	**0.020**	**-0.005**	**-0.017**	**0.030**	**-0.055**	**0.125**	**1.000**							
	0.1641	0.1514	0.6934	0.2231	0.030	<.0001	<.0001	--							
VolROA	**-0.095**	**-0.071**	**0.026**	**0.053**	**-0.051**	**-0.252**	**-0.135**	**0.001**	**1.000**						
	<.0001	<.0001	0.0559	<.0001	<.0001	<.0001	<.0001	0.928	--						
Turnover	**-0.220**	**-0.271**	**0.059**	**0.241**	**-0.178**	**0.282**	**-0.113**	**0.001**	**0.094**	**1.000**					
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.9512	<.0001	--					
Bid-Ask	**0.136**	**0.135**	**0.008**	**-0.162**	**0.135**	**-0.633**	**0.255**	**0.067**	**0.168**	**-0.314**	**1.000**				
	<.0001	<.0001	0.5663	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	--				
Analysts	**-0.128**	**-0.153**	**-0.041**	**0.211**	**-0.124**	**0.626**	**-0.181**	**-0.025**	**-0.140**	**0.275**	**-0.361**	**1.000**			
	<.0001	<.0001	0.0012	<.0001	<.0001	<.0001	<.0001	0.0747	<.0001	<.0001	<.0001	--			
Crosslisted	**-0.148**	**-0.188**	**0.011**	**0.198**	**-0.118**	**0.421**	**-0.129**	**-0.021**	**0.001**	**0.138**	**-0.260**	**0.414**	**1.000**		
	<.0001	<.0001	0.4058	<.0001	<.0001	<.0001	<.0001	0.1241	0.914	<.0001	<.0001	<.0001	--		
Herfindahl	**0.039**	**-0.015**	**-0.026**	**0.043**	**-0.036**	**0.080**	**-0.124**	**-0.014**	**0.031**	**-0.013**	**-0.074**	**-0.031**	**-0.077**	**1.000**	
	0.0025	0.2426	0.0425	<.0001	0.0049	<.0001	<.0001	0.3079	0.0263	0.3188	<.0001	0.0168	<.0001	--	
Synchronicity	**-0.222**	**-0.269**	**-0.041**	**0.339**	**-0.236**	**0.670**	**-0.181**	**-0.024**	**-0.060**	**0.408**	**-0.320**	**0.472**	**0.373**	**0.027**	**1.000**
	<.0001	<.0001	0.0041	<.0001	<.0001	<.0001	<.0001	0.1027	<.0001	<.0001	<.0001	<.0001	<.0001	0.0562	--

Table 2.7
Panel A: Linear Ownership and Synchronicity Regressions.

Linear panel data regression estimates for the dependent variable *Synchronicity* and explanatory variables, including *Concentration, Family, NonFamily, Multiple* and control variables are shown below. Lagged ownership and control variables are used to address reverse causality concerns. Industry and year dummy variables are included to control for fixed effects. All variables used in the analysis have been winsorized at the first and ninety-ninth percentiles. One, two, or three asterisks denote estimates are significantly different from zero at the 10, 5 and 1 percent levels, respectively.

	[1]	[2]	[3]	[4]
Intercept	-12.620 ***	-12.384 ***	-12.530 ***	-12.380 ***
Ownership Variables				
Concentration	-0.396 ***	-0.228 ***	-0.408 ***	-0.296 ***
Family		-0.203 ***		-0.134 **
NonFamily		-0.195 ***		-0.140 ***
Multiple			-0.189 ***	-0.153 ***
Control Variables				
Size	0.535 ***	0.527 ***	0.529 ***	0.525 ***
Growth	0.017	0.015	0.017	0.016
Leverage	0.009	0.009	0.010	0.010
VolROA	0.323 *	0.295 *	0.274	0.264
Turnover	0.301 ***	0.293 ***	0.286 ***	0.284 ***
Bid-Ask	12.993 ***	12.757 ***	12.803 ***	12.682 ***
Analysts	0.000	0.001	0.001	0.002
Crosslisted	0.377 ***	0.360 ***	0.361 ***	0.353 ***
Herfindahl	-0.167 **	-0.171 **	-0.180 **	-0.181 **
Year Dummies	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes
R^2	0.5744	0.5744	0.5772	0.5781
Observations	4102	4102	4102	4102
Time Series	13	13	13	13
Number of Cross Sections	644	644	644	644

Panel B: Cubic Ownership and Synchronicity Regressions

Panel data regression estimates to test for possible non-linear relationship between *Synchronicity* and are shown below. Lagged ownership and control variables are used to address reverse causality concerns. Industry and year dummy variables are included to control for fixed effects. All variables used in the analysis have been winsorized at the first and ninety-ninth percentiles. One, two, or three asterisks denote estimates are significantly different from zero at the 10, 5 and 1 percent levels, respectively.

	[1a]		[2a]		[3a]		[4a]	
Intercept	-12.230 ***		-12.253 ***		-12.235 ***		-12.253 ***	
Ownership Variables								
Concentration	-2.901 ***		-3.878 ***		-2.406 ***		-3.221 ***	
$Concentration^2$	7.981 ***		10.155 ***		6.873 ***		8.676 ***	
$Concentration^3$	-6.018 ***		-7.361 ***		-5.409 ***		-6.519 ***	
Family			0.111				0.094	
NonFamily			0.136				0.110	
Multiple					-0.151 ***		-0.148 ***	
Control Variables								
Size	0.520 ***		0.520 ***		0.518 ***		0.518 ***	
Growth	0.013		0.012		0.014		0.014	
Leverage	0.007		0.007		0.008		0.008	
VolROA	0.313 *		0.317 *		0.285		0.289 *	
Turnover	0.303 ***		0.301 ***		0.294 ***		0.294 ***	
Bid-Ask	12.517 ***		12.504 ***		12.443 ***		12.437 ***	
Analysts	0.001		0.001		0.002		0.002	
Crosslisted	0.371 ***		0.372 ***		0.364 ***		0.365 ***	
Herfindahl	-0.182 **		-0.183 **		-0.190 **		-0.191 **	
Year Dummies	Yes		Yes		Yes		Yes	
Industry Dummies	Yes		Yes		Yes		Yes	
R^2	0.5807		0.581		0.5823		0.5824	
Observations	4102		4102		4102		4102	
Time Series	13		13		13		13	
Number of Cross Sections	644		644		644		644	
Concentration*	0.256	min	0.271	min	0.247	min	0.264	min
	0.629	max	0.649	max	0.600	max	0.623	max

Panel C: Coefficient Tests

Test the null hypothesis of linearity, against the alternative that the regression is cubic. H_0: coefficients on $Concentration^2$ and $Concentration^3 = 0$; H_1: at least one of the coefficients is non zero. The hypothesis that the regression is linear is rejected at the 1% significance level against the alternative that it is cubic.

[1a]	[2a]	[3a]	[4a]
$Concentration^2$ - $Concentration^3 = 0$	$Concentration^2$ - $Concentration^3 = 0$	$Concentration^2$ - $Concentration^3 = 0$	$Concentration^2$ - $Concentration^3 = 0$
Statistic 61.14	Statistic 27.38	Statistic 44.45	Statistic 19.99
ProbChiSq <.0001	ProbChiSq <.0001	ProbChiSq <.0001	ProbChiSq <.0001
Reject	Reject	Reject	Reject
$Concentration^2 = 0$	$Concentration^2 = 0$	$Concentration^2 = 0$	$Concentration^2 = 0$
Statistic 60.07	Statistic 24.85	Statistic 41.44	Statistic 17.54
ProbChiSq <.0001	ProbChiSq <.0001	ProbChiSq <.0001	ProbChiSq <.0001
Reject	Reject	Reject	Reject
$Concentration^3 = 0$	$Concentration^3 = 0$	$Concentration^3 = 0$	$Concentration^3 = 0$
Statistic 60.07	Statistic 31.12	Statistic 47.39	Statistic 23.8
ProbChiSq <.0001	ProbChiSq <.0001	ProbChiSq <.0001	ProbChiSq <.0001
Reject	Reject	Reject	Reject

Table 2.8

Compare Synchronicity between *Family* and *NonFamily* Firms

Panel A presents results of a signed rank test to determine whether synchronicity is significantly different for matched pairs of *Family* (treated) and *NonFamily* (control) firms holding *Concentration, Size, Turnover, Bid-Ask, Herfindahl, and VolROA* constant. The sample period is from 2000-2012. *Synchronicity difference* represents the difference in *Synchronicity* for *Family* (treated) – *NonFamily* (control) firms. The results for the total sample suggest that there is no significant difference. The remaining columns present the results for each year in the sample. Only 2001 and 2002 indicate that there may be a significant difference between *Family* (treated) and *NonFamily* (control) firms. This result can only be applied to firms with ownership concentration between 10-50%. The number of *Family* and *NonFamily* firms, and matched pairs are available in Panel B.

	Total Sample	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Panel A: Signed Rank Test														
Synchronicity difference	**0.0174**	0.1516	-0.3175	0.0054	-0.3170	0.2438	0.2911	0.0396	0.1401	0.3220	0.1720	0.0191	-0.2780	-0.0921
p-value	**0.8465**	0.4449	0.0288	0.9215	0.0258	0.1551	0.1649	0.8728	0.5783	0.1162	0.3208	0.9078	0.1031	0.7116
			**		**									
Panel B: Number of Firms														
Family (Treated)	**2307**	202	216	224	228	202	195	145	140	142	167	153	150	143
NonFamily (Control)	**1453**	121	114	111	106	100	110	92	99	105	114	116	132	133
Matches	**1939**	189	181	193	210	173	157	114	113	115	132	126	117	119

Table 2.9
Compare Synchronicity between *Multiple* and *OnlyOne* Firms

This table presents results of a signed rank test to determine whether synchronicity is significantly different for matched pairs of *Multiple* (treated) and *OnlyOne* (control) firms holding *Concentration, Size, Turnover, Bid-Ask, Herfindahl, and VolROA* constant. The sample period is from 2000-2012. The results for the total sample suggest that there is a significant difference in synchronicity for *Multiple* (treated) and *OnlyOne* (control) firms. The analysis in this section is restricted to firms with 10-75% ownership concentration.

	Total Sample	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Panel A: Signed Rank Test														
Synchronicity difference	**-0.3007**	0.0347	-0.4501	-0.0878	-0.2242	-0.4869	-0.2008	0.0579	-0.6236	-0.4311	-0.2941	-0.2941	-0.3073	-0.2454
p-value	**<.001**	0.7471	0.0018	0.2946	0.2298	0.0316	0.2869	0.7388	0.0237	0.0058	0.1261	0.0002	0.1255	0.7116
	***		***			**			**	***		***		
Panel B: Number of Firms														
Family (Treated)	**1247**	98	118	112	115	103	97	72	66	82	88	90	104	102
NonFamily (Control)	**2151**	195	185	198	190	171	182	137	146	131	153	155	155	153
Matches	**1194**	97	113	109	112	100	95	70	61	78	79	85	101	94

Table 2.10
Synchronicity and Earnings Informativeness

The coefficient on $NI_{it} * SYNCHdr_{it}$ is significantly negative. This implies that the market attaches a lower value to earnings of high-synchronicity firms and that corporate earnings information is capitalized into stock prices to a lesser extent for these firms. Synchronicity is a valid (inverse) measure of firm-specific information incorporated into stock prices.

	[1]	[2]
Intercept	0.0293	0.0358
NI	-0.7978	-1.0385 *
*SYNCHdr * NI*	-0.3704 **	-0.4027 **
*Size * NI*	0.0693 **	0.0794 ***
*Growth * NI*	0.0581	0.0871 **
*Leverage * NI*	0.0239 *	0.0276 **
*Beta * NI*		-0.0123
*VolROA * NI*		0.4411
Year Dummies	Yes	Yes
Industry Dummies	Yes	Yes
R^2	0.0805	0.0813
Number of Observations	3617	3413
Time Series	13	13
Number of Cross Sections	595	595

Table 2.11
Ownership Structure and Earnings Informativeness

The following regressions test whether stock prices contain more information about earnings for different ownership structure variables where R_{it} is the market adjusted monthly returns compounded over the 12 month period ending the third month after the end of a firm's fiscal year end; *NI* is net income (earnings before extraordinary items) deflated by the market value of equity at the beginning of the fiscal year; Δ*NI* is the change in earnings between year *t*-1 and *t* scaled by the market value of equity at the end of fiscal year *t*-1; *OC* is a vector of ownership characteristics including concentration, family firm, and more-than-one; and CONTROL is a vector of control variables that includes *size, growth* (B/M), *leverage, risk* (beta) and *VolROA* (asset return volatility).

	[1]	[2]	[3]	[4]	[5]
Intercept	0.037	0.033	0.034	0.036	0.034
NI	-0.643	-0.588	-0.444	-0.610	-0.402
*Concentration * NI*	0.006	1.324			
Concentration^2 ** NI*		-2.606			
Concentration^3 ** NI*		1.270			
*Family * NI*			0.345		0.271
*NonFamily * NI*			-0.326		-0.369 *
*Multiple * NI*				0.771 **	0.738 **
*Size * NI*	0.049 *	0.045 *	0.037	0.044	0.033
*Growth * NI*	0.104 **	0.127 ***	0.107 **	0.100 **	0.104 **
*Leverage * NI*	0.029 **	0.028 **	0.035 **	0.030 **	0.037 ***
*Beta * NI*	-0.005	-0.037	0.014	0.000	0.018
*VolROA * NI*	0.409	0.368	0.302	0.437	0.330
Year Dummies	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes
R^2	0.0799	0.0821	0.0818	0.0813	0.083
Number of Observations	3413	3413	3412	3413	3411
Time Series	13	13	13	13	13
Number of Cross Sections	595	595	557	595	595

Figures

Figure 2.1
Average number of firms based on ownership concentration.

This figure shows the cross-sectional average number of *Family* and *NonFamily* firms based on ownership concentration.

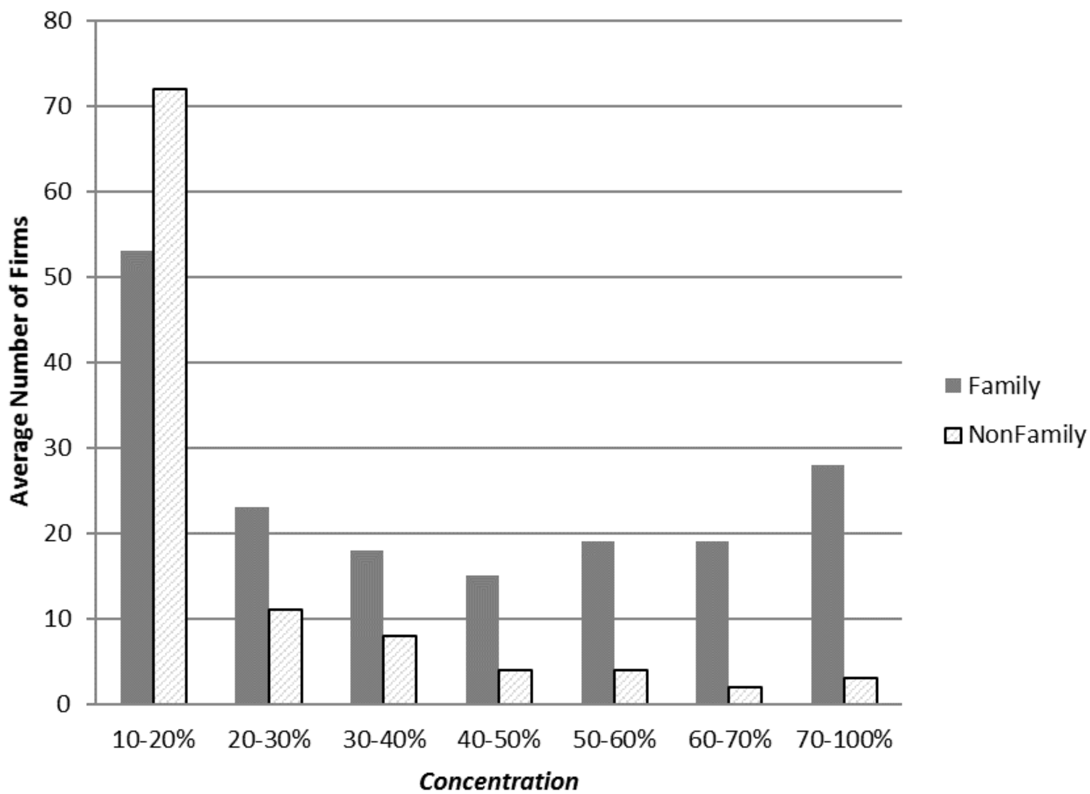
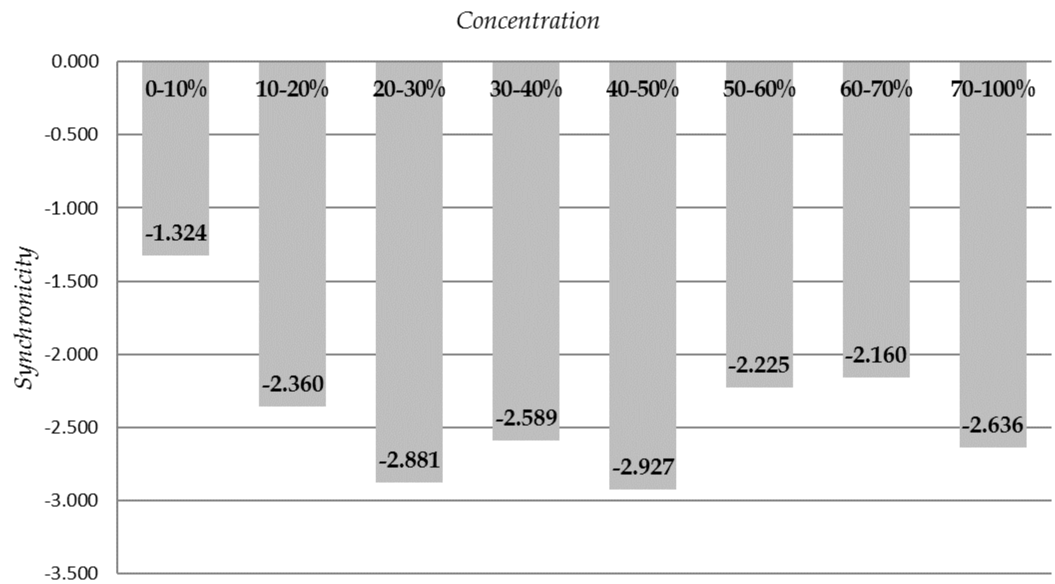


Figure 2.2
Synchronicity by Concentration

This figure details the time series average of cross-sectional sample size and synchronicity for each level of concentration. This graph shows the relationship between synchronicity and concentration (the percentage of voting equity held by the largest shareholder).



	Avg. Concentration							
	0-10%	**10-20%**	**20-30%**	**30-40%**	**40-50%**	**50-60%**	**60-70%**	**70-100%**
Avg. Number of Firms (N)	107	125	34	26	18	23	21	31
Synchronicity	-1.324	-2.360	-2.881	-2.589	-2.927	-2.225	-2.160	-2.636

Appendices

Appendix 2.A. Propensity Score Matching

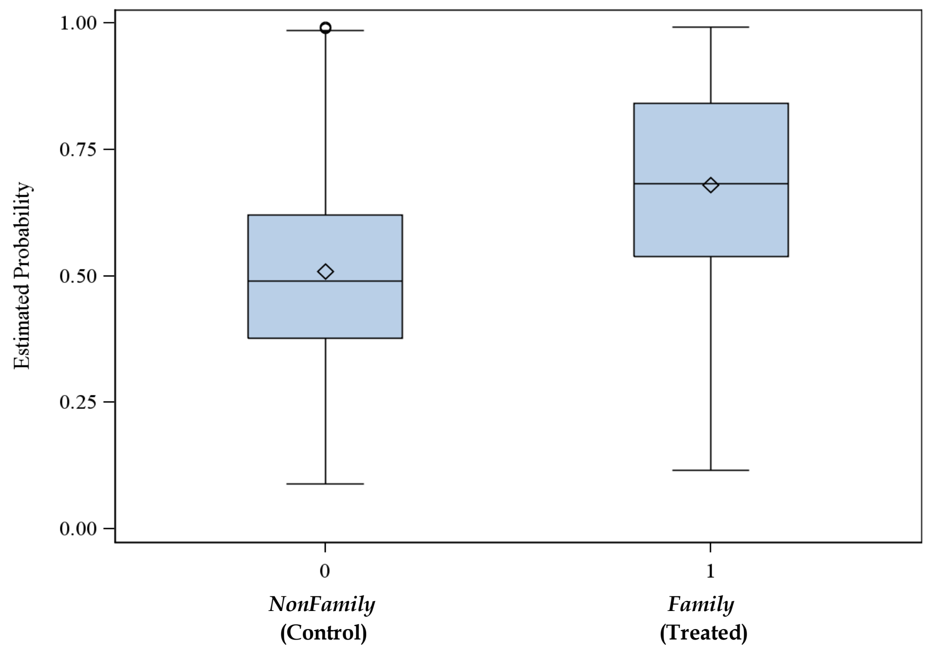
Propensity score matching (PSM) is performed to isolate not only the effect of family ownership on synchronicity from ownership concentration and other control variables but also the effect having multiple controlling shareholder on synchronicity from ownership concentration and other control variables.

Family firms and non-family firms

The characteristics of variables that are used in the multivariate logistic regression model before propensity scores are calculated to verify that there is in fact a difference between these characteristics for the two groups of firms are presented. The Wilcoxon-Mann-Whitney (rank-sum) test is used to evaluate differences between family firms (treated) and non-family firms (control). The results suggest that there is a significant difference between family firms and non-family firms for all characteristics.

Wilcoxon-Mann-Whitney (Rank-Sum) Test		
	Z	p-value
Concentration	-22.47	<.0001 ***
Size	2.48	0.013 **
Turnover	12.88	<.0001 ***
Bid-Ask	-6.77	<.0001 ***
Herfindahl	-5.14	<.0001 ***
VolROA	7.78	<.0001 ***

The propensity scores are calculated following the methodology outlined in section 2.3.5. The box plot compares the distributions of propensity scores for family firms and non-family firms. This is done to ensure that there is common support to compare synchronicity for the two groups of firms.



The results of a signed-rank test to evaluate the differences between matched pairs are reported below. Propensity scores were calculated for 2307 family firms and 1453 non-family firms. A total of 1939 matches were made. The differences between *Size*, *Turnover*, *Bid-Ask*, *Herfindahl*, *Concentration*, and *VolROA* of a family firm and non-family for each matched pair in the sample are represented by the variables: *Size_diff*, *Turnover_diff*, *Bid-Ask_diff*, *Herfindal_diff*, *Concentration_diff, and VolROA_diff*. The results indicate that the matches are a good fit: there is no significant difference between the control variables for the matched "treated" and the "control" firms.

Signed Rank Test to Evaluate Differences in Matches Between *Family* (Treated) and *NonFamily* (Control) Firms

	Avg	Signed Rank	p-value
Concentration_diff	0.002	33268	0.161
Size_diff	0.088	19334	0.423
Turnover_diff	-0.028	-15080	0.532
Bid-Ask_diff	0.000	27141	0.261
Herfindahl_diff	0.006	26738	0.168
VolROA_diff	0.001	-36672	0.127

It is important to note that matches can only be made for firms that have between 10 and 50% ownership concentration. There are not enough non-family firms with greater than 50% ownership concentration to match on all of the variables used to create propensity scores. The analysis in this section therefore is restricted to firms with 10-50% ownership concentration.

The next table reports the matched propensity scores for each year. It also presents the number of matches made in each year of the sample. The results of the signed-rank test suggest that there is no significant difference between the propensity scores for the matched pairs.

	Signed Rank Test			**Number of Firms**		
Year	*Pscore difference*	Signed Rank	p-value	*Family* (Treated)	*NonFamily* (Control)	*Matches*
2000	0.0003	644.50	0.3935	202	121	189
2001	0.0002	310.50	0.6613	216	114	181
2002	-0.0003	-1035.50	0.1833	224	111	193
2003	0.0002	991.50	0.2617	228	106	210
2004	0.0001	174.50	0.7923	202	100	173
2005	0.0003	613.50	0.2837	195	110	157
2006	-0.0003	-405.50	0.2533	145	92	114
2007	-0.0001	-58.50	0.8678	140	99	113
2008	0.0000	-33.00	0.9271	142	105	115
2009	-0.0001	39.00	0.9298	167	114	132
2010	0.0001	-56.50	0.8912	153	116	126
2011	-0.0006	-548.50	0.1364	150	132	117
2012	0.0001	-45.00	0.9056	143	133	119

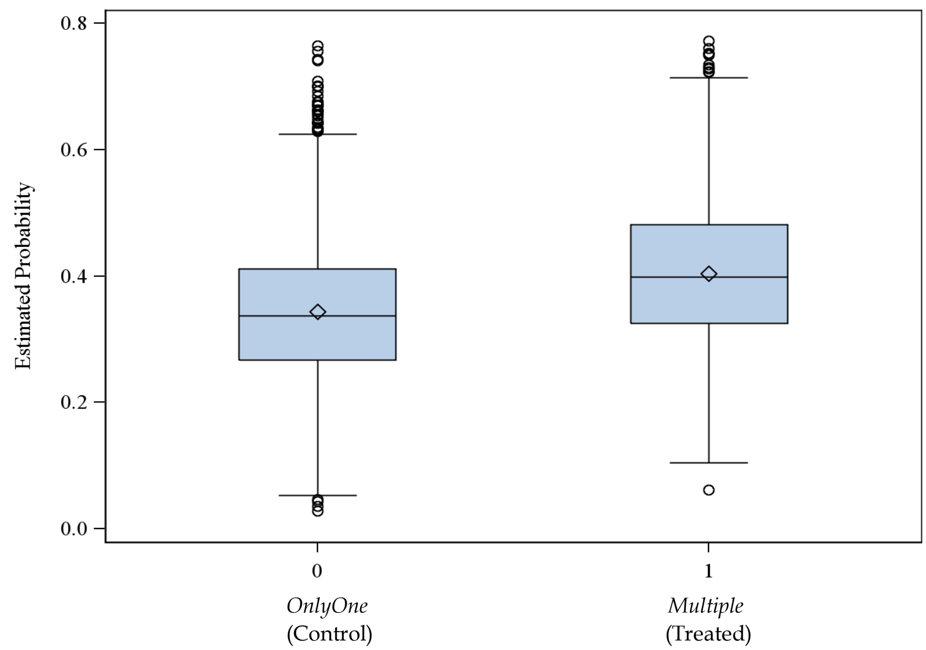
Multiple controlling shareholders

The characteristics of variables that are used in the multivariate logistic regression model before propensity scores are calculated to verify that there is in fact a difference between these characteristics for the two groups of firms are presented below. The Wilcoxon-Mann-Whitney (rank-sum) test is used to evaluate differences between firms classified as *Multiple* (treated) and *OnlyOne* (control). The results suggest that there is a significant difference between *Multiple* (treated) and *OnlyOne* for all characteristics except *Herfindahl*.

Wilcoxon-Mann-Whitney (Rank-Sum) Test

	Z	p-value
Concentration	3.0926	0.002 ***
Size	-5.5642	0.013 **
Turnover	-9.6413	<.0001 ***
Bid-Ask	7.5566	<.0001 ***
Herfindahl	0.4929	0.6221
VolROA	-3.7514	0.002 ***

The boxplot compares the distributions of propensity scores for *Multiple* and *OnlyOne* to ensure common support.



The results of a signed-rank test to evaluate the differences between matched pairs is presented below. Propensity scores were calculated for 1247 *Multiple* and 2151 *OnlyOne* firms. A total of 1194 matches were made. *Size_diff, Turnover_diff, Bid-Ask_diff, Herfindal_diff, Concentration_diff, and VolROA_diff* are the differences between *Size, Turnover, Bid-Ask, Herfindahl, Concentration, and VolROA* of *Multiple* and *OnlyOne* firms for each matched pair. The results indicate that the matches are a good fit, there is no significant difference between the "treated" and the "control" firms.

It is important to note that matches can only be made for firms that have between 10 and 75% ownership concentration. There are not enough matches for firms with greater than 75% ownership concentration to match on all of the variables. The analysis in this section is restricted to firms with 10-75% ownership concentration.

Signed Rank Test to Evaluate Differences in Matches Between *Multiple* (Treated) and *OnlyOne* (Control) Firms			
	Avg	Signed Rank	p-value
Concentration_diff	0.002	33267.5	0.161
Size_diff	0.088	19334	0.423
Turnover_diff	-0.028	-15079.5	0.532
Bid-Ask_diff	0.000	27141	0.261
Herfindahl_diff	0.006	26738	0.168
VolROA_diff	0.001	-36672	0.127

The next table compares the matched propensity scores for each year. It also presents the number of matches made in each year of the sample. The results of the signed-rank test suggest that there is no significant difference between the propensity scores for the matched pairs.

	Signed Rank Test			**Number of Firms**		
Year	*Pscore difference*	Signed Rank	p-value	*Multiple* (Treated)	*OnlyOne* (Control)	Matches
2000	0.0001	119.50	0.6695	98	195	97
2001	-0.0001	-161.50	0.6457	118	185	113
2002	-0.0002	-91.50	0.7835	112	198	109
2003	0.0000	0.00	1.0000	115	190	112
2004	-0.0003	-343.00	0.2402	103	171	100
2005	0.0001	330.00	0.2224	97	182	95
2006	0.0000	51.50	0.7655	72	137	70
2007	-0.0002	-60.50	0.6675	66	146	61
2008	0.0000	-35.50	0.8610	82	131	78
2009	-0.0001	-57.00	0.7826	88	153	79
2010	0.0002	286.50	0.2113	90	155	85
2011	-0.0002	-164.50	0.5799	104	155	101
2012	0.0000	119.50	0.6547	102	153	94

Chapter Three: *An experimental analysis of path-dependent financial behaviors and investor characteristics*[25]

3.1. Introduction

Path-dependent behavior exists when a decision-maker is influenced by past events. In some contexts, this may be optimal. For example, the ability to learn from past experiences can aid in human survival, helping us to recognize and quickly respond to predators and threats. This type of learning allows us to avoid repeating past mistakes and enforces behaviors associated with previous positive experiences. There are other times however when path dependence is patently sub-optimal. This is often true in the financial realm, yet there is abundant evidence that path-dependent behavior is exhibited by financial decision-makers. For example, managers are often influenced by historical or sunk costs (Arkes & Blumer, 1985). Individual investors trade more actively when their most recent trades are successful (De, Gondhi & Pochiraju, 2010). Investors are more likely to subscribe to initial public offerings if their personal experience with such investments has been profitable (Kaustia & Knüpfer, 2008). Investors whose 401(k) accounts have experienced greater returns tend to increase their savings rates (Choi, Laibson, Madrian & Metrick, 2009). And investor-age cohorts that have

[25] Co-authored work with Dr. Richard Deaves (McMaster University) and Dr. Brian Kluger (University of Cincinnati)

experienced high stock returns throughout their lives are less risk averse and are more likely to invest in stocks (Malmendier & Nagel, 2009).

It is well documented that, within investment portfolios, portfolio composition and risk taking vary as security prices and portfolio values change. For example, within stock portfolios, the disposition effect (DE), the tendency to more readily sell stocks which have performed well than those which have performed poorly subsequent to purchase, has been documented using both naturally-occurring data (e.g., Odean, 1998; Shefrin & Statman, 1985) and experimental data (e.g., Summers & Duxbury, 2012; Weber & Camerer, 1998), with even professional traders not being immune (e.g., Garvey & Murphy, 2004).[26] Nevertheless, DE is not universal, as the tendency to act in the opposite fashion, namely to sell losers more readily than winners, which we call a negative disposition effect (negDE), is exhibited by some (e.g., Dhar & Zhu, 2006).[27] The latter behavior at least has the potential to take advantage of the medium-term momentum prevalent in the data (Jegadeesh & Titman, 1993).

[26] DE is an example of a (relative) "price effect," which can be said to exist when security purchases or sales are influenced by their price paths. While DE is the only price effect we examine here, there are certainly others, such as the decision to repurchase a previously sold stock (Strahilevitz, Odean & Barber, 2011; Weber & Welfens, 2011). Note that price effects require individuals to look at stocks one at a time and are based on the adoption of a "narrow frame," while portfolio-level "wealth effects" (to be discussed later) adopt a broader frame. That said, even a focus on the portfolio can be too narrowly framed if one views returns over the short term rather than the long term (Benartzi & Thaler, 1995).

[27] NegDE could also be characterized as "return-chasing" behavior.

At the portfolio level, the preponderance of the evidence suggests that risk taking rises with increases in wealth, a tendency that has been called the house money effect (HM) (e.g., Ackert, Charupat, Church & Deaves, 2006; Thaler & Johnson, 1990).[28] Occasionally, though, it is found that a decline in risk taking occurs after improved circumstances in the manner of a negative house money effect (negHM) (e.g., Weber & Zuchel, 2005).[29] The evidence is more mixed in the domain of prior losses: researchers have observed in response to reduced wealth not only increases in risk taking, in the manner of a break-even effect (BE) (e.g., Post, van den Assem, Baltussen & Thaler, 2008),[30] but also decreases in risk taking, in accordance with a negative break-even effect (negBE) (e.g., Thaler & Johnson, 1990).[31]

It is useful to designate HM and BE, and negHM and negBE, as "wealth effects." Wealth effects are said to occur when risk taking changes in response to wealth changes. Note that while it is common to view DE (or negDE) as reflecting a change in risk taking, what is commonly observed as DE behavior need not

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[28] When some speak of HM they mean an increase in risk seeking after prior gains coupled with a decrease in risk taking after prior losses (e.g., Duxbury et al., 2013). In our usage, HM (and negHM) only refers to positive-domain and negative-domain behavior.
[29] NegHM can also be characterized as a "mood-maintenance effect" (Isen & Patrick, 1983).
[30] Some (e.g., Staw ,1976; Weber & Zuchel, 2005) use the term "escalation of commitment." Note that even DE, which entails sticking to past decisions despite losses, is also an escalation of commitment.
[31] NegBE can also be characterized as a "snake-bit effect."

imply any change in risk taking at all.[32] Suppose an investor holds two stocks (with equal non-diversifiable risk); stock A and stock B. Assume that A rises and B falls in price. A DE-investor would likely hold the loser B and sell the winner A. If one takes a very narrow frame only looking at the single stock under consideration then one could say that a reduction in risk taking has occurred since stock has been converted to cash, but surely sales rarely occur in isolation. For example, if the proceeds from A are used to buy another stock with equivalent risk, or if the money is used to increase the position in B, no decrease (or increase) in risk taking has occurred.[33] We believe it facilitates clarity to keep (composition-changing) DE and (risk-changing) wealth effects separate. So, by DE (or negDE) we mean a change in the composition of a stock portfolio due to the selling of certain stocks within the portfolio induced by changing prices of the individual stocks – without consideration of any changes in overall risk taking occurring (which are best viewed as wealth effects). Wealth effects on the other hand refer to changes in risk taking at the level of the portfolio induced by changes in overall portfolio value without any focus on the individual portfolio constituents (though

[32] Some view DE and HM as opposites. For example, Duxbury et al. (2013) characterize HM as the "reverse phenomenon" to DE (p. 612). Clearly, this is not so, *given our definitions.* While we (and many others) restrict the use of DE to indicate a particular stock-selling likelihood as a function of the price path, some papers (e.g., Massa & Simonov, 2005; Frino et al., 2008; and Duxbury et al. (2013, 2015)) use DE as the opposite of HM (i.e., risk avoidance vs. risk seeking).

[33] Or if a retiree is gradually winding down her portfolio and it's a question of which stocks are sold off for living needs. Also, note that the focus here is on non-diversifiable risk.

naturally the changing prices of the components of the portfolio have led to the change in portfolio value). As will be discussed below, both DE and wealth effects are (mostly) sub-optimal. For example, Odean (1998) finds that winners sold continue to increase in price while losers held continue to lose value, with winners sold in his sample outperforming losers held by 3.41% on a risk-adjusted basis.

Embedding the potential to display both DE and wealth effects in an experimental setting, this paper makes several contributions. First, since our design allows for the separation and clean identification of both DE and wealth effects for all individuals participating, inference is less ambiguous than in cases where both relative prices and portfolio values are changing at the same time. Another advantage of an experimental environment is that possible rational reasons for DE can be eliminated: one such reason is mean-reversion, and our setup eliminates this possibility (and participants should be able to see this).

Second, we investigate whether the tendency of an individual to exhibit a particular behavior makes it more or less likely that she will exhibit another behavior. This is important because it should allow researchers to more carefully model path-dependent behavior. Indeed, asset pricing models are beginning to incorporate path-dependent behavior in their models to explain hitherto resistant phenomena. For example, in the model of Barberis, Huang, and Santos (2001), investors receive utility not only from consumption but also from changes in wealth.[34] And the model of Grinblatt and Han (2005) seeks to explain momentum through the tendency of some investors to exhibit DE behavior.

Third, because we collect psychometric and demographic data via a questionnaire, it is possible to explore to what extent investor characteristics are associated with path-dependent behaviors. This too could facilitate modelling: for example, if we find that overconfidence strongly correlates with DE tendencies but not any wealth effects, then it is logical to believe that overconfidence should form part of the explanation of the former but not the latter. Further, cross-sectional findings may be of use to investment advisors in their attempts to debias clients once they know who is more susceptible to bias. Once again assuming overconfidence correlates with DE, a financial planner, administering a questionnaire to clients containing an overconfidence metric, should be able to intuit which clients are more likely to exhibit DE behavior and undertake appropriate educational activity.

To preview our results, the majority of our subject exhibit path-dependent biases, and we do find correlations among the biases. We find that DE is positively correlated with BE and negatively correlated with HM. We also find that HM is negatively correlated with BE. As for the first, a common theme for both DE and

[34] Incorporating HM and negBE as (sometimes) found by Thaler and Johnson (1990), their model predicts higher volatility in stock prices because of these effects. After prices rise/fall, investors are less/more averse to the risks involved in owning stock, inducing even further price increases/decreases.

BE is escalation of commitment. When two behaviors are positively correlated, it suggests that they may have a common psychological driver. This common psychological driver could be fear of regret.

In terms of whether and to what extent investor characteristics are associated with particular behaviors, we find that the existence of psychological bias (overconfidence and negative affect) leads to more bias in financial decision making. More specifically, overconfidence (impacting DE) and negative affect (impacting HM) appear to contribute to the existence of DE and wealth effects.

In the next section by way of background we review past research on path-dependent behavior. In section 3.3, the experimental design is explained. In section 3.4, the measures used to infer path-dependent behaviors are detailed. In the penultimate section the results are described and interpreted. Finally, section 3.6 concludes.

3.2. Literature Review

We first review the evidence on DE and wealth effects. It is extensive. While much of it is empirical, there are also numerous experimental studies. Some researchers focus on typical behavior; others explore heterogeneity and its determinants. It will be seen that DE and wealth effects are ubiquitous, affecting investors, both naive and sophisticated, as well as managers. Moreover, such effects are robust internationally. It is argued below that such behaviors are (mostly) sub-optimal.

While the tendency is to succumb to these biases, not all decision-makers do: some are not affected, while others exhibit the opposite bias to the norm (e.g., negDE instead of DE). The determinants of these biases are next explored. Explanations purporting to explain DE and wealth effects fall into two main categories: prospect theory-based and psychological. We end this literature review by considering common explanations in these veins.

3.2.1. Evidence of DE and wealth effects

3.2.1.1. Evidence of disposition effect (DE)

Since DE was first documented by Shefrin and Statman (1985), there have been numerous studies corroborating the finding.[35] Odean (1998) established the standard methodology for detecting DE based on a comparison of the proportion of gains realized (PGR) and the proportion of losses realized (PLR), finding strong evidence of this bias (i.e., PGR>PLR) in the extensive trading records of a large discount brokerage house in the U.S. Since then abundant research has corroborated this early work (Birru, 2015; Das, 2012; Dhar & Zhu, 2006; Frazzini, 2006; Frino et al., 2004; Garvey & Murphy, 2004; Genesove & Mayer, 2001; Heath et al., 1999; Jin & Schebrina, 2010; Jordan and Diltz, 2004; Kaniel et al., 2008; Lock & Mann, 2005; O'Connell & Teo, 2009). Evidence of DE has also been found using

[35] Shefrin and Statman (1985) measure DE as the ratio of stock redemptions to purchases being greater in the case of gains than in the case of losses.

market and trading data outside of the U.S.: in Israel (Shapira & Venezia, 2001); Finland (Grinblatt & Keloharju, 2001; Linnaimaa 2010); China (Chen, Kim, Nofsinger & Rui, 2007; Feng & Seasholes, 2005); Australia (Brown, Chappel, Da Silva Rosa & Walter, 2006); and Taiwan (Chou & Wang, 2011; Barber, Lee, Liu & Odean, 2007). The effect exists not only for naturally-occurring data but also for experimental data (Chui, 2001; Fogel & Berry, 2006; Kubinska, Markiewicz & Tyska, 2012; Magnani, 2015; Oehler, Heilmann, Läger, & Oberländer, 2003; Talpsepp, Vlcek & Wang, 2014; Weber & Camerer, 1998;).

DE behavior exists beyond equity markets. Heath, Huddart, and Lang (1999) find that executives are more likely to exercise their stock options when the underlying stock price exceeds the stock's highest price over the previous year than when the price falls below this reference point. Genesove and Mayer (2001) find evidence of DE in the U.S. housing market, with homeowners being reluctant to sell at prices below the original purchase price. And Ye (2014) find evidence of DE in takeover bids, as institutional investors of target companies are reluctant to realize sunk-cost losses, affecting both the takeover price and deal success.

Even professional investors are susceptible to DE behavior. In the U.S., Garvey and Murphy (2004) show that proprietary stock trader teams exhibit DE. Futures traders have also been shown to be susceptible to DE behavior (Choe & Eom, 2009; Frino, Grant and Johnstone, 2008; Locke & Mann, 2005). Further, mutual fund managers sell equities for a gain at a higher rate than those liquidated at a loss (Frazzini, 2006; Wermers, 2003). Using a sample of actively managed U.S. equity funds during 2007-2011, Singal and Xu (2011) find that 30% of mutual funds exhibit DE behavior and that these funds underperform non-DE funds by 4-6% per year. Jin and Scherbina (2011) examined the rate at which new mutual fund managers were willing to sell stocks at a loss versus that of continuing managers, finding that new managers tended to sell off inherited loser stocks, while continuing managers tended to hold on to the same loser stocks for longer. It's not as if the new managers are immune: a year after a new manager has assumed her position she demonstrates the same pattern of holding on to losers.

While both individual and professional investors exhibit DE behavior, the latter appear to be less susceptible. In Israel, Shapira and Venezia (2001) look at both professionally managed and self-managed investment accounts, and find DE is most pronounced for the latter. A weakened DE for professional traders is also found in the U.S. by Frazzini (2006) in a comparison of mutual fund managers and individual traders.

There is no longer a question of DE's existence. Indeed, it has proven to be a robust behavioral phenomenon. Later in this review section we consider what is driving DE, but first it is useful to consider its rationality or lack thereof. First, DE flies in the face of gains from tax-loss selling (Shefrin & Statman, 1985). When facing capital gains taxation the optimal trading strategy is to realize losses as they occur (Constantinides, 1983; Dammon, Zhang & Spatt, 2001). There is evidence that some investors do respond to this rational incentive. For example, both Odean (1998) and Grinblatt and Keloharju (2001) find that investors are more willing to realize losses in the month of December. And Ivkovic, Weisbenner and Jin (2009) find that individual investors are reluctant to sell mutual funds that have appreciated in value but are willing to sell losing funds.[36] So it appears that some investors understand tax-loss selling, but the fact that DE exists for the rest of the year remains puzzling.[37]

A second reason why DE is irrational is that it does not take advantage of medium-term momentum as documented by Jegadeesh and Titman (1993) and others. For example, Jin and Scherbina (2011) show that for mutual fund managers the (less frequent) selling of loser stocks substantially detracts from meaningful economic gains, suggesting that managers should be selling these stocks more often.

Are there circumstances that might lead to rational DE behavior, and if so can we really say that DE is irrational? Odean (1998) has shown that (potentially rational) explanations based on portfolio rebalancing, informed trading and mean-reversion fail to capture important features of the evidence. As for the first, while

[36] Of course, this is just "chasing winners" or capitalizing on momentum. Perhaps this ability to part with losers is due to the fact that individual investors are not *personally responsible* for shares purchased within their funds (and as our discussion of psychological determinants makes clear, this seems to be significant).
[37] Leal, Armada, and Duque (2010) show that in Portugal DE is strong during the *entire* year, suggesting that few investors in their sample take advantage of tax-loss selling.

optimal portfolio selection for investors who are expected-utility maximizers does involve rebalancing portfolios (Merton, 1969; Samuelson, 1969), and this rebalancing could provide a rational explanation for selling after gains and buying after losses, Odean investigates this possibility by both removing sales that could be motivated by such portfolio rebalancing from the data, and by looking at new purchases that could be motivated by the need to rebalance. In short, rebalancing did not explain the existence of DE.

The suggestion that DE behavior is the result of investors trading on private information is based on the notion that individuals hold on to stocks that have performed poorly because they possess positive private information on such stocks that has yet to be incorporated into share price, while they sell after a gain because their positive private information *has* been realized. Nevertheless there is no evidence that informed trading is behind DE behavior (Kaniel, Saar, & Titman, 2008; Odean, 1998; Strahilevitz, Odean, & Barber, 2011). For example, once again reminiscent of medium-term momentum (Jegadeesh & Titman, 1993), Odean finds that winners sold continue to increase in price while losers held continue to lose value, with winners sold in his sample outperforming losers held by 3.41% on a risk-adjusted basis.

Investors who subscribe to mean-reversion, namely that stocks that have recently done well will do poorly while stocks that have recently performed poorly will do well, would also follow a trading strategy consistent with DE. A number of researchers (Grinblatt & Keloharju, 2001; Kaustia, 2010; Weber & Camerer, 1998) have distinguished DE behavior from a mean-reversion trading strategy, and are able to rule out belief in mean-reversion as an explanation for DE.[38] In sum, rational models of trading have not been able to explain the bias.

3.2.1.2 Evidence of wealth effects

Next we turn to whether decision-makers adjust risk exposure as portfolio values change. Here there is somewhat less evidence. Much of the existing research is experimental. Some researchers focus on only gains; others focus only on losses; while still others look at behavior in both the gain and loss domains. To preview, most of the evidence points in the direction of house money effect (HM) after gains and breakeven effect (BE) after losses. Recall that both effects imply increases in risk taking after changes in wealth.

Beginning with experimental evidence, in the negative domain, consistent with BE, Staw (1976) found that there was a tendency for individuals to commit greater resources in an investment game after a loss, attempting to disentangle themselves from negative consequences (especially when individuals were

[38] For example, Kaustia (2010) finds that that investors are reluctant to realize losses regardless of whether a stock has outperformed or underperformed the market during the preceding month. And using experimental data, Weber and Camerer (1998) test mean-reversion by adding a condition to their experiment in which participants are forced to liquidate their holdings at random times and are then allowed to reinvest in any way that they choose. If participants are holding losses due to a belief in mean-reversion then they should repurchase the loser stocks. They find this not to be the case.

personally responsible) even at the expense of even greater losses. In the positive domain, Battalio, Kagel and Jiranyakul (1990) documented HM in an experiment in which participants, endowed with cash at the beginning of an experiment, were quite likely to take a fair gamble provided that lack of success in the gamble would still keep them in positive territory.[39] And Ackert, Charupat, Church and Deaves (2006) explored wealth effects in an asset market experiment where the level of cash endowment was manipulated. Examining whether participant behavior was consistent with higher asset prices after wealth increases and lower prices after wealth decreases, they concluded that the market price was higher when traders' endowments were larger, and this HM tendency persisted across trading periods.

In perhaps the most compelling demonstration of wealth effects to date, because of the large stakes at play, Post, Van den Assem, Baltussen and Thaler (2008) found evidence consistent with both HM and BE. Specifically, they made use of data from a popular television game show called *Deal or No Deal*. A total of 151 games played in the U.S., The Netherlands and Germany from 2002-2007 were considered. The game show environment provides an ideal opportunity to look at scenarios involving simple decision problems with very significant dollar

[39] Nevertheless, they found that HM diminished as the size of the potential loss approached the initial endowment. This is consistent with a prospect theory-based explanation (as will be described in later sections).

outcomes. As games progressed, the (likely) final wealth of contestants varied from round to round, making it possible to observe changes in risk attitude.

There is also empirical evidence of wealth effects. Low and Mann (2004) compared risk perception (measured using the VIX) to extreme changes in S&P 100 prices, and found that prior gains had a mitigating effect on the fear of future loss. Duxbury et al. (2013) used a dataset of individual traders in China and found that positive prior realized outcomes induced investors to choose stocks that were characteristically riskier going forward.

As in the case of DE, professional traders have also been shown to be susceptible to wealth effects. Coval and Shumway (2005) found evidence of BE among professional futures traders: traders with accumulated losses by the middle of the day tended to take more risk in the afternoon relative to traders facing gains by the middle of the day. And Garvey et al. (2010) found evidence of both HM and BE for professional traders. Using data on traders employed at a U.S. broker-dealer, traders' cumulative income tends to influence their subsequent trading behavior. Specifically, when traders experience large gains or losses they increase their trading (suggesting greater risk taking).

Can wealth effects be rational? Under decreasing absolute risk aversion (ARA), decreased risk aversion occurs after a wealth increase coupled with increased risk aversion after a wealth decrease. On the other hand, under increasing ARA, increased risk aversion occurs after a wealth increase coupled with decreased risk aversion after a wealth decrease. So it seems that a combination of HM/negBE or negHM/BE might be rational depending on preferences. Still, there are problems. First, most of the evidence is consistent with both HM and BE, which does not align with either increasing or decreasing ARA. Second, given that most wealth changes examined in experimental and empirical research are often extremely small relative to an individual's lifetime wealth it is hard to reconcile meaningful shifts in risk preferences with said wealth changes. In other words, meaningful changes in risk taking should only be induced by significant wealth changes (e.g., Rabin, 2000).

3.2.2. Heterogeneity in path-dependent behavior

3.2.2.1. Heterogeneity in DE

When investigated in the aggregate there is almost always strong evidence of the existence of DE. Nevertheless, when studies look more closely at behavior, there also tends to be a subset of investors who exhibit negDE. Evidence of heterogeneity has been documented both using "real-world" trading data (Dhar & Zhu, 2006; Grinblatt & Keloharju, 2001; Jordan & Diltz, 2004; Talpsepp, 2011); and using experimental data (Oehler, Heilmann, Läger, & Oberländerm, 2003; Weber, Welfens & Camerer, 2007).

For example, using naturally-occurring data, Dhar and Zhu (2006) use individual trading records and find that approximately 20% of the sample exhibit either no DE or negDE; and Jordan and Diltz (2004) find that 38% of their sample of U.S. day traders demonstrate negDE behavior, holding winners longer than losers. Using experimental data, Oehler, Heilmann, Läger, and Oberländer (2003) find that about 40% of participants exhibit negDE. Using both experimental and empirical data in Germany, Weber, Welfens and Camerer (2007) find that approximately 33% of investors in each sample sell losers more often than or equally often to winners. Different investor groups sometimes act differently: in Finland, Grinblatt and Keloharju (2001), and, in Estonia, Talpsepp (2011) document evidence of DE for domestic investors along with negDE for (presumably more sophisticated) foreign investors.

As suggested by the previously cited work showing that professional investors have a reduced DE, we would expect markers of sophistication to be associated with a lower DE. For example, one might expect that trading experience would point in the direction of sophistication. Indeed, there exists evidence that trading experience does help to diminish DE behavior (Barber, Lee, Liu & Odean, 2007; Brown, Chappel, Da Silva Rosa & Walter, 2006; Chou & Wang, 2011; Da Costa et al., 2013; Grinblatt & Keloharju, 2001). Another marker of sophistication is trading *frequency* (as opposed to experience), and this too leads to a reduced DE (Dhar & Zhu, 2006; Leal, Armada, & Duque, 2010; Seru, Shumway, Stoffman, & Danková, 2010). For example, Seru, Shumway, Stoffman and Danková (2010) find that while individuals are 2.8 times more likely to sell a stock when its price has increased in value than a stock that has decreased in value, there is a reduction of 2% in DE after executing an additional 100 trades. In China, Feng and Seasholes (2005) find that sophisticated traders are 67% less prone to DE, and trading experience (the number of positions taken by an investor over time) alone decreases DE by 72%.

Dhar and Zhu (2006) also looked at other markers of sophistication, finding that income, education and a professional occupation also led to a reduced DE. And Leal, Armada and Duque (2010) found that investors in the higher percentiles of transaction volume and portfolio value also were less prone to DE. Kumar and Lim (2008) conjecture that trade clustering is indicative of a (more sophisticated) broader frame, and find that those more likely to cluster their trades exhibit reduced DE. Learning may be efficacious: Weber, Welfens and Camerer (2007) find that investors who exhibit either DE or negDE drift towards neither bias over time.

3.2.2.2. Heterogeneity in wealth effects

While there is strong evidence of an increase in risk taking following a gain/loss, as in HM/BE, there have also been studies investigating wealth effects that have found behavior sometimes or always reflecting a *decline* in risk taking after wealth changes.[40] Notably, Thaler and Johnson (1990), in a survey investigating behavior

[40] In one case HM was found to be short-lived, dissipating by learning. Chakravarty and Ma (2009), in an experimental auction market, elicit "true values" from participants. When participants are

after both gains and losses, found that after prior gains individuals often integrated subsequent potential losses allowing them to cancel losses against prior gains, thus mitigating loss aversion and facilitating risk seeking. In accordance with HM, until winnings were depleted, it appeared that losses were not that painful. On the other hand, in the domain of losses, Thaler and Johnson found that an initial loss could cause an increase in risk aversion, particularly if the next choice did not offer the opportunity to break even. It turned out however BE was more likely to be exhibited when full monetary recovery was possible. So depending on the situation, both BE and negBE were observed in the loss domain.

Massa and Simonov (2005), using a dataset of Swedish households, found that for both real estate and financial gains individuals increased their holdings of risky assets, while for prior losses individuals decreased their risky holdings (i.e., negBE). In an experimental context, Weber and Zuchel (2005) subject participants to sequential decisions, finding that HM, negHM, BE, and negBE all resulted

endowed with large sums of money, the traders initially trade recklessly but then revert to rational behavior in the long term.

depending on the financial decision frame used.[41,42] Frino, Grant, and Johnstone (2008), examining the behavior of futures traders in Australia, showed that, consistent with HM/negBE, risk taking increased/decreased after morning gains/losses. O'Connell, and Teo (2009) used a currency trade database and found that institutions mildly increased risk taking following gains in accordance with HM, but aggressively reduced risk taking following losses in the manner of negBE. Gamble, Johnson and Murphy (2014) used a dataset of U.S. retail trades, showing that investors with large losses or large gains in the first six months of the year *decreased* risk over the subsequent six months, which they argued was evidence of both negHM and negBE.

[41] Two treatments are used in which subjects were faced with two frames of the same decision problems: one treatment was framed as if the assets were part of a portfolio while in the other treatment subjects were faced with lottery decisions. In the portfolio treatment subjects become more risk averse after a gain (negHM) and they are more risk taking after a loss (BE). Participants in the lottery treatment became more risk taking after a gain (HM) and showed a small increase in risk aversion after a loss (negBE). The key contribution of this study is that participants' responses were dependent on the framing of the problem.

[42] Davis, Joyce, and Roelofs (2010) analyzed whether differences in the timing of participation payments influences behavior in a sequential decision experiment. Subjects were able to accept a varying level of risk by purchasing information about the value of a good before purchasing the good. The decision of a participant to purchase "assurance information" is related to the mitigation of risk: paying a show-up fee at the beginning of the experiment led to more risk-averse behavior. This evidence was argued to be in support of HM, with subjects (arguably) viewing a payment physically received before beginning the experiment as their own money while a payment that was promised to be paid after the experiment with the rest of their earnings was considered "house money." Nevertheless, it could also be interpreted as negHM, since after receiving cash at the beginning of the experiment participants became more risk averse.

3.2.3. DE and wealth effects considered simultaneously

There have been two notable antecedents to our research in jointly considering DE and wealth effects. Calvet, Campbell, and Sodini (2009) use data from Swedish households, investigating behavior both at the portfolio level and at the individual-stock level. They document that households take greater risk in their portfolios as they become richer (HM behavior), while at the individual-stock level households are more likely to sell stocks that have had positive returns than stocks with negative returns (DE behavior). And Duxbury et al. (2015) use investor-level account data from China to investigate whether DE and HM coexist.[43] In their sample, they find that 87.6% demonstrate DE, 61% are susceptible to HM, and 53.5% simultaneously succumb to both. Indeed, there is a significant negative correlation between HM and DE (implying that HM may moderate DE behavior).

While these two papers are empirical, our approach is experimental. Both approaches contribute and complement. One advantage of an experimental approach, as we have stated above, is that a cleaner demarcation of the two effects can be chiselled into the experimental environment. In particular, DE is examined when there are no changes in aggregate wealth, and wealth effects are examined when there are no changes in relative prices.

[43] They also claim to look at HM at the stock level, but in our parlance this is a price effect, not a wealth effect. And at the aggregate portfolio level they view DE behavior as the opposite of HM (whereas in our parlance at the level of the portfolio we call this negHM).

3.2.4. Explanations of DE and wealth effects

There are two main competing hypotheses behind DE and wealth effects, namely those related to prospect theory, and those associated with psychological drivers. Though we will keep the two categories separate, since psychology underlies risk preferences, including prospect theory parameter values (e.g., Charupat et al., 2013) it is not really true that these categories are mutually exclusive. We begin with explanations based on prospect theory.

3.2.4.1. Path-dependent behavior and prospect theory (PT)

Kahneman and Tversky's prospect theory (PT) (1979, 1992), as the principal model of non-expected utility risk preferences, was from the beginning used as a possible explanation of DE behavior. The main characteristics of PT are: utility is a function of changes from the status quo; losses are felt more keenly than gains (loss aversion); while expected utility-type utility function concavity exists in the positive domain, convexity (suggesting risk seeking) exists in the negative; and a non-linear inverted S-shaped probability weighting function is used to weight utilities. An explanation of behavior based on PT must then be based on these characteristics.[44]

[44] Those modeling PT to account for path dependence routinely ignore probability weighting.

Prospect theory (PT) and DE

Simple explanations of DE using PT focus on the concavity/convexity of the value function (ignoring the loss aversion kink). They also require the integration of prior outcomes, where integration in a nutshell means that one moves up and down along the value function (i.e., away from zero) as asset values change (Thaler, 1985). If an investor is holding a stock that has risen in value since purchase then he thinks of the stock as trading at a gain.[45] PT, suggesting risk aversion over gains, says that the individual will sell the stock. If a stock is instead trading at a loss, then PT, suggesting risk seeking over losses, implies that an individual will hold on to the stock awaiting reversal.[46] This behavior of readily selling winners and holding on to losers renders DE.

While early work tended to be satisfied with verbal "stories" of this type, researchers began to more formally model PT and DE. It turned out that PT did not predict DE behavior reliably: indeed in many cases negDE was predicted. Gomes (2005) modelled a 2-period 2-asset economy, where one asset was risky and the other risk-free, finding that utility over annual gains and losses always failed to predict DE. Kyle, Ou-Yang and Xiong (2006) looked at the liquidation decision

[45] The reference point is usually the purchase price. But it has been shown that reference points can reset. Arkes, Hirshleifer, Jiang and Lim (2010) find that reference points reset faster after gains than losses.
[46] Probability weighting can lead to risk seeking/aversion in the positive/negative domain despite concavity/convexity.

of a risky project under PT and found that the behavior of PT investors was inconsistent with DE. Kaustia (2010) combined PT with exogenous liquidity shocks and also found that PT was unlikely to explain DE: specifically, the theory predicted that the propensity to sell decreases as the stock price is further from the purchase price (whether a gain or loss). In the implementation of Hens and Vlcek (2011), PT will predict DE under the assumption that an individual already holds the stock in question, but (inconveniently) for most of the PT parameters that predict DE, an investor would never purchase the stock in the first place. Li and Yang (2012) develop a full equilibrium model. Using preference parameters from Tversky and Kahneman (1992), they are able to show that the concavity and convexity of the PT value function can predict DE. While most explanations that link PT to DE focus on the concavity/convexity of the value function, Li and Yang also incorporate loss aversion in their general equilibrium model. They show that depending on the skewness of the dividend process, loss aversion will predict either DE or negDE behavior.[47] Yao and Li (2013) model a market in which PT

[47] Negatively skewed dividends lead to DE behavior. When dividends are negatively skewed, the odds of bad news are very small, but when bad news does occur the magnitude is significant. If we consider the loss aversion kink in the value function, the large loss will result in investors being at a position far from the kink and they will continue to hold the loss. Gains, for negatively skewed dividends, will be small but will occur more frequently. The investor will be closer to the kink when facing gains and will be more likely to sell. Non-skewed dividends, on the other hand, will result in negDE. For non-skewed dividends, loss aversion tends to result in a negative relation between risk aversion and returns. When facing gains individuals are pushed further from the loss aversion kink and they are more likely to hold a stock, generating negDE behavior.

investors interact with constant-relative-risk-aversion investors, leading to DE for PT investors. In sum, PT may or may not predict DE depending on the formulation of the model.

Another stream of this literature has been somewhat more successful in accounting for DE. The required innovation is realization utility, which is based on the notion that investors receive utility or disutility at the moment that transactions occur. Shefrin and Statman (1985) use a numerical example to heuristically demonstrate that for an investor with a PT value function if utility is derived from realized gains and losses at the time of sale, then DE arises. More rigorous work in this vein has been performed by Barberis and Xiong (2009, 2012), Henderson (2012), and Ingersoll and Jin (2013).[48]

Barberis and Xiong (2009) perform two separate implementations of PT.[49] They first model trading behavior for individuals with PT preferences using utility based on annual stock-level trading profits. While there is heterogeneity in the results depending on the expected return on a stock and the number of trading periods in a year, the majority of results predict negDE rather than DE. In their second implementation of PT, Barberis and Xiong (2009) define PT over *realized* gains and losses. At each moment of sale, the investor receives a "jolt" of PT utility.

[48] See Frydman et al. (2014) for neural evidence consistent with realization utility.

[49] Note that in each implementation of PT the trading models are based on one risky asset and one risk-free asset.

In this case there is again heterogeneity in the results depending on the expected return of the stock and the number of trading periods in a year, but now DE is predicted more often than negDE. Barberis and Xiong (2012) further developed an infinite-horizon model that included transaction costs and liquidity shocks. This model successfully predicted a strong DE – but at a cost: unless forced by a liquidity shock, investors only sell stocks trading at a gain and never at a loss.

Henderson (2012) formulated a model in which investors may voluntarily sell losers when they have become sufficiently large. Using the PT preference values of Tversky and Kahneman (1992) along with realization utility, she finds that investors will realize gains when they are relatively small but will wait to sell losses until they are larger. It is for this reason investors will realize losses more rarely than gains implying DE behavior. Ingersoll and Jin (2013) also model realization utility finding a similar pattern to Henderson (2012). Investors will take frequent small gains and occasional large losses. The outcome of their model predicts magnitudes and frequencies of realized gains and losses in line with the trading data of Odean (1998): 58% of sales should be gains and investors realize 14% of possible gains and 11% of losses. While there is growing support for the use of realization utility to account for DE, Ben-David and Hirshleifer (2012) present evidence that suggests DE should not be interpreted solely as a preference for realizing gains versus losses. Specifically, they find that there is little evidence of sign (i.e., gain vs. loss) realization preference. Exploring how the size *and* sign of profits influence investor trades, they conclude that sign alone is only a minor contributor to DE. Ben-David and Hirshleifer also estimate the probabilities of investors purchasing additional shares of current winners/losers (where it is to be noted that the purchase of new shares does not constitute a realization). If investors are only focused on immediate realization utility, the probability of buying an additional share of a winner/loser that an investor holds should be approximately equal. This is not the case, however, suggesting that DE is more complicated than a gain vs. loss phenomenon.

Prospect theory (PT) and wealth effects

A preference for increased risk taking after wealth changes of *either* sign can be explained using PT by loss aversion coupled with outcome integration. It is easiest to simplify by assuming a two-part linear value function, with a kink at the origin and a steeper slope in the negative domain (reflecting loss aversion). After a change in wealth of either sign, the investor moves away from the loss-averse kink. If fresh risky choices are unlikely to move the investor back to the origin (i.e., their reference point), risk taking should rise (i.e., both HM and BE).

The work introduced earlier by Post, Van den Assem, Baltussen and Thaler (2008) based on the game show 'Deal or No Deal,' uses maximum likelihood procedure to estimate prospect theory parameters for contestants. They find that prospect theory with slow adjustment of reference points provides a plausible explanation for the reluctance of individuals to take a 'deal' and instead increase risk taking after both gains and losses (demonstrating both HM and BE effects). In fact, they find that prospect theory does a better job than expected utility theory of explaining the path-dependent pattern that they find in their sample. The expected utility model predicts 76% of the 'Deal or No Deal' decisions in their sample whereas prospect theory predicts 85%.

It is important to note that the majority of studies that attempt to link PT to DE use models with one risky and one risk-free asset. It is not difficult to argue that, this being so, these studies are not testing DE but are instead testing wealth effects. For example, in a world with one risky and one risk-free asset a decision to sell a stock after a gain could be the result of a change in risk preference (in this case an increase in risk aversion) with the investor shifting their wealth to the risk-free asset, this in turn could just as easily be interpreted a wealth effect rather than DE.

3.2.4.2 Path-dependent behavior and psychology

The two main psychological drivers argued to be (or empirically tested to be) behind DE are overconfidence (in its various manifestations) and regret (or, more broadly, the tendency to experience negative affect, which is known as negative affectivity). As for wealth effects, there is far less research, but we will review some recent work relating them to overconfidence and negative affectivity.

Overconfidence and DE

Logically, overconfidence (and self-deception in general) may lead to DE. For example, we spoke earlier about a possible relationship between DE and informed trading, whereby an investor might believe that a stock he owns that has risen in price should now be sold off as the market has discovered the investor's private information, whereas a stock that has fallen hasn't had the investor's private information incorporated into share price yet. Of course, being informed is not necessary: overconfidently believing oneself to be is sufficient to generate DE behavior. Along these lines, investors may want to avoid realizing losses so as to be able to turn a blind eye to indicators that signal low ability (Hirshleifer, 2001). Moreover, self-attribution bias may lead to DE because individuals with this bias will be reluctant to admit to themselves that they may have formed inaccurate beliefs, leading to a stubborn refusal to sell (Ben-David & Hirshleifer, 2012).

Related to overconfidence are an internal locus of control and confidence, and there is some evidence that these may be positively linked to DE. Chui (2001) experimentally finds that DE is stronger for traders with an internal locus of control versus an external locus of control. An internal locus of control means that individuals feel that outcomes are under their control, and as a result such investors demonstrate more commitment to their investment decision, whereas those with an external locus of control feel as though outcomes are beyond their control. Further, Kadous, Tayler, Thayer, and Young (2014) experimentally investigate confidence in investing ability and the propensity to hold losing stocks.[50] They find that individuals with high confidence in their own investment ability will hold losing stocks longer than those with low confidence. They suggest that the high confidence in their own ability results in a stronger commitment to their initial investment decision.

Research by Kumar (2009a) and Zuckerman (2009) relates stock-level overconfidence to stock-level DE. Specifically, Kumar shows that difficult-to-value stocks (i.e., young stocks with high idiosyncratic uncertainty and low turnover) are associated with *both* high DE and investor overconfidence (as proxied by Odean's (1999) post-trade sell-buy return differential). In Zuckerman, investor overconfidence is measured in a novel way using target price estimates from Yahoo!Finance postings, with investors being considered overconfident if they post target prices that are updated too little in reaction to underlying stock price movements (showing perhaps excessive confidence in their initial target prices). Stocks with many such overconfident investors tend to have high idiosyncratic volatility, high share turnover, a high market-to-book ratio and high beta, with the latter being considered "overconfidence characteristics." It turns out that

[50] Kadous, Tayler, Thayer, and Young (2014) also investigate self-regard, which can be defined as the overall evaluation of oneself. They find that Individuals low in self-regard are found experimentally to hold losing investments longer than those with high self-regard. They suggest that it may be that individuals with low self-regard may not have the emotional resources needed to protect their self-image from the potential fallout associated with recognizing losses.

portfolios of stocks with the highest loading on these overconfidence characteristics have an average PGR-PLR of 8.24, while those portfolios with low loadings have PGR-PLR of 4.48.

Negative affectivity and DE

While we all like to think that most of our decisions are made by the conscious rational component of our brain (sometimes called System 1), there is abundant evidence that the unconscious, often emotion-driven component of our thought processes (System 1) makes or influences important decisions.[51] Roiser, de Martino, Tan, Kumaran, Seymour, Wood, and Dolan (2009) suggest that increased connectivity between the control and affective brain regions (that is control over emotional reactions) results in weaker behavioral effects. In the case of DE, even if individuals know that it is rational to sell a stock at a loss, the emotional reaction to the loss may override the rational decision. Indeed, there is evidence that when people decide to stop holding on to losers there is increased activity in the control mechanisms of the brain (Campbell-Meiklejohn, Woolrich, Passingham, & Rogers, 2008).

The particular emotion most often pointed to in the case of DE is regret. Shefrin and Statman (1985) were the first to suggest regret as part of the solution

[51] See Kahneman, Daniel. 2011. *Thinking, Fast and Slow*. New York: Farrar, Straus and Giroux for many references.

to the DE puzzle. Selling a stock for a loss induces regret and therefore individuals may hold on to losing investments to avoid experiencing this emotion. By holding on to the loser stock they are also able to maintain the belief that perhaps the stock will bounce back. So, investors may postpone trades that trigger negative affect, instead opting to sell stocks that have made gains in order to induce positive affect.

Experimental papers by Weber and Camerer (1998) and Summers and Duxbury (2012) were designed to induce more (or less) regret in certain treatments.[52] As for the first, these researchers created a market condition where participants were forced to sell all of their stock holdings at the end of trading periods. While this condition forced investors to experience emotions related to realizing their gains/losses, it also created a clean slate for investors to consider a reinvestment strategy that would generate the most profits and positive emotions in the future. Indeed there was a reduced DE after such forced sales, suggesting the centrality of regret.

Summers and Duxbury (2012) created an experimental setting in which after a stock falls in value either regret or disappointment will be felt, with the stronger emotion, regret, being felt when personal responsibility for the purchase of the stock is borne and the weaker emotion, disappointment, being felt when

[52] Also see Fogel and Berry (2006) who use a survey and a series of experiments to document that DE is highly related to the reduction of anticipated regret, and that personal responsibility enhances regret.

personal responsibility is not present. In the realm of gains, personal responsibility leads to (stronger) rejoicing on a sale, while the absence of personal responsibility leads to (weaker) elation.[53] In order to test whether disappointment and elation are sufficient to drive DE, or if (stronger) regret and rejoicing are needed, Summers and Duxbury manipulate the emotions investors feel in different experimental scenarios by varying whether or not individuals actively choose stocks. They find no evidence of DE in settings where individuals do not choose the stocks, suggesting that regret and rejoicing are necessary emotions to produce DE.

Along these lines, Lehenkari (2012) links DE and anticipated regret using trading data in Finland. First providing evidence that DE exists in the Finnish market, she then goes on to show that stocks purchased by traders exhibit a more pronounced DE than those received via inheritance or gift. Consistent with Weber and Camerer (1998) and Summers and Duxbury (2012), the logical reason for this is that investors who are personally responsible for their initial investment decision are even more reluctant to face the regret of poor choices.

Some, such as Lehenkari (2012), favour the term "escalation of commitment." This is meant in the sense of doggedly sticking to your guns in the face of losing investments. In the case of DE, this entails holding on to losing

[53] Also see Mellers, Schwartz, Ho, and Ritov (1997). Landman (1987) experimentally shows that the emotions regret and rejoicing are stronger after action than after inaction.

stocks. On the other hand, in the case of BE, escalation of commitment would involve increasing risk taking in the face of losses. It has been argued that anticipated regret and escalation of commitment are closely related. Wong and Kwong (2007) provide experimental evidence that there are two dimensions to escalation of commitment. The retrospective responsibility dimension explains people's need to justify their initial decisions, while the prospective emotional dimension explains the influence of anticipated regret. Anticipated regret about withdrawal is expected to promote escalation behavior, which can be used as an explanation for individuals holding on to losing stocks.

The argument has been made that emotional reactions to decision outcomes are best characterized not by specific emotions (such as regret) but rather by broader measures of positive or negative affect (Connolly & Butler, 2006). This suggests that such broad measures might be more useful explanatory variables of DE behavior than mere regret.[54]

[54] Pointing towards a *negative* relationship between negative affectivity and escalation of commitment is Wong et al.(2006), who find that individuals who are low in NA tend to escalate more when they are held responsible for a prior decision than when they are not. Negative outcomes should induce stronger negative affect among those with high NA than those with low levels. Wong et al. find that NA induced by receiving negative, self-relevant feedback leads people to be more likely to withdraw from the current situation. When a prior personally responsible decision receives negative feedback, a person's negative affect increases the likelihood of adopting an avoidance-withdrawal strategy to cope with the negative situation (Miller et al., 1988 and Endler & Parker, 1990).

Overconfidence and wealth effects

To our knowledge there is no *direct* evidence linking overconfidence and wealth effects. However there is reason to believe that overconfidence may enhance the tendency to increase risk taking after gains (i.e., HM) due to a *combination* of self-attribution bias and a positive relationship between overconfidence and risk taking. Gervais and Odean (2001) argue that overconfidence increases subsequent to success (e.g., good investment returns) via self-attribution bias. Overconfidence has been related to increased risk taking through a greater willingness to gamble on fair bets (Campbell, Goodie, & Foster, 2004; Goodie, 2003). So we conjecture the following: wealth increases, cause an increase in overconfidence, which in turn induces greater risk taking.

Negative affectivity and wealth effects

Hytönen et al. (2014) provide the most direct evidence in this vein. Using neural data and an experimental design based on Post, Van den Assem, Baltussen and Thaler (2008), they both confirm the path dependence of risk preferences and investigate its neural basis. They conclude that increased risk taking after both gains (HM) and losses (BE) is related to increased activity of the affective brain processes and a decreased activity of deliberative brain processes. In other words, wealth changes trigger emotional responses which hamper a rational reaction leading to rising risk taking. Specifically, wealth increases induce positive affect which increases risk taking, and wealth decreases induce negative affect which *also* increases risk taking. This latter asymmetry may seem odd *prima facie*. Yet it is supported by research finding that negative affective states lead to increased risk taking (Andrade & Iyer, 2009; Demaree et al., 2012; Leith and Baumeister, 1996).

There are also studies that look at negative and positive affect and risk taking. It is important to note that while these studies provide insight into how affect may influence risk preferences, they do not directly link affect to wealth effects. Kuhnen and Knutson (2011), who utilized an experimental neuroeconomic setting where changes in emotional state were induced exogenously by exposing subjects to positive, negative or neutral images. While they conclude that positive emotional states such as excitement lead to increased risk taking and confidence in the evaluation of investment options, they also find that negative emotional states (such as anxiety) had the effect of *reducing* risk taking. Also on the contra side is what happens at the level of the market. There is evidence that in the aggregate positive and negative affect and mass mood impact markets. In particular, events apparently inducing positive affect lead to increased market value, while events apparently inducing negative affect lead to decreased market levels. For example, in terms of positive affect, sunshine is strongly and significantly positively correlated to stock returns (Hirschleifer & Shumway, 2003). In terms of negative affect, Kamstra, Kumar and Levi (2003) find that seasonal affective disorder (SAD), a form of depression has a negative effect on stock returns. Kaplanski and Levy (2010) find that aviation disasters are related to decreased market levels. This arguably occurs through the channel of a positive/negative affective state leading to higher/lower risk taking.

Finally, there is another force perhaps suggesting enhanced wealth effects (of either direction) through the mediation of affect. Roiser et al. (2009) suggest that increased connectivity between the control and affective brain regions (that is control over emotional reactions) results in weaker behavioral effects, and since individuals with higher NA and/or regret are more prone to emotional responses the emotional-driven component of their thought process may lead to bias. In other words, the tendency to experience and be influenced by affect (whether negative or positive) may contribute to bias. Perhaps running counter to this is Schwarz (1990; p. 527) who suggests that "…negative affective states foster the use of effortful, detail-oriented, analytical processing…" This implies that negative affect might be related to less bias in decision making.[55]

[55] A further complication comes from the suggestion that different negative emotions will induce different decision-making behavior. For example, Baillon, Koellinger and Treffers (2016) provide experimental evidence that sadness induces decisions that are closer to payoff-maximizing behavior, whereas decision-makers experiencing fear deviate more from profit-maximizing behavior.

3.3. Experimental Design

Six experimental sessions were run at McMaster University using a total of 100 undergraduate business students.[56] After a brief introduction to the session, the students were asked to fill out a questionnaire designed to elicit some psychological tendencies and basic demographic data.[57] After completion of the questionnaire, instructions for the trading session were handed out.[58] Students were given time to read through the instructions, after which a brief review and question-and-answer session was held to ensure full understanding. The questionnaire was followed by a trading session. Students were paid according to performance immediately upon completion of the experimental task. On average, these sessions took two hours. Payouts ranged from $23.00 to $50.00. What follows, is a description of the questionnaire and market set-up.

3.3.1. Questionnaire

3.3.1.1. Psychological measures

Negative emotion-based variables

Five questions were designed to intuit to what extent respondents were likely to allow negative emotions (such as regret) to influence their choices. In personality

[56] Sessions were run between December, 2010 and March 2012.
[57] The questionnaire is provided in Appendix 3.A. Multiple versions of the questionnaire provided in Appendix 3.A were given. The only difference between versions was the ordering of questions.
[58] These are provided in Appendix 3.B.

psychology, a five-factor model known as the "Big Five" has received much support (Larsen & Buss, 2008). One of the trait groupings is often termed "emotional stability," with adjectives such as calm, composed and poised characterizing one polar extreme, and anxious, excitable and nervous characterizing the other extreme. While all of us can be composed at times and at other times nervous, what makes this realm a trait is the tendency for people to vary in their *habitual* disposition in this realm. Those low on emotional stability are said to exhibit "neuroticism" (Norman, 1963) or "negative affectivity" (NA) (Watson & Clark, 1984). Mano (1994) has shown that those with a high level of NA have a higher willingness to buy insurance against large losses. We conjecture that a high level of NA may be associated with some of the biases analyzed in our study.

The NA instrument is derived from questions taken from the International Positive Affect-Negative Affectivity Schedule – Short Form (I-PANAS-SF), proposed by Thomson et al. (2007), and based on the PANAS instrument developed by Watson, Clark and Tellegen (1988).[59] We use the five questions from

[59] PANAS is the most commonly used instrument to measure positive affect (PA) and negative affect (NA) in academic research. PANAS was originally developed for North America and uses 20 items to measure PA and NA. One criticism of the measure has been that some of the items have been found to be redundant or have ambiguous meanings to English speakers from non-North American cultures. A shorter survey, the I-PANAS-SF, was developed to address this issue. It is comprised of two sets of 5 questions to measure PA and NA.

I-PANAS-SF designed to measure NA.[60] Each question is based on a 1-5 Likert scale, where a response of 1 indicates "never" and a response of 5 indicates "always". For example, one of the NA questions is, "Using a 5-point scale (where never = 1 and always = 5), thinking about yourself and how you normally feel, to what extent do you generally feel **upset**." *NA*, as a variable, is calculated as the average of these 5 questions.

Where NA is a broad measure of negative emotion, regret is a specific negative emotional state that involves blaming oneself for a bad outcome and includes feeling a sense of loss or sadness over action or inaction. For example, one might regret a bad investment decision and wish that they had made a different choice. One question is used to investigate the propensity to regret investment decisions. Based on a Likert scale (1-5), where 1 indicates "never" and 5 indicates "always," the question is as follows, "Thinking about past investments you have made, when a decision has not worked out well (even if you felt you made a careful decision using all the facts), how often did you experience **regret**? "[61]

[60] The five NA questions correspond to questions 1-5 in the questionnaire provided in Appendix 3.A.

[61] If a participant has never invested, they are asked to answer '0.' Of the subjects surveyed, 23 submitted a response of '0.' We use the mean of the other responses to the regret question to fill in these missing values to keep more observations when we conduct empirical analysis. Tests have also been conducted discarding the missing regret responses, instead of replacing the missing responses with the mean, and there is no significant impact on the results.

Overconfidence variables

Overconfidence, defined as an inflated sense of one's abilities, can influence financial decisions. There are various manifestations of overconfidence. We focus on two: miscalibration and the better-than-average effect.[62]

Miscalibration (*MIS*) is the extent to which one thinks their knowledge is more accurate than it really is. Ten questions were included as a series of calibration questions based on confidence intervals, designed to measure miscalibration. For example, individuals are asked to construct a 90% confidence interval by giving a lower bound and an upper bound response to trivia questions, with definite numerical answers, such that they are 90% sure the correct answer lies between the interval. For example, one of the questions is "what is the of the total number of medals that Greece won at the first Olympics in 1896?" The measure constructed for *MIS* is based on the responses to the 10 miscalibration questions.[63] The maximum possible value of 0.9 indicates high overconfidence. A properly calibrated individual will have a *MIS* value of 0. While underconfidence is possible, no one in the experiment falls into this category.

The second overconfidence variable is the better-than-average effect (*BTA*). An individual is deemed to be better-than-average when they overestimate their

[62] See review article by Glaser and Weber (2010).

[63] Each response for each individual is coded as a '1' if the correct answer to the question lies within the upper and lower bound provided; the response is coded as '0' otherwise. To calculate MIS the sum of the coded responses is divided by 10 and subtracted from 0.9.

own abilities relative to others. Two questions, the first involving self-perceived investing skill and the second involving self-perceived performance expectation were designed to ascertain to what extent subjects were characterized by *BTA*. For example, the first question asked: "If you had to guess, what percentage of participants in this session have better investing skills than you?" The response to each of the *BTA* questions ranged from 0-100. The measure constructed for *BTA* is 100 minus the average response to the two questions. A value greater than 50 indicates positive *BTA* (with higher values indicating a more pronounced effect). A value less than or equal to 50 indicates negative (or zero) BTA.

2.3.1.2. Demographics

The questionnaire included questions to collect basic demographic data including the variables: *Age, Sex, Courses,* and *Year*.[64] Given that we restricted our pool to undergraduate business students, only meaningful variability in *Sex* was anticipated (and this turned out to be true).

3.3.2. Market set-up

Our experiment consisted of twenty repetitions or periods of an investment task, conducted with a customized computer program written using Fischbacher (2007)

[64] *Year* and *Courses* are used to determine education. *Year* determines the participant's year in university. It is an indicator variable set to '1' if the student is a senior (4th year) and is '0' otherwise. *Courses* is the number of relevant courses (i.e., finance, economics, statistics, and probability) that the participant has completed or is currently enrolled in.

z-Tree (Zurich Toolbox for Readymade Economic Experiments) programming language. Recruited students could only trade securities with the experimenter at prices determined by random draws with known probability distributions, and not with each other.[65] The investment task was an individual choice with an initial decision, and two subsequent stages. The initial decision was a choice between two predetermined portfolios consisting of two types of shares and cash. After subjects made their choice, stock prices randomly increased or decreased.[66] At this juncture, subjects could rebalance their portfolio. After rebalancing, stock prices again changed randomly. In the final stage, subjects' ending portfolio values were recorded, and then the next period commenced. There was no carry-over of wealth from period to period. The sequence of events for a period is illustrated in Figure 3.1.

To provide more detail, at the beginning of each period, subjects were endowed with $2400 of experimental cash, half of which they were obligated to invest in either of two risky investment portfolios. The risky portfolios included two stocks named "GREEN" and "GOLD." The first portfolio consisted of eight GREEN shares and four GOLD shares, and the second portfolio consisted of four GREEN shares and eight GOLD shares. Both stocks were initially priced at $100

[65] Because there was no interaction among participants (i.e., they did not trade with each other), the number of students attending each session was irrelevant.
[66] Price change draws were operationalized by dice rolls (with rotating students used as monitors).

per share, so with either choice the subject would hold $1200 in cash balances, which earned no interest.

Both types of stocks could change in value in the two subsequent stages according to independent binomial distributions.[67] The price of each stock could either increase by 50% or decrease by 25% at each stage.[68] These values were chosen to isolate relative price changes and overall wealth changes, making it possible to separate the behavioral biases we study.

Notice that a subject's initial choice is irrelevant in terms of statistical properties of the portfolio. Since the distributions governing the prices of the GREEN and GOLD asset are the same, portfolio risk and return are the same. The only difference is labelling.[69]

Table 3.1 shows how a trader's wealth could change depending on whether one or both of his stocks rose or fell at t=1. From this point on we will speak in terms of the 8-stock and the 4-stock. The former is the stock (whether GREEN or

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[67] The price change path for each stock is illustrated in Figure 3.2. Please note that each trial is specifically a Bernoulli distribution, a special case of binomial distribution where a single trial is conducted. To be consistent with the literature in this area we will use the term binomial distribution throughout this chapter.

[68] Price changes were realized by the rolling of two dice, one for each type of stock. High die values (4, 5 and 6) signify a stock going up, and low die values (1, 2 and 3) signify a stock going down. These results were implemented manually by the experimenter, and inputted into the z-Tree program.

[69] We could have endowed each subject with a portfolio at t=0. We chose not to do so because of previously discussed evidence (Summers & Duxbury, 2012) that the disposition effect is likely to be stronger (and perhaps even requires) choice responsibility for the initial allocation.

GOLD) that the subject, in a given round, initially bought eight shares of. Analogously, the 4-stock is the stock (whether GREEN or GOLD) that the subject, in a given round, initially bought four shares of. There are four possibilities, which are named Cases A, B, C and D at t =1 (which are ranked from highest to lowest wealth).

Case A corresponds to the situation where both stocks rise in value, while Case D corresponds to the situation where both stocks fall. In both Case A and Case D there is a change in wealth but not a change in relative prices. Case C corresponds to the outcome where the 4-stock price has increased and the 8-stock price has decreased, but the magnitudes are such that there is no gain or loss in wealth relative to the initial portfolio endowment. Case B is less straightforward, as both relative prices and wealth are altered.

The reason for this particular design now becomes clear. Case A, which has witnessed no change in relative prices but a positive change in wealth allows for the investigation of HM (or negHM) behavior, while Case D, which has witnessed no change in relative prices but a negative change in wealth allows for the investigation of BE (or negBE) behavior. As for DE (or negDE) behavior, this can be investigated in Case C where relative prices have changed and wealth has not.

At Stage 1 (t=1), subjects were allowed to rebalance their portfolio. They could purchase or sell shares of either asset from the experimenter. Borrowing, short sales, and fractional share transactions were not allowed. After rebalancing, stock prices once again increased or decreased according to the binomial distribution as described earlier. Finally, a screen displayed prices, portfolio values and earnings for the period.

Appendix 3.B contains the instructions for the investment task. At the end of each session, one period was randomly assigned (using a 20-faced die) to be the payoff market. Subjects were paid in cash based on their earnings in the randomly selected period.

3.4. Inferring path-dependent behaviors

Before considering behavioral biases, we consider optimal behavior. Subjects' choices can be summarized by two portfolio weights. Let w_8, w_4 and w be the subjects' chosen percentages of wealth invested in the 8-stock, 4-stock and cash, respectively at t=1; and let v_8 and v_4 be the percentages of risky assets that the subject has chosen to invest in the 8-stock and the 4-stock assets.[70] Since both risky assets have the same expected return, a risk-averse subject should either invest entirely in cash, or diversify risk by selecting v_8 and v_4 to be 50%. The amount invested in cash, w, should depend on the subjects' degree of risk aversion.[71]

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[70] More specifically, $v_8 = w_8/(w_8+w_4)$ and $v_4 = 1- v_8$.

[71] A risk-loving subject would hold no cash, and invest entirely in either one of the stocks. A risk-neutral subject would hold also no cash, and be indifferent between any allocations of the two risky stocks.

3.4.1. Detecting the disposition effect (DE)

Detecting the disposition effect in our design requires some working assumptions. We cannot simply attribute changes in a subjects' portfolio to the disposition effect because the subject was constrained in choosing their initial position. The subjects had to initially choose $w_0 = 50\%$, $v_{0,8} = 67\%$ and $v_{0,4} = 33\%$.[72] After the first die rolls, the risky stocks change value, and subjects can change their portfolios. But the change may not reflect DE; it may simply be that the subject is adjusting their weights to values they would have originally chosen had they not been constrained. Although we can measure whether subjects' choices are sub-optimal, we cannot conclude with certainty whether they are due to DE behavior.

We consider two approaches to measuring DE, each based on a different assumption regarding what subjects would have chosen had they not been constrained. First, assume that subjects are risk-averse and would have chosen the optimal equal weights for both risky stocks ($v_{0p,8} = v_{0p,4} = 50\%$).[73] Under this assumption, DE can be detected in Case C. Since wealth is unchanged, and the 8-stock price has declined, $v_{8C} > 50\%$ (where the C subscript signifies Case C) would mean that the subject is overweighting the loser, consistent with DE behavior. Similarly $v_{8C} < 50\%$ would signify negDE behavior.

[72] Where the 0 subscript refers to the initially forced position at t=0.

[73] Where the subscript 0p indicates the *preferred* choice at t=0.

As an alternative assumption, assume that the allocation between the two risky assets is affected only by relative price changes, and the cash to stocks ratio is affected only by wealth changes. Under this assumption, the v_8 chosen by the subject in Case A should be the same as their choice in Case D, and this should also be the same as what the subject would have originally chosen, because the relative price in all three instances is the same. Under this assumption, $v_{8C} > v_{8D} = v_{8A}$ would point to DE behavior, and $v_{8C} < v_{8D} = v_{8A}$ would signify negDE behavior.

3.4.2. Detecting wealth effects

Wealth effects are potentially observed in the two pure wealth-change cases A and D. However, we cannot just look at the change in the amount of aggregate risky asset. The problem is the same as for the disposition effect. The change in w is non-informative since participants were forced to begin at 50%.

To measure wealth effects, we again assume that changes in relative prices affect only the mix of risky stocks, and changes in wealth affect only the fraction of cash chosen. The initial cash to stocks allocation if subjects were unconstrained would have been the same as the allocation in Case C, which features a relative price change and no wealth change. Comparing cash allocations in Case A, when wealth increases, to Case C is used to detect HM (and negHM). Comparing cash allocations in Case D, when wealth increases, to Case C can similarly detect BE (and negBE).

These comparisons, along with those discussed earlier for the disposition effect are summarized in Table 3.2. In section 3.5.2 we will use these comparisons to construct measures for both disposition and wealth effects.

3.5. Results

3.5.1. Psychometric and demographic data

Definitions and descriptive statistics for the psychometric and demographic variables based on the questionnaire are shown in Table 3.3. In terms of demographics, 60.6% of the sample is male. Given that our subjects are undergraduate business students, there is not much variation in *Age* and the education variables (*Courses* and *Year*). The average *Age* is 21, and 62% of the sample are in their 4th year (the remainder of subjects being in their 3rd year). The number of finance, economics, statistics and probability courses taken by subjects is between 5 and 20, the average of which is 10.5.

On average, subjects in our sample are overconfident. The measure used for *MIS* has a maximum possible value of 0.9, indicating high overconfidence, whereas a properly calibrated individual will have a value of zero. The average value for *MIS* in the sample is 0.69, indicating substantial overconfidence. The average sample score for *BTA* was 60.66. This is in line with abundant evidence in the literature concluding that most of the time most people are overconfident (e.g., Bhandari & Deaves, 2006; Lundeberg, Fox & Puncohar, 1994; Svenson, 1981).

Negative affectivity (*NA)* and *Regret* are both are based on a 1-5 Likert scale. *NA* ranged from 1 to 4.20 (with an average *NA* score of 2.30), and *Regret* ranged from 1 to 5 (with an average regret score of 2.54). Our sample contains at least some subjects who are either less emotionally balanced, more prone to regret, or both.

Table 3.3 also presents correlation coefficients for the psychometric and demographic variables. All significant correlations between psychological variables are positive. Thus, individuals who exhibit one bias are more likely to be subject to other biases. For example, *MIS* and *BTA* are both positively correlated with *NA*. This is consistent with Ifcher and Zarghamee (2014), who find that emotions associated with *NA*, such as sadness, have been shown to enhance a sense of personal control while diminishing careful thought processes.

As for *Sex*, once again expectations are fulfilled. First, *NA* is negatively correlated with being male. This is in line with past research, as women typically self-report more negative affectivity than men (Charupat et al., 2013; Fujita et al., 1991). Second, *BTA* is positively correlated with being male. Indeed, there is an abundance of evidence that supports men being generally more overconfident than women (e.g., Barber & Odean, 2001; Croson & Gneezy, 2009; Niederle & Vesterlund, 2007).

3.5.2. Measures of path-dependent behavior

Details of the constructed path-dependent behavior measures are available in Table 3.4. We consider several continuous disposition effect measures, based on the comparisons summarized in Table 3.2. The first, DE_{avg1}, is defined as $\bar{v}_{8c} - 0.5$ (the difference between the average of a subjects' portfolio weight for the 8-Stock over all instance of case C and 0.50). Positive values reflect DE behavior; negative values reflect negDE behavior. We also consider a second measure disposition measure, DE_{frq1} based on instances or frequencies, counting the proportion of instances in Case C where the subject chooses a portfolio weight for the 8-Stock greater than 0.5, with, again, higher values signifying more pronounced DE behavior. Both measures assume that subjects would have initially chosen equal weights in the risky assets ($v_{0,8} = v_{0,4} = 0.50$) had they been unconstrained.

We also consider a second set of analogous DE measures based on the assumption that the subject would have initially chosen the same v_8, as they later chose in situations where wealth changed but relative prices did not change. DE_{avg2} is the difference between the subjects' average portfolio weight in Case C and the same subjects average weight in Cases A and D.[74] Similarly, DE_{frq2} counts the proportion of instances in Case C where the subject chooses a portfolio weight for the 8-Stock greater than the average weight chosen in Cases A and D.

[74] $DE_{avg2} = \overline{v_{8C}} - \overline{v_{8AD}}$.

We use a similar method to assess path-dependent wealth behaviors. For the house money effect, HM_{avg} is the change in the average percentage of aggregate risky assets selected in Case A minus the average percentage held in Case C.[75] HM_{frq} is the fraction of Case A observations where the subjects weight for risky assets is greater than the average weight of risky assets held in C. Finally, we construct BE_{avg} and BE_{frq} to assess the breakeven effect. These measures are identical to the HM measures, except Case A is replaced with Case D.

Table 3.4, shows the correlation matrix for our path-dependent measures. All the 'avg' and 'freq' disposition measures are strongly positively correlated.[76] Our subjects do display path-dependent behaviors. Table 3.5 displays frequencies using both the 'avg' and the 'freq' approaches. In both cases, we can conclude that DE is more common than negDE (with DE occurring 61.1-64.5% of the time), and these differences are strongly statistically significant. HM and BE are also more

[75] $HM_{avg} = \overline{w_A} - \overline{w_c}$.

[76] Although we cannot directly test the different assumptions used to justify our DE measures, we can do some indirect tests. If a subject would have initially chosen a portfolio with $v_{0,8}$ equal to 50%, then the subject should still choose v_8 equal to 50% when faced with a portfolio decision with unchanged relative prices, but similar wealth, that is v_{8A} and v_{8D} should also be equal to 50%. We can also test the separability assumption. If v_8 only depends on relative prices, and is invariant to wealth changes, then v_{8A} should be equal to v_{8D}. Both of these indirect predictions are not borne out.[76] A t-test with the null hypothesis that the average v_8 in Case A is equal to 0.5 rejects the null ($p < 0.001$). The corresponding test for Case D also rejects the null ($p < 0.001$). To examine separability, we conduct a paired t-test with the null that the subject's average v_8 in Case A equals the average v_8 in Case D. Again, we reject the null ($p = 0.03$). The results of these tests will be examined further in a paper based on the work accomplished in this chapter, 'Path-dependent financial behaviors and investor characteristics: and experimental analysis.'

common than negHM and negBE in a statistically significant sense, but we can conclude this only using the 'freq' approach. In sum, we can strongly conclude that in our data DE is modal, and more weakly conclude that HM and BE are modal.

There are special cases for which DE or wealth effect variables cannot be determined. DE_{avg} could not be determined for one individual in the sample who always held all cash in Case C resulting in v_{8C} as undefined. HM_{avg} cannot be determined for an individual if they always hold all cash in Case C and Case A, or if they always hold all stock in Case C and Case A. Further, it is not possible to determine BE_{avg} for an individual who always holds all cash in Case C and Case D, or if always hold all stocks in Case C and Case D. Each of these scenarios represents a boundary situation in which we are uncertain as to whether an individual has no change in risk preference, or if they would prefer to change their risk preference but are limited by the boundary. There are 20 individuals that labelled as not measured for HM_{avg}, and there are 13 individuals that are labelled as not measured for BE_{avg}.

Are people who are prone to one behavior also more prone to another? Table 3.4 presents correlations among the path-dependent behaviors. Positively correlated behaviors may have common psychological drivers. Notably, DE is positively correlated with BE. Individuals demonstrating DE behavior refuse to throw in the towel and stubbornly hold on to losers. On the other hand, individuals demonstrating BE behavior increase risk taking. Each of these behaviors can be seen as forms of escalation of commitment (Lehenkari, 2012; Staw, 1976; Weber & Zuchel, 2005; Wong & Kwong, 2007), and so it might be the case that they share the same psychological driver. Arguably, this common driver is the fear of regret that will be experienced if (*ex post*) bad investments are sold. This is consistent with the previous discussion arguing that the greater tendency to experience negative emotions might be positively associated with DE and BE.

We also report that DE is negatively correlated with HM, and BE is negatively correlated with HM. We have no compelling reasons for these tendencies. That said, the former aligns with Duxbury et al. (2015), who argue that this negative relationship is beneficial in that one bias serves to ameliorate the other.[77] As for the latter, Post et al. (2008) document increased risk taking after both gains and losses, which might seem to point to a positive relationship between HM and BE, but it is important to note that in Post et al. BE and HM were documented for *different* individuals, unlike in our experiment where we are able to look at evidence of HM and BE for the *same* individual.

[77] It should be noted however that Duxbury *at al* (2015) appears to be using the terms HM and DE as opposites (with the former implying risk seeking and the latter risk avoidance). Also see Duxbury et al. (2013), Massa and Simonov (2005) and Frino *et al* (2008) for this interpretation.

3.5.3. Psychometric and demographic variables and path-dependence

We now explore the potential impact of the psychometric and demographic variables collected at the start of sessions on the various path-dependent behaviors. Table 3.7 presents the relevant regressions. Note that we conduct regressions using sign-based path-dependent behavior subsamples. For example, we split the DE sample into those subject to DE (DE>0) and those subject to negDE (DE<0). This is because an increase in DE in negative territory implies bias reduction, while an increase in DE in positive territory implies bias worsening.[78] To preview, our results, while mostly lining up with expectations, are somewhat weak. We begin by detailing our expectations (as suggested by our previous literature review), and then turn to the results. In our discussion we focus on the positive behaviors (DE, HM and BE) rather than their negative counterparts, primarily because predictions of impacts are more sharply delineated based on antecedent research.

3.5.3.1. Expectations

In this section, we set out our expectations with respect to the impact of our psychological and demographic measures on path-dependent behaviors. Table 3.6 provides a summary of predictions. Beginning with variants of overconfidence

[78] As an example of how this matters, we see in Table 3.7 that males are more subject to both DE and negDE (i.e., bias in this area in general). In regressions run for the full sample (i.e., without such sign-based subsamples), available in Table 3.8, we find this tendency disappears.

(*MIS* and *BTA*), consistent with our previous discussion of the literature, a positive relationship between overconfidence and DE is anticipated (e.g., Kumar, 2009). As for overconfidence and wealth effects, rather more tentatively, we conjecture that overconfidence will positively impact HM (but not necessarily BE). Overconfidence has been related to increased risk taking through a greater willingness to gamble on fair bets (Campbell, Goodie & Foster, 2004; Goodie, 2003). Gervais & Odean (2001) argue that overconfidence increases subsequent to success (e.g., good investment returns) via self-attribution bias. So the mechanism is conjectured to be as follows: wealth increases, causing an increase in overconfidence, which in turn induces greater risk taking. Given that both of our overconfidence metrics are subject to measurement error and further that there is abundant evidence that males are more overconfident than females (e.g., Acker & Duck, 2008; Barber & Odean, 2001), it is not inappropriate to view *Sex* as a "mopping up" proxy for overconfidence. On this basis it is logical to expect a positive relationship between *Sex* and both DE and HM.[79]

We next turn to the expected impact of negative emotions (i.e., as measured

[79] The evidence on direct effects is mixed. Da Costa Jr. *et al* (2008) find evidence of DE for males but not for females, primarily because the females in their experiment did not tend to hold on to their losing stocks. On the other hand, Rau (2014) finds that women have a significantly higher DE than men. As for wealth effects, Lam and Ozorio (2013) find that males are susceptible to HM in a casino setting. Note that while men take on more risk than women (e.g., Booth & Nolen, 2012; Holt & Laury, 2002; Kumar, 2009b; Sutter & Rutzler, 2010), this is not the same as their being more susceptible to wealth effects, as these entail a positive relationship between risk taking and wealth changes.

by *NA* and *Regret*).[80] Beginning with DE, as mentioned previously, prior work has linked regret and DE (e.g., Summers & Duxbury, 2012). It was also argued that emotional reactions to decision outcomes may be better characterized by more far-reaching measures of affect (Connolly & Butler, 2006), implying that NA supplements regret.[81] This point aside, since *Regret* is measured in our experiment based on a single question (for which 23 responses were not applicable), given likely measurement error, it would not be surprising if some of the tendency to experience regret is picked up by NA. As for negative emotions and wealth effects, recall that the neural evidence of Hytönen et al. (2014) pointed in the direction of a positive relationship between wealth changes of either sign and negative emotions.

Finally, aside from *Sex*, our demographic variables (*Age, Year* and *Courses*) are all likely to be markers of sophistication, and previous research suggests that such markers may lead to lower levels of bias of all kinds (e.g., Dhar & Zhu, 2006; Feng & Seasholes, 2005; Shapira & Venezia, 2001).

[80] Not only are men more overconfident than females, they are also less subject to negative affect (Charupat et al., 2013). On balance, however, given the preponderance of evidence on gender differences in overconfidence, we expect the impact of overconfidence to dominate, implying that males will be more subject to both DE and HM.

[81] Also note that negative affect may lead to reduced cognitive ability, leaving individuals more susceptible to behavioral biases. For example, one component of NA, the emotion anger, has been shown to reduce the motivation to process new information carefully which can lead to a bias in decision-making (Inbar & Gilovich, 2011).

3.5.3.2. Regression Analysis

We conduct regressions based on subsamples of subjects that demonstrate positive behaviors (DE, HM or BE) and those that demonstrate negative behaviors (negDE, negHM, negBE).[82] It is appropriate to use such sign-based subsamples for these regressions since potential variables impacting positive behaviors will not necessarily have the same impact on negative behaviors (negDE, negHM, negBE).[83]

Table 3.7 presents linear regressions with the path-dependent behaviors as dependent variables and *NA*, *BTA*, *Regret*, *MIS*, *Age*, *Year*, *Sex* and *Courses* as explanatory variables. Definitions for the psychometric and survey variables are in Panel A of Table 3.3.[84] Turning to Panel A of Table 3.7, which provides regressions where positive path-dependent behaviors (DE, HM and BE) are the dependent variables, wherever there are indications of impact, these always conform to the expectations outlined previously. DE is positively influenced by overconfidence (with *Sex* being significant at 10% in the frequency regression). DE is also positively related to negative emotions (with *NA* being significant at 10% in

[82] White's test for heteroscedasticity was run for each regression. Failing to reject the null hypothesis of homoscedasticity, we use heteroscedasticity-consistent standard errors whenever heteroscedasticity cannot be rejected. In all cases there is no evidence of multicollinearity.
[83] It is important to note that regressions were also run using all path-dependent variables as measured as well as for the absolute values of path-dependent variables, the results are available in Table 3.8 and Table 3.9 respectively.
[84] Note that ln(*Age*) is used in place of *Age* in the regression analysis because age is positively skewed.

the average regression). Also as predicted, HM is positively related to overconfidence (with *MIS* being significant at 10% in the average regression, and *Sex* being significant at 5% in the frequency regression) and negative emotions (with *Regret* being significant at 10% in the frequency regression). Further, we find that *Courses* (suggesting sophistication) is negatively related to HM (at 5% significance in the frequency regression). Finally, though we had no clear prior, BE is positively impacted by overconfidence (with *BTA* being significant at 10% in the frequency regression).

In sum, many variables have insignificant coefficients or their significance levels are low, so all conclusions must be tentative. Indeed, our expectations were only sometimes realized, see Table 3.6 for a summary of our expectations and our realizations. In considering the effect of overconfidence (*MIS* and *BTA*), negative affect (*NA* and *Regret*), *Sex* and sophistication (*Courses, Age, Year)* on DE, HM and BE, we formed expectations in 10 out of 12 cases. In 7 out of these 10 cases our expectations were realized.

Expectations are much more ambiguous in the case of the three negative path-dependent behaviors, so for this reason we will be briefer. We focus on cases where strong (1%) statistical significance is detected. For negDE, *Year* has a negative impact (which is logical as sophistication should reduce bias) and *Sex* has a positive impact (suggesting more bias of this type for males). For negHM, *NA* has negative influence (suggesting perhaps logically that mood maintenance is not a strong tendency for those low on emotional stability) while *Sex* too has a negative impact (suggesting that males are less prone to mood maintenance). And, finally, *Regret* positively impacts negBE (suggesting, logically, that those most prone to regret – as well as its anticipation – are wary about putting themselves in an exposed position).

3.6. Conclusion

Our experimental design presents subjects with a simplified portfolio choice task featuring two risky assets and cash The design allows potential observation of several path-dependent biases, in which subjects' subsequent portfolio choices might be affected by recent asset performance. The experimental assets are designed such that there is a high likelihood of observing both cases where relative prices change but wealth remains constant, and cases where wealth changes but relative prices are unchanged, permitting us to disentangle the path-dependent behaviors.

The majority of our subjects exhibit path-dependent biases and given our design, we are able to investigate in an unambiguous comprehensive fashion whether the tendency of an individual to exhibit a particular behavior makes it more or less likely that they will exhibit another behavior. To our knowledge this is an innovation and we do find correlations among the biases. Subjects prone to the disposition effect are more likely to also be prone to the breakeven effect, and less likely to display the house money effect. We also find that the house money effect is negatively correlated with the breakeven effect. These correlations hint at the possibility that common psychological factors may drive all the path-dependent behaviors.

While we do not include treatments to manipulate psychological variables, we do measure overconfidence, regret and negative affect using questionnaire instruments. Though this exercise can only be viewed as exploratory several patterns do emerge. Broadly speaking, though precise mechanisms remain murky, the existence of psychological bias (overconfidence and negative affect) leads to more bias in financial decision-making. Further, consistent with expectations, overconfidence (impacting DE) and negative affect (impacting HM) appear to contribute to the existence of DE and wealth effects.

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Tables

Table 3.1
Portfolios at Stage 1

After the initial portfolio choice, stock prices can either increase to $150, or decrease to $75. Four outcomes, labelled Cases A through D, are possible. Each subject holds 8 shares of 1 stock and 4 shares of the other. Relative Price, the ratio of the 8-Stock price to the 4-Stock price, is shown for each Case. 8-Stock Value, and 4-Stock Value are the possible values of the subjects' holdings of each stock, Cash is the cash balance, and Total Wealth shows the possible wealth levels at Stage 1.

Case	8-Stock Price	4-Stock Price	Relative Price	8-Stock Value	4-Stock Value	Cash	Total Wealth
A	150	150	1	1200	600	1200	3000
B	150	75	2	1200	300	1200	2700
C	75	150	1/2	600	600	1200	2400
D	75	75	1	600	300	1200	2100

Table 3.2
Detecting Path-dependent Behaviors

Since subjects' initial portfolio allocations are constrained, measuring the disposition effect requires an assumption about what the subject would have chosen if unconstrained. Two assumptions are considered. The first assumption is that the subject would have chosen an optimally diversified initial portfolio. The second assumption is that the subjects' initial mix of risky stocks would be the same as the mix we observe with unchanged relative prices of risky stocks, but altered wealth; and that the initial mix of cash and aggregate risky assets would be the same as the mix we observe with unchanged wealth, but altered relative prices. The mix of risky stocks is denoted by v_8, with the additional letter subscript for cases A, B, C and D. The proportion of risky assets to aggregate wealth is w, with additional letter subscripts as above. The relation between the portfolio weights in the cases as specified is used to detect the specified path-dependent effects.

	Assumption I: Optimal initial portfolio.	Assumption II: Wealth effects and relative price effects are separable.
Disposition (DE)	$v_{8C} > 0.50$	$v_{8C} > v_{8D} = v_{8A}$
Negative Disposition (negDE)	$v_{8C} < 0.50$	$v_{8C} < v_{8D} = v_{8A}$
House Money (HM)	-	$w_A > w_C$
Negative House Money (negHM)	-	$w_A < w_C$
Breakeven (BE)	-	$w_D > w_C$
Negative Breakeven (negBE)	-	$w_D < w_C$

Table 3.3
Psychometric and demographic data

Panel A is a key describing the survey measures computed from subject responses collected in the initial questionnaire. Panel B displays the mean, standard deviation, sample size, minimum value, and maximum value for each of the survey measures. Panel C displays Pearson correlations between the survey measures.

Panel A: Survey Measures

Negative affectivity (NA)	The average response to our subset of survey questions from I-PANAS-SF. The response to each question is based on a 1-5 Likert scale. A higher value indicates less emotional balance.
Better-than-average (BTA)	BTA was calculated as 100 minus the average of the responses to the following two questions: "What percentage of participants in this session have better investing skills than you?" and "What percentage of participants in this session will end up making more money than you?" A value greater than 50 signifies the better-than-average effect, with a higher value indicating a higher effect. A value less than or equal to 50 indicates no effect.
Regret	Average response to the question: "Once again using a 5-point scale (where never = 1 and always = 5), thinking about past investments you have made, when a decision has not worked out well (even if you felt you made a careful decision using all the facts), how often did you experience regret?"
Miscalibration (MIS)	Subjects provide ten percent confidence intervals to ten trivia questions. MIS is 0.9 minus the percentage where the correct answer falls in the interval. The maximum value of 0.9 indicates high overconfidence; a properly calibrated individual will have a value of 0. While underconfidence is possible, no one in the experiment falls into this category.
Year	Senior year indicator variable set to 1 if the respondent is a senior (4th year in undergraduate program, set to zero otherwise.
Age	Respondent age (in years).
Sex	Indicator variable set to 1 if the respondent is a male, set to 0 otherwise.
Courses	Number of relevant courses (i.e. finance, economics, statistics and probability) that the respondent has completed or is currently enrolled in.

Panel B: Descriptive Statistics

	Mean	Standard Deviation	Sample Size	Minimum	Maximum
NA	2.3020	0.6270	100	1.00	4.20
BTA	60.6575	20.9598	100	10.00	100.00
Regret	2.5404	0.9555	100	1.00	5.00
MIS	0.6947	0.1636	97	0.10	0.90
Year	0.6224	0.4873	98	0.00	1.00
Age	21.3535	2.1961	99	20.00	41.00
Sex	0.6061	0.4911	99	0.00	1.00
Courses	10.4646	2.9814	99	5.00	20.00

Sample size is less than 100 for some items, as a few subjects did not answer all of the questions on the survey.

Panel C: Pearson Correlations

	NA	BTA	Regret	MIS	Year	Age	Sex	Courses
NA	+1.00							
BTA	+0.45**	+1.00						
Regret	+0.26**	-0.01	+1.00					
MIS	+0.22*	-0.07	+0.02	+1.00				
Year	-0.06	-0.11	-0.00	+0.02	+1.00			
Age	-0.16	-0.16	+0.04	-0.22*	+0.28**	+1.00		
Sex	-0.31*	+0.47**	-0.08	-0.03	-0.06	-0.13	+1.00	
Courses	+0.16	+0.15	+0.04	+0.09	+0.23*	-0.07	+0.00	+1.00

One or two asterisks signify that the null hypothesis of zero correlation can be rejected at 5%, or 1% significance levels, respectively.

Table 3.4
Path-dependent Measures

Panel A is a key describing the measures constructed to detect path-dependent behaviors. Panel B reports the correlations among the measures.

Panel A: Path-dependent Measures

DE_{avg1}	$\overline{v_{8C}} - 0.5$	Average difference between the subjects' portfolio weight for the 8-Stock and 0.50, under Case C. Positive values indicate the disposition effect (DE). Negative values indicate the anti-disposition effect (negDE).
DE_{freq1}	$\sum_{Case\ C} \delta_C$	Fraction of observations where the portfolio weight for the 8-Stock is greater than 0.50, under Case C. Positive values indicate the disposition effect (DE). Negative values indicate the anti-disposition effect (negDE). n_c is the number of Case C observations, and $\delta_C = \begin{cases} \frac{1}{n_c}, & if\ v_8 > 0.5 \\ \frac{-1}{n_c}, & if\ v_8 < 0.5 \\ 0, & otherwise. \end{cases}$
DE_{avg2}	$\overline{v_{8C}} - \overline{v_{8AD}}$	Average difference between the subjects' portfolio weight for the 8-Stock Case C and the corresponding average over Cases A and D. Positive values indicate the disposition effect (DE). Negative values indicate the anti-disposition effect (negDE).
DE_{freq2}	$\sum_{Case\ C} \delta_{AD}$	Fraction of observations in Case C where the portfolio weight for the 8-Stock is greater than the average over Cases A and D. Positive values indicate the disposition effect (DE). Negative values indicate the anti-disposition effect (negDE). n_c is the number of Case C observations, and $\delta_{AD} = \begin{cases} \frac{1}{n_c}, & if\ v_8 > \overline{v_{8AD}} \\ \frac{-1}{n_c}, & if\ v_8 < \overline{v_{8AD}} \\ 0, & otherwise. \end{cases}$
HM_{avg}	$\overline{w_A} - \overline{w_C}$	Average difference between the subjects' fraction of risky assets and between Cases A and C. Positive values indicate the house money effect. Negative values indicate the mood maintenance effect.
HM_{freq}	$\sum_{Case\ A} \delta_A$	Fraction of observations in Case A where the subjects weight for risky assets is higher than the average in Case C. Positive values indicate the house money effect (HM). Negative values indicate the mood maintenance effect (negHM). n_A is the number of Case A observations, and $\delta_A = \begin{cases} \frac{1}{n_A}, & if\ w_A > \overline{w_C} \\ \frac{-1}{n_A}, & if\ w_A < \overline{w_C} \\ 0, & otherwise. \end{cases}$
BE_{avg}	$\overline{w_D} - \overline{w_C}$	Average difference between the subjects' fraction of risky assets and between Cases D and C. Positive values indicate the breakeven effect. Negative values indicate the snake-bit effect.
BE_{freq}	$\sum_{Case\ D} \delta_D$	Fraction of observations in Case D where the subjects weight for risky assets is higher than the average in Case C. Positive values indicate the breakeven effect (BE). Negative values indicate the snake-bit effect (negBE). n_D is the number of Case D observations, and $\delta_D = \begin{cases} \frac{1}{n_D}, & if\ w_D > \overline{w_C} \\ \frac{-1}{n_D}, & if\ w_D < \overline{w_C} \\ 0, & otherwise. \end{cases}$

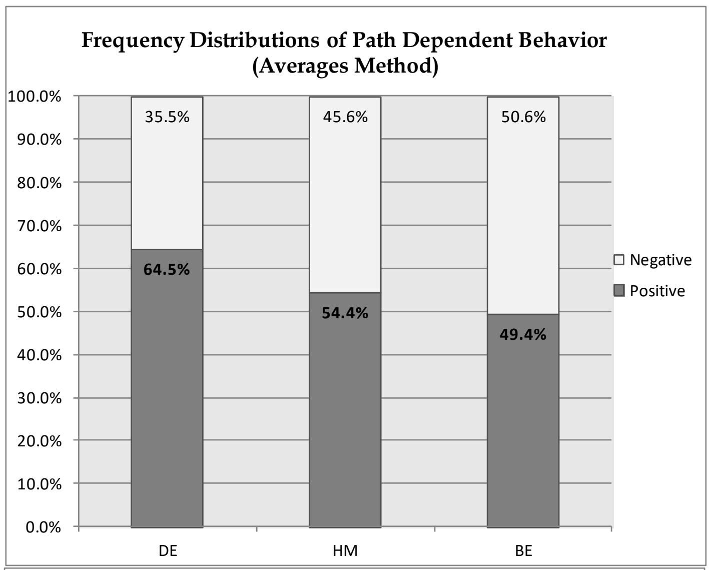
Panel B: Pearson Correlations

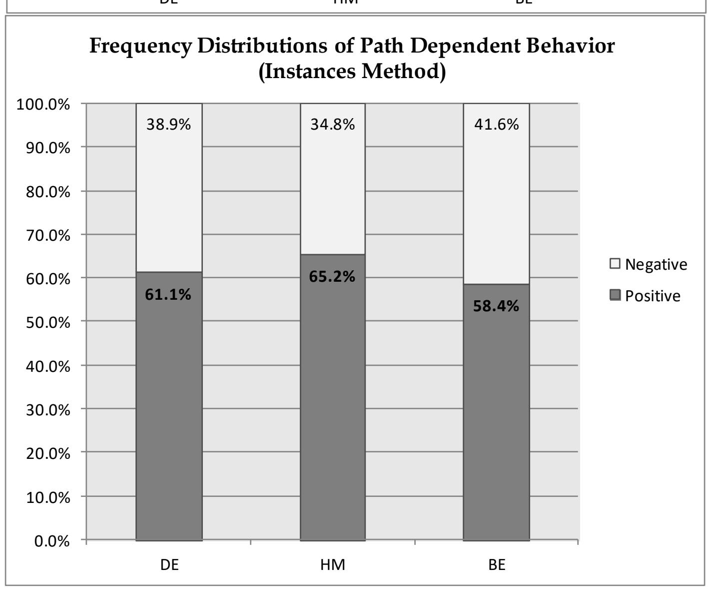
	DE_{avg1}	DE_{freq1}	DE_{avg2}	DE_{freq2}	HM_{avg}	HM_{freq}	BE_{avg}	BE_{freq}
DE_{avg1}	+1.00							
DE_{freq1}	+0.94**	+1.00						
DE_{avg2}	+0.88**	+0.80**	+1.00					
DE_{freq2}	+0.80**	+0.82**	+0.80**	+1.00				
HM_{avg}	-0.41**	-0.44**	-0.42**	-0.36**	+1.00			
HM_{freq}	-0.34**	-0.38**	-0.41**	-0.34**	+0.79**	+1.00		
BE_{avg}	+0.39**	+0.44**	+0.34**	+0.35**	-0.11	-0.30**	+1.00	
BE_{freq}	+0.39**	+0.43**	+0.34**	+0.40**	-0.37**	-0.38**	+0.72**	+1.00

One or two asterisks signify that the null hypothesis of zero correlation can be rejected at 5%, or 1% significance levels, respectively.

Table 3.5
Frequencies of Path-dependent Behaviors

Panel A: Frequency Distributions
The values in the table are the percentage of subjects, excluding no effect or not measured, in each category. No effect means that the path-dependent measure is equal to zero. Not measured means that the behavior could not be observed. For DE, this signifies that the subjects held only cash in Case C, so v_8 is undefined. For HM, subjects that hold no cash in Case C cannot decrease cash if wealth rises. Similarly, for BE, subjects that hold all cash in Case C cannot decrease cash if wealth falls.





Panel B: Binomial Test

A binomial test was run to check whether the proportion of positive DE, HM and BE observations is statistically different from the proportion of negative DE, HM and BE respectively.

Path-dependent Effect	Average Method		Frequency Method	
	Binomial test p-value	Significant difference	Binomial test p-value	Significant difference
DE	<0.0001	***	<0.0001	***
HM	0.1440	-	<0.0001	***
BE	0.9151	-	0.0042	***

Panel C: Frequency Distributions Including All Subjects

Each path-dependent behavior is categorized as follows. DE_{avg1} can range from -0.5 to +0.5, and both BE_{avg} and HM_{avg} can range between -1 and +1. We arbitrarily choose cut points of 10% of the possible range to classify the behavior as either strong or marginal. So, for example, subjects whose DE is greater than 0 but less than or equal to +0.5 are classified as "marginal disposition effect." The values in the table are the number of subjects, out of 100 total, in each category. Not measured means that the behavior could not be observed. For DE, this signifies that the subjects held only cash in Case C, so v_8 is undefined. For HM, subjects that hold no cash in Case C cannot decrease cash if wealth rises. Similarly, for BE, subjects that hold all cash in Case C cannot decrease cash if wealth falls.

Path-dependent Behavior					
negDE -0.5≤DE<-0.05	Marginal negDE -0.05≤DE<0	No Effect DE=0	Marginal DE 0<DE≤+0.05	DE 0<DE≤+0.5	Not Measured
29	4	6	6	54	1
Mood Maintenance -1≤HM<-0.1	Marginal Mood Maintenance -0.1≤HM<0	No Effect HM=0	Marginal House Money 0<HM≤+0.1	House Money 0.1<HM≤+1	Not Measured
8	28	1	12	31	20
Snake Bit -1≤BE<-0.1	Marginal Snake Bit -0.1≤BE<0	No Effect BE=0	Marginal Breakeven 0<BE≤+0.1	Breakeven 0.1<BE≤+1	Not Measured
23	21	0	21	22	13

Table 3.6
Predictions of the Relationships Between Psychometric and Demographic Variables and Path-dependent Behaviors.

This table details our expectations with respect to the impact of our psychological and demographic measure on path-dependent behaviors. Below each prediction (in brackets) is the actual result from linear regressions conducted with path-dependent behaviors as dependent variables and *NA, BTA, Regret, MIS, Age, Year, Sex* and *Courses* as explanatory variables. More detailed regression results are available in Table 3.7 and Table 3.8.

	Disposition Effect DE	House Money HM	Breakeven BE
Overconfidence			
BTA	+	+	?
MIS	(insignificant)	(+ for *MIS*)	(+ for *BTA*)
Negative Emotion			
NA	+	+	+
Regret	(+ for *NA*)	(+ *Regret*)	(insignificant)
***Sex* (Male = 1)**	+	+	?
	(+)	(+)	(insignificant)
Sophistication			
Year (Senior = 1)	–	–	–
Courses	(insignificant)	(- for *Courses*)	(insignificant)
Age			

Table 3.7
Path-dependent Behaviors and Psychometric and Demographic Variables

Panel A: Positive Domain
Linear regression estimates for dependent variables corresponding to the each of the positive path-dependent behaviors, measured using the average and frequency methods, are shown below. Only subjects who display the behavior comprise the sample for each regression. Abbreviated explanatory variables include negative affect (NA), better-than-average (BTA) and miscalibration (MIS). t-Statistics are displayed under the coefficient estimates. One, two, or three asterisks denote estimates are significantly different from zero at the 10, 5 and 1 percent levels, respectively.

Dependent Variable	Const.	NA	Regret	BTA	MIS	Sex	EDUC	Year	LN(Age)	Adj R^2	N
Disposition (DE_{avg1})	-0.079	.062	-0.007	0.001	0.080	0.060	-0.007	0.045	0.152	0.003	56
	.15	1.82*	.36	1.11	0.72	1.51	1.15	1.33	0.11		
Disposition (DE_{frq1})	0.536	.072	0.037	-0.002	0.227	0.156	-0.017	0.005	-0.037	-0.003	52
	.49	.86	.71	.75	.93	1.74*	-1.10	.06	-0.13		
House Money (HM_{avg})	-0.486	0.006	0.025	-.000	0.006	0.050	0.002	0.051	0.082	-0.084	41
	.64	.14	1.15	.06	1.76*	0.74	0.36	1.00	0.44		
House Money (HM_{frq})	1.335	0.003	0.090	-0.002	-0.234	0.180	-0.030	0.119	-0.101	0.064	41
	.98	.03	2.00*	.93	-1.00	2.52**	-2.36**	1.37	0.29		
Breakeven (BE_{avg})	-0.301	-0.041	0.025	-0.001	0.137	0.002	-0.007	0.002	0.156	-0.121	43
	.18	1.09	1.28	.63	.97	.04	1.29	.11	.27		
Breakeven (BE_{frq})	-1.295	0.037	0.009	0.004	0.116	-0.076	-0.005	-0.081	0.584	-0.123	44
	.33	.42	.21	1.83*	.42	.83	.28	.72	.43		

Panel B: Negative Domain

Linear regression estimates for dependent variables corresponding to the each of the negative path-dependent behaviors, measured using the average and frequency methods, are shown below. Only subjects who display the behavior comprise the sample for each regression. Abbreviated explanatory variables include negative affect (NA), better-than-average (BTA) and miscalibration (MIS). t-Statistics are displayed under the coefficient estimates. One, two, or three asterisks denote estimates are significantly different from zero at the 10, 5 and 1 percent levels, respectively.

Dependent Variable	Const.	NA	Regret	BTA	MIS	Sex	EDUC	Year	LN(Age)	Adj R^2	N
Anti-Disposition ($NegDE_{avg1}$)	-2.450	-0.038	0.002	-0.002	-0.320	**0.165**	**0.018**	-0.192	0.968	0.227	32
	.87	.64	.10	1.15	1.65	**2.91*** **	**2.07** **	1.82	0.97		
Anti-Disposition ($NegDE_{frq1}$)	-7.786	-0.087	0.009	-0.004	-0.688	**0.247**	**0.035**	**-0.500**	2.964	0.271	34
	1.40	.82	0.250	1.25	1.66	**2.49** **	**2.03***	**3.18*** **	1.53		
Mood Maintenance ($NegHM_{avg}$)	-2.760	**-0.127**	0.018	-0.001	0.144	0.040	-0.008	-0.093	1.102	0.012	35
	1.23	**2.87*** **	.58	.86	.69	.72	1.57	1.61	1.57		
Mood Maintenance ($NegHM_{frq}$)	**-11.674**	-0.152	0.053	0.003	0.500	**-0.415**	-0.002	**-0.456**	**4.09**	0.009	23
	1.94*	1.14	1.01	.70	.81	**3.41*** **	0.08	**2.14***	**2.02***		
Snake Bit ($NegBE_{avg}$)	0.503	-0.041	**0.056**	**-0.005**	0.002	**0.154**	0.006	-0.051	-0.075	0.104	39
	.78	.86	**3.24*** **	**2.36** **	.01	**2.33** **	.89	.88	.43		
Snake Bit ($NegBE_{frq}$)	0.644	0.098	-0.014	-0.000	-0.110	**-0.262**	-0.029	0.136	0.110	0.110	29
	.39	1.06	.26	.02	.32	**2.33** **	1.71	1.13	.28		

Table 3.8
Path-dependent Behaviors and Psychometric and Demographic Variables - All Path-Dependent Variables

Linear regression estimates for dependent variables corresponding to the each of the path-dependent behaviors, measured using the average and frequency methods, are shown below. Subjects who display positive, negative or no behavior comprise the sample for each regression. Subjects for whom the path-dependent behavior could not be observed (not measured) are excluded. Abbreviated explanatory variables include negative affect (NA), better-than-average (BTA) and miscalibration (MIS). t-Statistics are displayed under the coefficient estimates. One, two, or three asterisks denote estimates are significantly different from zero at the 10, 5 and 1 percent levels, respectively.

Dependent Variable	Const.	NA	Regret	BTA	MIS	Sex	EDUC	Year	LN(Age)	Adj R^2	N
Disposition (DE_{avg1})	0.5604	0.0754	-0.0016	**0.0034**	-0.2063	-0.0223	**-0.0251**	**0.1098**	-0.1701	0.064	94
	0.79	1.66	-0.07	**1.95***	1.54	0.36	**2.94*****	**2.08****	0.86		
Disposition (DE_{frq1})	1.482	0.146	-0.037	0.005	**-0.598**	0.047	**-0.057**	0.129	-0.310	0.028	94
	0.73	1.18	0.56	1.16	**1.74***	0.31	**2.74*****	0.91	-0.53		
House Money (HM_{avg})	-0.721	0.005	0.017	-0.002	0.243	0.020	0.003	-0.017	0.183	-0.065	77
	0.77	0.07	0.55	0.86	1.18	0.28	0.37	0.27	0.71		
House Money (HM_{frq})	-2.408	-0.111	0.073	-0.005	0.072	0.281	0.025	-0.177	0.888	-0.045	77
	1.02	0.68	0.91	1.12	0.15	1.59	0.89	1.08	1.38		
Breakeven (BE_{avg})	0.544	0.017	-0.026	0.002	-0.134	0.004	-0.010	0.034	-0.159	-0.018	82
	0.98	0.45	-1.19	1.43	0.94	0.08	1.52	0.73	1.05		
Breakeven (BE_{frq})	**5.674**	0.119	-0.066	**0.010**	**-1.088**	**0.357**	-0.010	-0.003	**-1.731**	0.180	82
	2.54**	0.87	-0.90	**2.03****	**2.38****	**2.09****	1.39	0.02	**2.94*****		

Table 3.9
Path-dependent Behaviors and Psychometric and Demographic Variables
Absolute Values of Path-Dependent Variables

Linear regression estimates for dependent variables corresponding to the each of the path-dependent behaviors, measured as absolute values, using the average and frequency methods, are shown below. Subjects who display positive, negative or no behavior comprise the sample for each regression. Subjects for whom the path-dependent behavior could not be observed (not measured) are excluded. Abbreviated explanatory variables include negative affect (NA), better-than-average (BTA) and miscalibration (MIS). t-Statistics are displayed under the coefficient estimates. One, two, or three asterisks denote estimates are significantly different from zero at the 10, 5 and 1 percent levels, respectively.

Dependent Variable	Const.	NA	Regret	BTA	MIS	Sex	EDUC	Year	LN(Age)	Adj R^2	N
Disposition (DE_{avg1})	0.580	0.021	0.008	0.000	-0.040	**0.085**	-0.001	0.002	-0.155	0.008	94
	0.79	0.65	0.47	0.32	-0.40	**2.24****	0.20	0.06	0.69		
Disposition (DE_{frq1})	1.043	0.004	0.015	-0.003	-0.012	**0.209**	0.002	-0.105	-0.149	0.006	94
	0.63	0.05	0.40	1.16	0.05	**2.44****	0.12	1.28	0.29		
House Money (HM_{avg})	0.588	-0.055	0.014	-0.001	0.143	0.036	-0.002	0.017	-0.116	-0.065	77
	0.69	1.44	0.65	0.60	1.13	0.78	0.20	0.38	0.44		
House Money (HM_{frq})	-2.174	0.071	0.029	-0.001	0.114	0.029	-0.018	-0.102	0.907	-0.045	77
	1.04	0.76	0.54	0.37	0.37	0.26	0.93	0.97	1.43		
Breakeven (BE_{avg})	0.216	-0.038	**0.033**	**-0.002**	0.136	0.052	-0.001	-0.005	-0.017	0.031	82
	0.32	1.30	**2.02****	**2.24****	1.38	1.53	0.22	0.14	0.08		
Breakeven (BE_{frq})	-0.691	0.025	-0.024	0.001	-0.195	-0.058	-0.006	-0.062	0.528	-0.069	82
	0.36	0.31	0.52	0.23	0.70	0.60	0.39	0.65	0.91		

Figures

Figure 3.1
Sequence of Events

Each session includes twenty repetitions or periods of the investment task. This flowchart illustrates the sequence of events for one period.

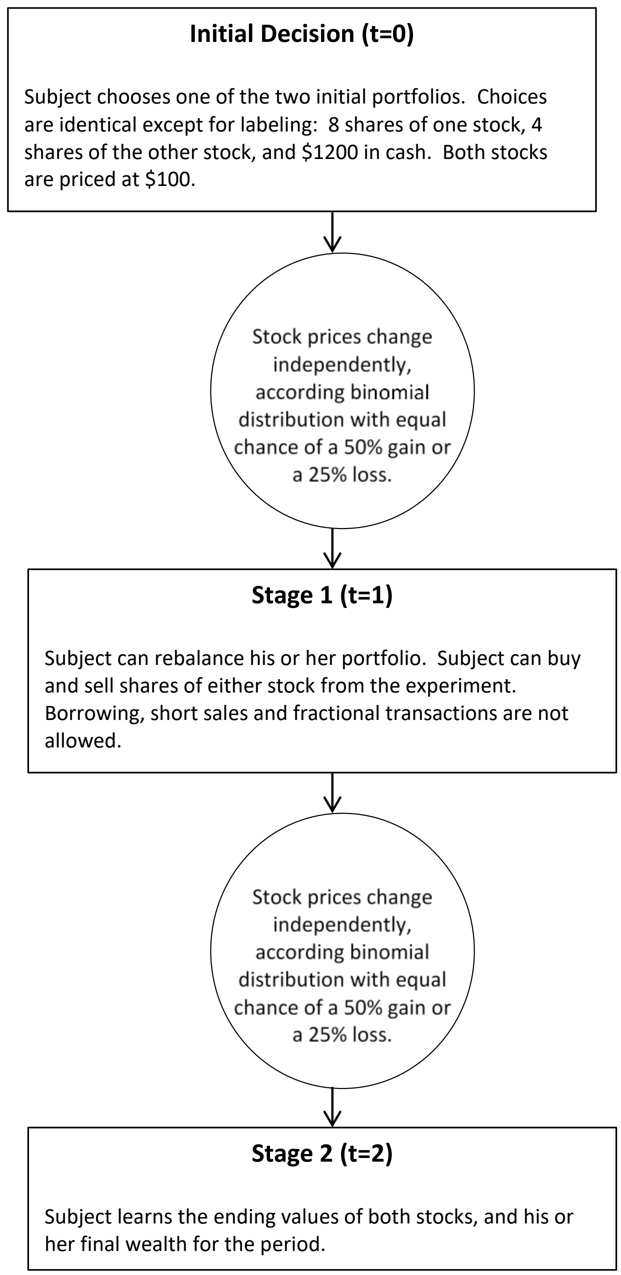
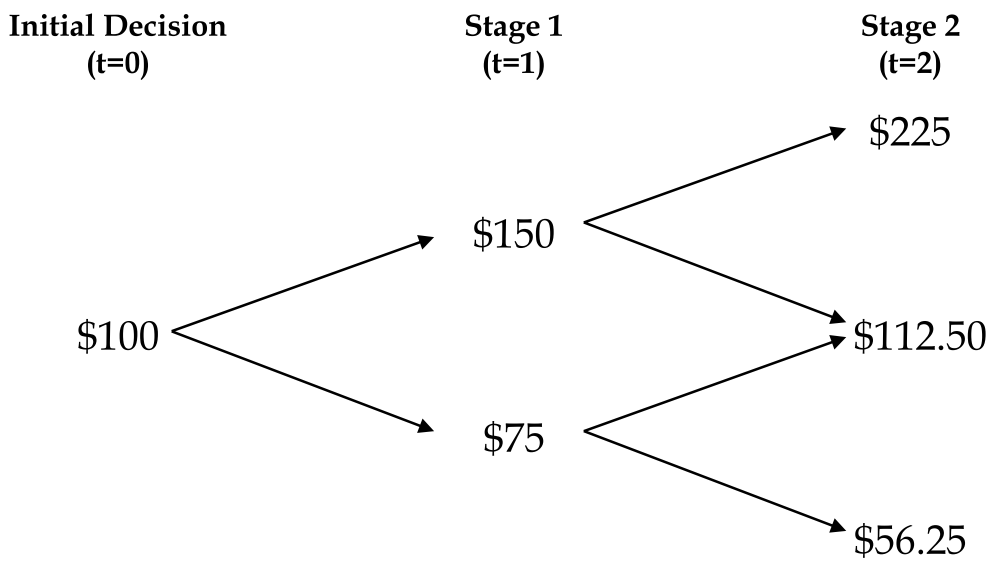


Figure 3.2
Security Price Change Tree

The price of each stock can either increase by 50% or decrease by 25% at each stage. After the initial portfolio choice, stock prices can either increase to \$150, or decrease to \$75 at Stage 1 (t=1).



Appendices

Appendix 3.A. Initial Questionnaire

Subjects completed the following questionnaire prior to starting the investment task portion of the experiment. There are several sections to the questionnaire, with instruments to measure negative affect, regret, miscalibration, and the better-than-average effect, as well as a demographic survey.

The NA instrument is derived from questions 1-5, which are taken from the International Positive Affect-Negative Affectivity Schedule – Short Form (I-PANAS-SF), proposed and tested for validity by Thomson et al. (2007), based on the PANAS instrument developed by Watson, Clark and Tellegen (1988). PANAS is the most commonly used measure to measure positive affect (PA) and NA in academic research and consists of 20 item, for instance guilty, upset, afraid for NA. Since PANAS was developed for North America, some of the items are either have been found to be redundant or have ambiguous meanings to English speakers from non-North American cultures. The I-PANAS-SF has been developed to address these ambiguities. It is comprised of two sets of 5 questions to measure PA and NA. We used the NA questions from I-PANAS –SF.

If a participant has never invested, they are asked to answer '0.' Of the subjects surveyed, 23 submitted a response of '0.' We use the mean of the other responses to the regret question to fill in these missing values in order to keep more observations when we conduct empirical analysis. Tests have also been conducted discarding the missing regret responses, instead of replacing the missing responses with the mean and there is no significant impact on the results.

Finally, the demographic questions ask about gender, financial support and academic background. We construct the variables, Year and Courses from these questions. Year is an indicator variable set to '1' if the student is considered to be a senior (4^{th} year) and is '0' otherwise. Courses counts the total number of relevant courses (i.e., finance, economics, statistics, and probability) that the subject has completed or is currently enrolled in. Given that we restricted our pool to undergraduate business students, only meaningful variability in sex was anticipated (and this turned out to be true).

QUESTIONNAIRE

This questionnaire is comprised of three parts. Part A asks several personality-based questions. Part B tests your general knowledge. And Part C concludes with some basic demographic questions.

Part A

The 8 questions that follow deal with your personality. In the first five, you will be asked to think about yourself, and how you normally feel. You will be asked to how often you feel a certain way. Please answer these questions to the best of your ability using a 5-point scale. If you always feel a certain way "5" should be your answer. If you never feel that way "1" should be your answer. Frequency of feelings between these extremes should be answered with "2" or "3" or "4" as appropriate.

1. Using a 5-point scale (where never = 1 and always = 5), thinking about yourself and how you normally feel, to what extent do you generally feel **upset**.
   Circle the appropriate number:

   1 2 3 4 5

2. Using a 5-point scale (where never = 1 and always = 5), thinking about yourself and how you normally feel, to what extent do you generally feel **hostile**.
   Circle the appropriate number:

   1 2 3 4 5

3. Using a 5-point scale (where never = 1 and always = 5), thinking about yourself and how you normally feel, to what extent do you generally feel **ashamed**.
   Circle the appropriate number:

   1 2 3 4 5

4. Using a 5-point scale (where never = 1 and always = 5), thinking about yourself and how you normally feel, to what extent do you generally feel **nervous**.
   Circle the appropriate number:

   1 2 3 4 5

5. Using a 5-point scale (where never = 1 and always = 5), thinking about yourself and how you normally feel, to what extent do you generally feel **afraid**.
   Circle the appropriate number:

   1 2 3 4 5

6. If you had to guess, what percentage of participants in this session have better investing skills than you? This percentage is:

   ___________%

7. One's payoff today will depend on trading performance. If you had to guess, what percentage of participants in this session will end up making more money than you? This percentage is:

   ___________%

8. Once again using a 5-point scale (where never = 1 and always = 5), thinking about past investments you have made, when a decision has not worked out well (even if you felt you made a careful decision using all the facts), how often did you experience **regret**? (If you have never invested, answer '0.')
   Circle the appropriate number:

   0 1 2 3 4 5

Part B

Next we would like to assess your general knowledge. For the following series of questions with clear-cut numerical answers, please provide 90% confidence intervals. Such an interval has a lower bound and an upper bound such that you are 90% sure that the correct answer lies in this interval. Note that, if your intervals are too wide, correct answers will fall in your interval more than 90% of the time, while, if you intervals are too narrow, correct answers will fall in your interval less than 90% of the time.

	LOWER BOUND	**UPPER BOUND**
9. The number of countries in the United Nations		
10. The year of Shakespeare's death		
11. The elevation (in meters above sea level) of Mt. Everest		
12. The total number of goals scored at World Cup 2010		
13. The land area in the world (in millions of sq km)		
14. The year in which Edison invented the electric light bulb		
15. GDP per capita of Italy (in thousands of $US) in 2008		
16. The population of Brazil as of July 2010 (in millions)		
17. The number of medals that Greece won at the first Olympic Summer Games in 1896		
18. The gestation period (i.e., period from conception to birth) of an elephant (in months)		

Part C
Finally we ask a few simple demographic questions.

19. What year are you in university?

    ____

20. What is your sex? (m = male; f = female)

    ____

21. What is your age?

    ____

22. What is your primary means of financial support? (a = self-supported; b = parent or relative; c = spouse or significant other; d = scholarship, financial aid or other loans; or e = other)

    ____

23. How many economics and finance courses have you successfully completed or are currently enrolled in at the university level?

    ____

24. How many statistics and probability courses have you successfully completed or are currently enrolled in at the university level?

    ____

Appendix 3.B. Instructions

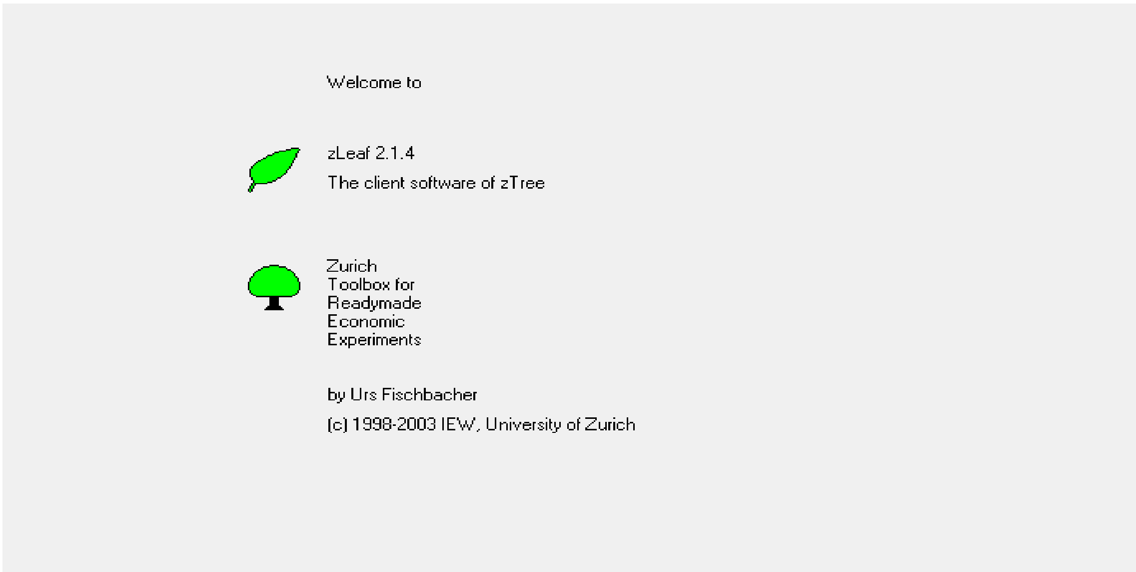
1. Introduction.
You are about to participate in an experiment in financial decision-making. If you follow these instructions carefully, depending on how events unfold, you may earn a considerable amount of money, which will be paid to you in cash at the end of today's session.

Everything you need to know about this experiment is included in these instructions. Everything contained in these instructions and everything you hear in this session is an accurate representation of this experiment. Be sure to ask any questions that you may have during this instruction period, and ask for assistance, if needed, at any time.

All participants receive the same instructions.

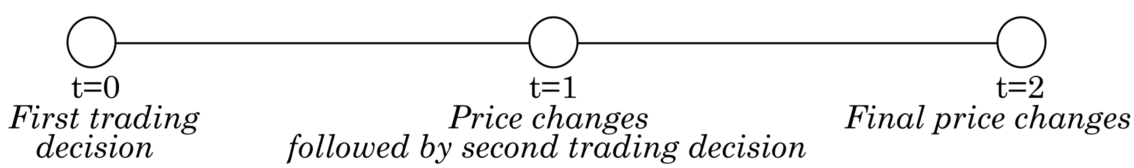
We are going to conduct a series of 20 markets. Each market will be conducted in identical fashion. In a market you will be endowed with cash and you can buy and sell shares of two different stocks in a sequence of two periods. These stocks, which are called GOLD and GREEN, can go up and down in value as a market progresses. Your earnings will be based on both your decisions and the prices of these 2 stocks. The details of how earnings will be calculated are explained below. All earnings in the experiment are denominated in "trading dollars." When you collect your earnings, trading dollars will be converted to Canadian dollars at the rate of 100 Trading Dollars equals 1 Canadian dollar.

2. Computer. When you are placed at a terminal, you should see the following screen. If you do not see this screen, please notify one of the persons administering the experiment.

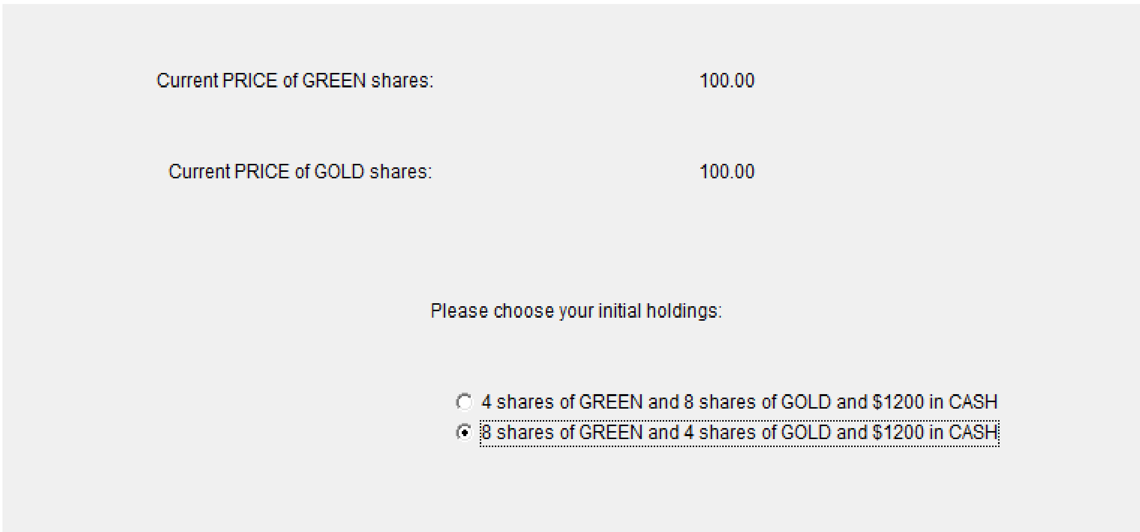


3. Periods. As stated above, each market will run for two periods. At the beginning of the first period (t=0), students are endowed with cash and must make a trading decision based on given stock prices. At the end of the first period (t=1) stock prices will randomly change according to known probability distributions. Dice rolls will be made to determine the new pries. After prices change and stocks are revalued, we are at the beginning of the second period (still t=1), and trading decisions again have to be made. At the end of the second period (t=2) once again stock prices will randomly change according to the same known probability distributions. At this point the second period and the market in question will end, portfolio values will be recorded and we will move to the next market. Note that 20 such markets will be run. There will be no carry-over of cash and stocks from market to market. This means that each market begins afresh with the same allocation of cash. The time line below summarizes these points.

Time line of events



4. Initial Market Conditions. At the beginning of the market al.l participants receive an endowment of $1200 in cash plus $1200 more which must be spent on shares. The GREEN and GOLD stocks are initially priced at $100 per share. While you will have considerable flexibility later, in the first period your trading activity is quite restricted. You must buy either 4 shares of GREEN along with 8 shares of GOLD *or* 4 shares of GOLD along with 8 shares of GREEN. *These are your only two choices initially!* In either case, exactly $1200 will be spent on stocks.

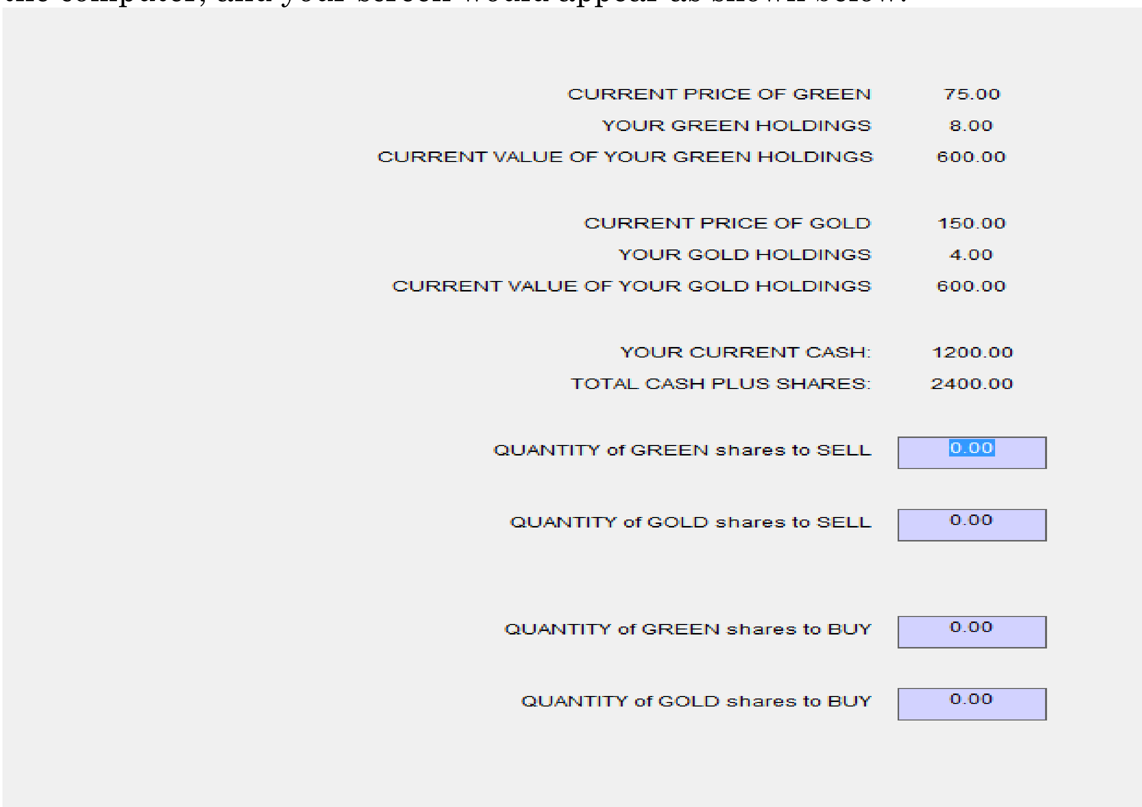


When you have chosen your initial position, press "Continue." Your cash and stocks will exist as book entries on your computer.

5. Price change distributions. The same price change distribution holds for each stock. At the end of each period, a stock will either increase in value by 50% (from $100 to $150 in the first period) or decrease in value by 25% (from $100 to $75 in the first period). These events will both occur with a 50% probability. This implies that the expected per period return is 12.5%. Price changes are realized by the rolling of two dice, one for each type of stock. High die values (4, 5 and 6) signify a stock going up, and low die values (1, 2 and 3) signify a stock going down. Since one die will be for GOLD and the other for GREEN, it is clear that price changes are independent.

6. Changes in portfolio value. Your portfolio was initially valued at $2400 ($1200 in shares and $1200 in cash), but depending on stock price changes your portfolio value will have increased, decreased or stayed the same by the end of the first period. The computer will automatically track the value of your portfolio.

For example, suppose you initially chose 8 GREEN shares and 4 GOLD shares. Further, suppose the experimenter rolls a "3" on the GREEN die and a "6" on the GOLD die. This means that the GREEN stock price has fallen to $75, and the GOLD has risen to $150. The experimenter will input these values into the computer, and your screen would appear as shown below.

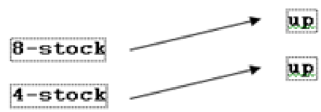


The screen shows the current price of GREEN, your GREEN holdings (number of shares), and the current value of your GREEN holdings (the GREEN price times the number of GREEN shares you own). Corresponding information for the GOLD stock as well as your current cash holdings are shown as well.

7. Second period trading. Second-period trading, unlike first-period trading, is quite flexible. You can buy and sell as many shares as you like provided you have the wealth to do so. For example, you could sell all your shares just holding cash for the last period. Or you could put the additional $1200 now at your disposal entirely into stocks so that you are not holding any cash going forward. The only requirement is that after adjusting your portfolio, the sum of the value of your GOLD stock plus the value of your GREEN stock plus your cash must equal the end-of-period-one portfolio value.

We provide in the form of a 4-page booklet some tables to assist you in making your choices. For each possible set of first-period price changes (there are 4 such sets), these tables show a range of possible portfolio choices. These choices are far from exhaustive. To give you a sense of how these tables work, refer to the first page (Case A), which shows possibilities when both stocks go up in value in the first period. Below we provide the upper part of the first page.

CASE A: BOTH STOCKS RISE IN VALUE. In the table below the "8-stock" is the one (either GREEN or GOLD) that you originally bought 8 shares of, and the "4-stock" is the one (either GREEN or GOLD) that you originally bought 4 shares of. Each statement below corresponds to a possible portfolio choice. You have to choose how many shares of each stock to buy or sell. Each statement says what each possible action implies in terms of portfolio weights.



If want $0 in cash (0%) buy 12 of 8-stock (100%) and sell 4 of 4-stock (0%)
If want $0 in cash (0%) buy 2 of 8-stock (50%) and buy 6 of 4-stock (50%)
If want $0 in cash (0%) sell 8 of 8-stock (0%) and buy 16 of 4-stock (100%)

Note that instead of referring to GOLD and GREEN in these tables, we refer to the 8-stock (i.e., the stock that you originally bought 8 shares of) and the 4-stock (i.e., the stock that you originally bought 4 shares of). The first 3 rows of the table (which are the only rows shown) are appropriate for someone who wants to hold only stocks and no cash. The first of these 3 rows is for someone who wants to only hold the stock that she originally purchased 8 shares of (whether GREEN or GOLD), and the last of these 3 rows is for someone who wants to only hold the stock that she originally purchased 4 shares of (whether GREEN or GOLD). The second row has the investor holding, usually after portfolio changes, an equal amount of each stock. The numbers in parentheses indicate the percentages invested in cash, the 8-stock and the 4-stock respectively after the actions (in terms of buying and selling the 2 stocks) specified in each row are undertaken. Looking at the first 2 rows, simple interpolation tells us that another possibility is to buy 11 shares of the 8-stock and to sell 3 shares of the 4-stock. Moreover, since we allow fractional shares (up to 2 decimal places) you could even buy 11.5 shares of the 8-stock and sell 3.5 shares of the 4-stock.

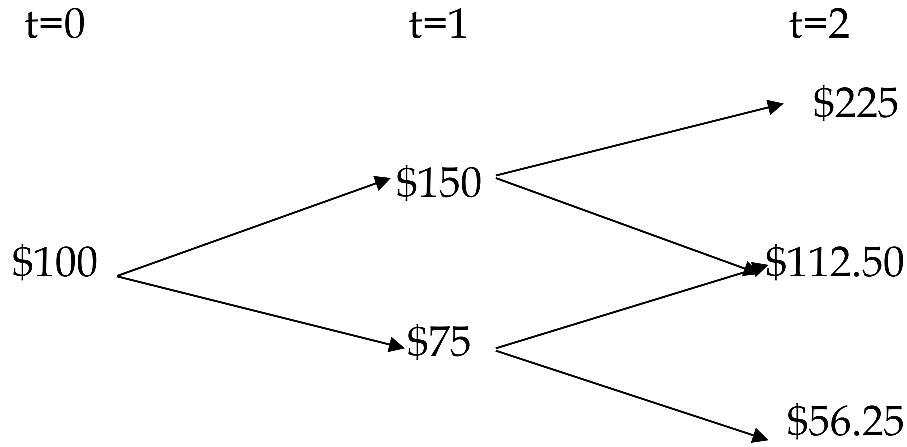
These tables are designed to provide only a rough guideline. You may also use a calculator to facilitate your selection.

The previous screen shot illustrates how you can buy and sell shares. Simply enter the amount of GREEN and/or GOLD you wish to buy or sell in corresponding boxes, and press "Continue."

The computer will not allow you to spend more cash than you have. That is, if you attempt to buy more shares than you can afford, it will return an error message.

8. End of period 2. After all participants have chosen their allocations, the two dice will again be rolled to determine the new prices for the GREEN and GOLD stocks. As before, stocks either go up in value by 50% or decline in value by 25%. The tree diagram below shows all possibilities.

Tree diagram of possible price changes



At the end of the second period the value of your portfolio is recalculated based on the sequence of dice rolls.

Continuing the earlier example, suppose the next dice rolls were a “5” for the GREEN and a “3” for the GOLD. The experimenter would enter these into the program, and your screen would appear as below.

CURRENT PRICE OF GREEN	112.50
YOUR GREEN HOLDINGS	8.00
CURRENT VALUE OF YOUR GREEN HOLDINGS	900.00
CURRENT PRICE OF GOLD	112.50
YOUR GOLD HOLDINGS	4.00
CURRENT VALUE OF YOUR GOLD HOLDINGS	450.00
YOUR CURRENT CASH:	1200.00
YOUR EARNINGS FOR THIS PERIOD	2550.00

For simplicity, this screen is based on no action being taken at t=1 (i.e., neither purchases nor sales occur for either of the 2 stocks). Note that such inaction is a possible choice.

9. After a market ends. After a market ends, the program will keep track of your end-of-market wealth and a new market will begin. There is no-carry-over of cash and shares. This means that you begin each market with $2400 total worth of cash and stocks.

10. Payoff. Your payoff will be randomly drawn from among all markets. Suppose that the number 13 is drawn from 1-20. Then a $5 appearance fee plus whatever your final portfolio value was during market 13 will be what you take from the room. It should be noted that while you can leave with as much as $50.00, the worst you will do is $20.75.

Chapter Four: *Cognitive ability, emotional stability and risk and time preferences: An experimental analysis*[85]

4.1. Introduction

There is increasing evidence that cognitive ability (IQ) has a meaningful impact on the key preference parameters underlying financial decision-making.[86] For example, Dohmen, Falk, Huffman, and Sunde (2010) find that those with higher levels of cognitive ability not only take on more risk but also save more.[87] Grinblatt, Keloharju, and Linnainmaa (2011, 2012) find that stock market participation is monotonically related to IQ and that high-IQ investors demonstrate better market timing, stock-picking skills and trade executions. Increased cognitive ability has also been associated with being more patient and with increased investment (Funder & Block, 1989). Given the observation that individuals are experiencing increasingly crushing levels of credit card debt and insufficient levels of retirement savings, and that these behaviors may stem in part from both risk and time preferences it is important to understand the

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[85] Co-authored work with Dr. Lucy Ackert (Kennesaw State University), Dr. Richard Deaves (McMaster University) and Dr. Quang Nguyen (Middlesex University).

[86] IQ and cognitive ability are not equivalent (Urbina 2011). It is reasonable to say however that IQ, a metric resulting from various administered tests, is one noisy estimator of various aspects of multi-faceted cognitive ability. Nevertheless, for ease of expression we will generally treat the acronym and adjectival phrase as congruent.

[87] There is growing evidence that time preference and risk preference are related (Abdellaoui, Diecidue, & Öncüler, 2011; Andreoni & Sprenger, 2012; Gerber & Rohde, 2010), but we like most other researchers treat them as separable.

characteristics driving these preferences (Angeletos, Laibson, Repetto, Tobacman, & Weinberg, 2001; Bar-Gill, 2004; Meier & Sprenger, 2010; Shamosh et al., 2008).[88]

While there is increasing evidence that IQ has an impact on both risk and time preferences (Booth, Cardona-Sosa, & Nolen, 2014; Christelis, Jappelli, & Padula, 2010; Dohmen, Falk, Huffman, & Sunde, 2010), it has been demonstrated that IQ alone is not able to fully explain preference parameters (Benjamin, Brown, & Shapiro, 2013). Research in psychology shows that those with high levels of emotional stability, or EQ, have better life outcomes (Almlund, Duckworth, Heckman, & Kautz, 2011), suggesting that EQ may be an important determinant in this context.[89] For example, mass emotion, induced by weather (Hirshleifer & Shumway, 2003), day length (Kamstra, Kramer, & Levi, 2002, 2003), national sporting success (Edmans, Garcia, & Norli, 2007) and aviation disasters (Kaplanski & Levy, 2010), has been documented as potentially moving stock markets. Indeed,

[88] Farkas and Johnson (1997) document gaps between people's retirement savings attitudes, intentions and behavior, with 76% of their participants believing they should save more for retirement and 55% reporting being behind in their savings. Bernheim (1995) uses the 1993 Luntz Webber/Merrill Lynch survey and reports a shortfall of 10% between how much income individuals believe they should save and how much they are currently saving for retirement.

[89] Emotional stability is a component of a trait family that some call Neuroticism/Emotional Stability (and which is within the popular "Big Five" trait family model of personality psychology (Larsen & Buss, 2008). According to the *American Psychology Association* dictionary definition, Emotional Stability is "predictability and consistency in emotional reactions, with absence of rapid mood changes," while Neuroticism is "a chronic level of emotional instability and proneness to psychological distress" (Almlund et al., 2011). As we will describe in the literature review in section 4.2, the emotion-based metric that we employ here is designed to estimate NA and because EQ is a quick mnemonic along the lines of IQ, we use Emotional Stability and EQ synonymously.

recent work has documented the relationship between EQ and key risk-taking and time preference parameters (Charupat, Deaves, Derouin, Klotzle, & Miu, 2013; Epper, Fehr-Duda, & Bruhin, 2011; Manning et al., 2014).

While there has been work done that has established important associations between IQ and risk and time preferences (Barberis, Huang, & Thaler, 2006; Dohmen et al., 2010; Frederick, 2005; Read, Loewenstein, Rabin, Keren, & Laibson, 1999); EQ and risk preferences (Charupat et al., 2013) and EQ and time preferences (Manning et al., 2014; Walther, 2010), research investigating whether relationships exist for both IQ and EQ is rather limited.[90]

In this paper, we report the results of an experiment designed to explore, uniquely we believe, whether a relationship exists between proxies for both cognitive ability (IQ) and emotional stability (EQ) and the key parameters in risk preference and time-preference models. Specifically, we focus on cumulative prospect theory and quasi-hyperbolic discounting, both of which nest models grounded in rationality. To preview we find that both IQ and EQ independently matter, with IQ dominating for risk preference and EQ for time preference.

[90] In fact, to our knowledge there is one other study that is somewhat similar to ours. Hirsh, Morisano, and Peterson (2008) look at time preferences (delay discounting) and interactions between EQ (neuroticism) and IQ (cognitive ability). Using 97 undergraduate students at McGill University, they find that decreased EQ is associated with higher discounting rates, but only for individuals with higher IQ scores.

The plan of this chapter is as follows. In section 4.2 we review the relevant literature on the measurement of cognitive ability (IQ) and emotional stability (EQ), provide background on the risk-taking and time-preference models employed here (namely cumulative prospect theory and quasi-hyperbolic discounting), and review past research on the impact of IQ and EQ on time preference and risk taking. Section 4.3 presents our hypotheses, and section 4.4 details our research design. In the penultimate section our findings are presented and interpreted. Finally, section 4.6 concludes.

4.2. Literature Review

4.2.1. Cognitive ability and emotion in decision-making

There is abundant evidence that decision-making involves both cognitive and emotional processes (Benjamin et al., 2013; Sanfey, Rilling, Aronson, Nystrom, & Cohen, 2003; Vastfjall & Slovic, 2013). Dual process theories of the mind (also referred to as "two-system" theories) are well-documented theories that formalize the interaction between cognitive and emotional processes by portraying decision-making as the result of the interaction of two information processing systems, "System 1" and "System 2" (Chaiken & Trope, 1999; Kahneman, 2003; Stanovich & West, 2000).[91] "System 2" refers to a cognitive, deliberative system described as

[91] There is evidence from neuroimaging and EEG studies that corroborate dual-process decision-making (De Martino, Kumaran, Seymour, & Dolan, 2006; Moreira, Pinto, Almeida, Barros, & Barbosa, 2016; Roiser et al., 2009).

being complex, reflective, controlled, and slow. "System 1" on the other hand is an emotional, impulsive system described as simple, reactive, automatic, and fast.

Individuals choices are the result of both systems, and vary depending upon the strength of each system in a given decision-making scenario (Fudenberg & Levine, 2006; Loewenstein & O'Donoghue, 2005; Metcalfe & Mischel, 1999). Shiv and Fedorikhin (1999) provide an example of this in a study in which they ask individuals to choose between two alternatives: chocolate cake and fruit salad. They find that if processing resources are limited, then individuals tend to choose the chocolate cake, the alternative with a higher affective dimension, but when the availability of cognitive processing resources is high, the individuals are more likely to choose the fruit salad, the alternative with the higher cognitive dimension, but arguably is less desirable on an affective dimension. There is also evidence that positive and negative mood may influence processing capabilities, and that happy individuals will process information in a less systematic manner than individuals in a negative mood (Isen, 2001; Luce, Bettman, & Payne, 1997; Vastfjall & Slovic, 2013).

When it comes to financial decision-making there have been several convincing studies that have found patterns in risk and time preferences that deviate from what rational choice theory would predict (Frederick, Loewenstein,

& O'Donoghue, 2002; Kahneman & Tversky, 1979; Rabin, 2002; Shapiro, 2005). These findings have led to an increased interest in understanding how individuals are making financial decisions. While there is increasing evidence that cognitive ability has an impact on both risk and time preferences (Banks & Oldfield, 2007; Benjamin et al., 2013; Booth et al., 2014; Christelis et al., 2010; Dohmen et al., 2010; Funder & Block, 1989; Kézdi & Willis, 2003; Parker & Fischoff, 2005), it has been demonstrated that cognitive ability alone is not able to explain risk and time preference parameters. For example, Benjamin et al. (2013) use a sample of Harvard undergraduates with perfect SAT scores on the Math component of the test (indicating that these are individuals with high cognitive abilities), and find that only 36% of the students are risk-neutral and 67% are perfectly patient, suggesting that cognitive ability alone is not able to explain risk and time preferences.

This evidence, along with the notion that the utility of decision outcomes has both cognitive and affective (emotional) components, has led to an increased interest in understanding the potential role that both cognitive and emotional processes play in the decision-making process (Kahneman, 2011; Kahneman & Snell 1990; Kahneman, Wakker, & Sarin, 1997; Rottenstreich & Hsee, 2001).

4.2.2. Measuring IQ

There are a variety of instruments available to measure cognitive ability (IQ) (Urbina, 2011), with the Wechsler Adult Intelligence Scale (WAIS) being one of the most commonly used.[92] The problem with this test (with its 11 modules) and its kin is the lengthy time taken for administration, making it infeasible for experimental and survey research.

Fortunately, Frederick (2005), introduced a simplified 3-item cognitive reflection test (CRT) to measure cognitive ability. This test employs three simple questions which have correct numerical answers as well as incorrect but intuitive answers. In each case the correct answer requires one to pause and resist reporting the first answer that comes to mind, in other words "cognitively reflect," hence the name of the test. For example, consider the following question taken from the test:

A bat and ball cost $1.10. The bat costs one $1.00 more than the ball. How much does the ball cost?

A little thought indicates that the ball costs 5 cents and the bat $1.05 (for the required sum of $1.10 and difference of $1.00.) The incorrect, intuitive, answer that is naturally occurring to many people, and likely an indicator of less reflection

[92] When we refer to IQ in the context of this paper we are referring to cognitive ability. It is important to note that Intelligence Quotient (IQ) and cognitive ability are not equivalent (Urbina, 2011).

on the answer, is that the ball costs 10 cents. People sometimes anchor on the difference between $1.10 and $1.00, erroneously arriving at a 10-cent cost for the ball. The other two questions of the CRT are in the same vein.[93]

Due to its ease of use, and the fact that it has been shown to strongly correlate not only with more extensive tests of cognitive ability but also with the risk and time preference items that these tests are associated with (Frederick 2005), we employ it in the present study as a proxy for IQ.[94]

4.2.3. Measuring EQ

Analogous to IQ, emotional stability will be referred to as EQ. Those high in EQ tend to exhibit calm and grace under pressure, while those low in EQ are often anxious, excitable and nervous. In measuring EQ one can either focus on innate tendencies or on the ability of individuals to overcome their emotions, with the metric employed here taking the former approach.[95]

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[93] Appendix 4.A. provides the full survey. The CRT questions are B-1 to B-3.

[94] Frederick (2005) finds a significant and positive correlation between CRT scores and the SAT (Scholastic Achievement Test), ACT (American College Test), Wonderlic Personnel Test (WPT), and "need for cognition" scale (NFC) test scores. And when compared to other cognitive ability measures CRT was ranked as either the best or second best predictor of the decision-making behaviors tested.

[95] An alternative approach to tease out EQ is not to focus on innate tendencies but rather on the ability of individuals to overcome their emotions. Salovey and Mayer (1990) first coined the term "emotional intelligence" (EI) which they defined as "the ability to monitor one's own and others' feelings and emotions, to discriminate among them and to use this information to guide one's thinking and actions." They postulated that there were three fundamental aspects of EI: appraisal and expression of emotion, regulation of emotion and utilization of emotion (Mayer & Salovey, 1993; Mayer, Salovey, Caruso, & Sitarenios, 2001; Salovey & Mayer, 1990; Schutte et al., 1998).

In personality psychology, a widely examined five-factor model known as the “Big Five” has been used to determine an individual’s core personality traits based on five broad categories: conscientiousness, agreeableness, extraversion, openness to experience and neuroticism (Fiske, 1949; Goldberg, 1981; Larsen & Buss, 2008; McCrae & Costa, 1987; Norman, 1967).[96] Neuroticism is used as an indicator of EQ, with those exhibiting neuroticism or negative affectivity (NA) said to be low in EQ (Watson & Clark, 1984).

Specifically, our instrument to measure EQ is based on the International Positive Affectivity-Negative Affectivity Schedule – Short Form (I-PANAS-SF), proposed and tested for validity by Thompson (2007). Using a 5-point Likert scale, ranging from ‘1’ (never) to ‘5’ (always), participants are asked how often their feelings tend in the direction of 10 adjectives, some of which correspond to negative emotions (“upset” is an example), others of which correspond to positive emotions (“attentive” is an example).[97] The average score on the 5 negative adjectives (which is called “negative affectivity” or NA) is used to proxy for EQ.[98]

The average score on the 5 positive adjectives, less our focus, yields “positive affectivity,” or PA, the tendency to experience positive emotions.

[96] See Larsen and Buss (2008).

[97] The I-PANAS-SF questions are A-1 to A-10 in Appendix 4.A.

[98] Note that a low average value for NA implies high EQ. When we construct an EQ variable for analysis and testing we use 5 minus the average NA value, so that an increase in the EQ variable indicates high emotional stability.

Previous neuroscience and behavioural studies have investigated the role that positive affective states play in decision-making. Since emotions can play a positive role in decision-making (Bechara, Damasio, Tranel, & Damasio, 1997), it is possible that high-PA individuals may act in a manner closer to rationality.

4.2.4. Time preference and the quasi-hyperbolic discount function parameters

The discounted-utility model proposed by Samuelson (1937) is based on the notion that intertemporal decision-making can be explained by a single parameter, the subjective discount rate of time preference. One of the main psychological assumptions underlying discounted-utility models is that the subjective discount rate should be constant for all time periods. Since its introduction there have been a number of patterns in decision-making that are inconsistent with discounted-utility model predictions.[99] Individuals tend to show inconsistent time preferences depending on the time until rewards are available. Though individuals should be patient over short time horizons (Rabin, 2002; Shapiro, 2005) there is evidence of present bias (Frederick et al., 2002) and individuals' preferences for smaller more immediate rewards to larger delayed rewards (Rachlin, Raineri, & Cross, 1991). These inconsistent preferences are related to a declining rate of time preference and preference reversals. (Benzion, Rapoport, & Yagil, 1989; Chapman & Elstein, 1995; Frederick et al., 2002; Green, Myerson, & McFadden, 1997; Kirby &

[99] See Frederick et al. (2002) for a good review of time preference anomalies, models and measures.

Maraković, 1995; Laibson, 1997; Millar & Navarick, 1984; Pender, 1996; Prelec & Loewenstein, 1991; Rachlin et al., 1991; Thaler, 1981).

Thaler (1981) provides an example of a declining rate of time preferences in a study in which individuals are asked to indicate the amount of money that would make them indifferent between receiving $15 immediately and some amount of money in one month, one year and ten years. The median responses to this question imply average annual discount rates of 245% in one month, 120% in one year and 19% in ten years. In terms of preference reversals, an example would be the case when an individual prefers $115 in two years over $100 in one year, but also prefers $100 today over $115 in one year.

Models that account for these characteristics propose a hyperbolic (Kirby & Maraković, 1995; Laibson, 1997; Strotz, 1955) or a quasi-hyperbolic function (Loewenstein, 1996; Phelps & Pollak, 1968; Shefrin & Thaler, 1988). Hyperbolic models are characterized by a relatively high subjective discount rate over short horizons and a relative low subjective discount rate over long horizons, accounting for the declining rate of time preferences and preference reversals that have been previously documented (Ainslie, 1992). Quasi-hyperbolic discounting is a simplified model of hyperbolic discounting that encapsulates the basic characteristics of hyperbolic discounting. Future payoffs are discounted by a constant factor, β, that represents delay preference (present bias) and an exponential factor, ρ, that grows at a constant rate with length of delay (pure rate of time preference.

To measure time preference in our participants we follow Benhabib, Bisin, and Schotter (2010) who propose the following three-factor model to test exponential, hyperbolic, quasi-hyperbolic discounting:

$$(1)\ D(t;\ \rho,\ \beta,\ \theta) = \beta(1-(1-\theta)\rho t)^{\frac{1}{(1-\theta)}} \quad \text{for t>0,}$$

where ρ is the pure rate of time preference, β is present bias and θ is "hyperbolicity." When θ approaches 1 this reduces to the quasi-hyperbolic discount function:

$$(2)\ D(t;\ \rho,\ \beta) = \beta exp^{-\rho t} \quad \text{for t>0.}$$

It turns out that estimating the full model with unrestricted θ does not improve R-square, compared to estimation of the quasi-hyperbolic model, so in the interest of reducing the number of parameters that must be estimated as well as to maintain clarity of interpretation for the remaining parameters we estimate (2) (Benhabib et al., 2010; Tanaka, Camerer, & Nguyen, 2010).

Most researchers would argue that present bias (β<1) is inconsistent with rationality. The same would be true in the case of β>1, which would indicate a "future bias." Therefore β=1 can be said to be consistent with rationality. If we let $\beta^*=|1-\beta|$, then rationality implies that this deviation of β from one (β^*) should equal zero. As for ρ, there is no "right" answer, but as Dohmen et al (2010) argue, it is hard to reconcile high pure rates of time preference with rationality.

4.2.5. Risk preference and prospect theory parameters

(Cumulative) prospect theory (Kahneman & Tversky, 1979; Quiggin, 1982; Tversky & Kahneman, 1992) characterizes *positive* risk preferences as:[100]

(3) $V(P) = \sum_{i=1}^{n} \pi_i v(z_i)$,

where v(.), the value function, is akin to the utility function of expected utility theory (EUT). As is quite conventional, the value function is modelled as the following two-part power function:

$(4a)\ v(z) = z^{\alpha}$, $\quad 0 < \alpha$ if $z \geq 0$;

$(4b)\ v(z) = -\lambda(-z)^{\beta}$, $\quad 0 < \beta, \lambda$ if $z < 0$.

[100] Prospect theory (see Wakker (2010) for an excellent, comprehensive review) is not the only positive theory of decision making under risk and uncertainty. It is however the most popular one, in large part because it generally performs quite well (Barberis, 2013).

Typically, it is found that $0 < \alpha < 1$ and $0 < \beta < 1$, reflecting concavity for gains and convexity for losses; and $\lambda > 1$, because people are generally unwilling to take a fair bet on a coin flip (i.e., loss aversion).

Instead of weighting values by probabilities as in EUT, prospect theory uses transformations of probabilities to generate "decision weights." If all outcomes are non-negative one first orders them as $z_1 > z_2 > \ldots > z_{n-1} > z_n$. Corresponding probabilities are written as $q_1, q_2, \ldots q_n$. Then the rank of each outcome is calculated, where rank is defined to be the probability of receiving a superior outcome (so the rank of z_k is $\sum_{i=1}^{k-1} q_i$). The appropriate decision weight attached to z_i is the difference between the transformed rank of the next-best outcome z_{i+1} and the transformed rank of z_i,

$$(5)\ \pi_i = w(\,q_1 + \ q_2 + \cdots + q_i) - w(\,q_1 + \ q_2 + \cdots + q_{i-1}).$$

In our experiment, we only consider simple binary prospects. When both outcomes are in the same domain (3) reduces to (3′):

$$(3')\ V(P) = w(q_1)v(z_1) + \ [1 - w(q_1)]v(z_2).$$

For the probability weighting function, Prelec (1998)'s, single-parameter axiomatically-derived function, which also tends to fit the data well (Stott, 2006), is used:

$$(6a) \quad w(q) = exp[-(-ln(q))^{\gamma}], \quad 0 < \gamma \; if \; z \geq 0;$$

$$(6b) \quad w(q) = exp[-(-ln(q))^{\delta}], \quad 0 < \delta \; if \; z < 0.$$

Given that typically α and β are close to each other, as are γ and δ (e.g., Tversky and Kahneman 1992), to conserve on parameter estimation we impose equality restrictions for both cases in our estimation, yielding:

$$(4a') \quad v(z) = z^{\alpha}, \qquad 0 < \alpha \text{ if } z \geq 0;$$

$$(4b') \quad v(z) = -\lambda(-z)^{\alpha}, \qquad 0 < \alpha, \; \lambda \text{ if } z < 0;$$

$$(6a') \quad w(q) = exp[-(-ln(q))^{\gamma}], \; 0 < \gamma, \; 0 \leq q \leq 1 \, .$$

Note that probabilistic insensitivity implies γ<1, and as γ approaches 1, rational non-weighting of probabilities emerges. Further, if λ=1, there is no loss aversion, again consistent with rationality. As for α, the matter is less clear. Nevertheless Rabin (2000) has shown that EUT must imply virtually no risk aversion for small to moderate gambles, else unreasonably high degress of risk aversion would result for large gambles. Taken together, α = γ = λ = 1 is the gold standard for rationality (i.e., EUT-like behavior).[101] Therefore, as before, if we let $\alpha^*=|1-\alpha|$, $\gamma^*=|1-\gamma|$ and $\lambda^*=|1-\lambda|$, then rationality implies that $\alpha^* = \gamma^* = \lambda^* = 0$.

4.2.6 Risk and time preferences

There is a strand of literature that measures risk *and* time preferences for individuals, and investigates the relationship between them (Anderhub, Güth, Gneezy, & Sonsino, 2001; Anderson & Stafford, 2009; Eckel, Johnson, & Montmarquette, 2005; Epper et al., 2011; Gerber & Rohde, 2010; Leigh, 1986). Most of these studies measure patience by inferring subjective discount rates using choices over time and measure risk tolerance based on the curvature of an individual's utility function (Anderhub et al., 2001; Anderson & Stafford, 2009; Eckel et al., 2005; Epper et al., 2011; Gerber & Rohde, 2010; Leigh, 1986). The main finding is that individuals who are more risk averse tend to be more impatient (place higher subjective discount rates on future outcomes).

There is also some evidence that there are interaction effects between risk and time preferences (Ahlbrecht & Weber, 1997; Andersen, Harrison, Lau, & Rutström, 2008; Baucells & Heukamp, 2010; Coble & Lusk, 2010; Keren & Roelofsma, 1995; Noussair & Wu, 2006; Weber & Chapman, 2005). Anderson and Stafford (2009) find a positive correlation between degrees of risk aversion and

[101] Koebberling and Wakker (2005) provide a decomposition of risk aversion into these three parameters.

impatience. Eckel et al. (2012) conduct a study using high school students and find that individuals with higher levels of patience are less risk averse. Following the finding in the psychology literature that there is a positive correlation between probability weighting and hyperbolic discounting (Myerson, Green, Hanson, Holt, & Estle, 2003; Rachlin et al., 1991), Epper et al. (2011) look at the relationship between probability weights and discount rates. In their case, they find that the only variable related to decreasing discount weights is the degree of probability weighting.

The correlation between risk and time preferences is line with the argument that there is commonality between the two, that is rewards that may be received in the future are inherently uncertain, which may increase the perception of risk associated with future payoffs (Halevy, 2008; Prelec & Loewenstein, 1991; Saito, 2011). Gerber and Rohde (2010) conduct an experiment in intertemporal choice and find that preference reversals are related to the perceived risk associated with the future reward that they are offered. In an experiment by Chesson and Viscusi (2000), individuals are asked to make choices in which the risk in payment dates are manipulated, rather than the risk in the size of the rewards. They find evidence of declining discount rates as well as a positive relationship between aversion to timing risk and ambiguity aversion, suggesting that uncertainty may be processed similarly for choices of both time and risk. Andreoni and Sprenger (2012) indicate that present bias is the result of a preference for certainty.

While it may be that the correlations between risk and time preferences are the result of risk preferences (utility curvature or probability weighting) causing intertemporal discounting, it is also possible that there is an additional factor that is driving the departures of risk and time preference from what EUT and DUT would predict. Prelec and Loewenstein (1991) suggest that individuals sensitivities to risk and delay are the result of a common driving force underlying risk taking and discount behavior. Epper et al. (2011) recognize that it is possible that cognitive ability may contribute to the correlation between risk and time preferences, but do not find evidence to support this. Epper et al. (2011) also point out that there is less known empirically about the role that emotion may play in explaining risk preference (probability weighting) and time preferences.

4.2.7. IQ and preferences

There is abundant evidence that cognitive abilities are related to both risk and time preferences, with much of the evidence indicating that an increase in cognitive ability is associated with risk neutrality and increased patience (Benjamin et al., 2013; Dohmen et al., 2010; Oechssler, Roider, & Schmitz, 2009).

4.2.7.1. IQ and risk preferences

As previously mentioned, there is evidence of risk aversion over small stakes gambles, even though theoretically individuals should be making risk-neutral choices (Kahneman & Tversky, 1979; Rabin, 2000). One potential contributor to this behavior is that lower cognitive skills are related to decreased information processing, distorting the perceptions of risk and increasing risk aversion in individuals (Christelis et al., 2010). For example, Christelis et al. (2010), find that cognitive abilities are more strongly positively associated with the tendency of individuals to invest in stocks, arguably more information-intensive assets, than to invest in bonds, less information-intensive assets.[102]

There have also been studies that find a positive relationship between increased cognitive load and risk aversion (Benjamin et al., 2013; Whitney, Rinehart, & Hinson, 2008). Booth et al. (2014) conduct an experimental lottery with 219 college students in the U.K. and find a significant positive association between cognitive ability and willingness to take on risk. Taylor (2013) finds an inverse relationship between CRT scores and risk aversion in hypothetical risky choices.

There is evidence that those with higher levels of cognitive ability are able to save more while taking on more risk, and these findings are robust to the various ways in which cognitive ability has been measured (Ballinger, Hudson, Karkoviata, & Wilcox, 2011; Banks & Oldfield, 2007; Christelis et al., 2010; Kézdi & Willis, 2003). Ballinger et al. (2011) find a significant effect of cognitive abilities on saving behavior after controlling for demographic and personality differences in

[102] In this study, Christelis et al. (2010) use the Survey of Health, Ageing and Retirement in Europe (SHARE) dataset of individuals in 11 European countries. This survey includes data on wealth and portfolio composition as well as three measures of cognitive skills.

individuals, including procrastination and impulsiveness. Banks and Oldfield (2007) use numeracy levels to measure cognitive ability and find that numeracy levels are strongly correlated with retirement savings as well as with knowledge and understanding of pension fund arrangements and perceived financial security.

4.2.7.2. IQ and time preferences

Higher cognitive ability has been related to increased patience (Ahn et al., 2011; Funder & Block, 1989; Parker & Fischoff, 2005; Rabin & Weizsäcker, 2009; Shamosh et al., 2008; Shamosh & Gray, 2008; Shoda, Mischel, & Peake, 1990). Funder and Block (1989) use an experimental study comprised of five sessions in which participants are asked to choose between receiving $4.00 immediately or waiting to receive $4.80 at the end of the experiment. They find that participants with higher IQ are more patient and "invest more." Shamosh and Gray (2008) provide a detailed literature review and meta-analysis of 24 studies investigating the relationship between cognitive ability and patience. They find clear evidence that preference for immediate reward is associated with lower intelligence. More specifically they find that IQ and working memory are negatively correlated with higher discounting rates indicative of preference for smaller immediate rewards. Looking at studies that make use of fMRI data, they explain that the link between intelligence and patience is related to process region of the brain known to support the integration of diverse information.

There is also an area of research that looks at the ability of patience to predict IQ and vice versa. Shoda et al. (1990) find that children who display the ability to wait longer and do not succumb to the impulse to take an immediately inferior reward (marshmallows and pretzels) will achieve higher SAT scores a decade later. Parker and Fischoff (2005) use vocabulary test scores of children to predict, approximately seven years later, their tendency to prefer larger later rewards to smaller sooner rewards.

4.2.7.3. IQ and risk and time preferences

There is evidence that IQ is related to *both* risk and time preferences. More specifically, higher cognitive ability increases an individual's ability to recognize that experimental choices are a small piece of a much longer stream of related choices, and that this in turn generates more patient, risk-neutral behavior (Barberis et al., 2006; Read et al., 1999).

Frederick (2005) finds that high performance on the proposed cognitive reflective test (CRT) is negatively correlated with impatience and risk aversion. Oechssler et al. (2009) make use of the CRT of Frederick (2005) and find that individuals with high CRT scores are more likely to choose risk neutral outcomes, while those with low CRT scores are less patient. Dohmen et al. (2010) use a sample of 1,000 adults in Germany and measure risk aversion using a real stakes lottery. They find that individuals with high cognitive ability will take on more risks and are more patient. Benjamin et al. (2013) find that Chilean high school students with higher standardized test scores make choices that are associated with greater risk neutrality and patience in small-stakes prospects. They also investigate the role that cognitive load plays in preferences and find that increasing cognitive load increases impulsive behavior and risk aversion. Burks, Carpenter, Goette, and Rustichini (2009) use a sample of 1,000 trainee truck drivers in the U.S. and find that lower cognitive ability is associated with greater risk aversion and more pronounces impatience.

4.2.8. EQ and preferences

There has been work done that has established an important association between emotion and rationality in decision-making (Charupat et al., 2013; Damasio, 1994; Elster, 1998; Grossberg & Gutowski, 1987; Lo & Repin, 2002; Loewenstein, 2000; Peters & Slovic, 2000; Slovic, Finucane, Peters, & MacGregor, 2004). Research indicates that people become more emotional when dollars are gained or lost (Lo & Repin, 2002). Further, their choices are impacted by emotion. For example, people are more likely to insure against emotionally vivid events (Johnson, Hershey, Meszaros, & Kunreuther, 1993). And the disposition effect (Odean, 1998), the tendency to (sub optimally) hold on to losing investments longer than winning investments, is stronger in the presence of emotional triggers (Summers & Duxbury, 2012). Mass emotion, induced by weather (Hirshleifer & Shumway, 2003), day length (Kamstra et al., 2002, 2003), national sporting success (Edmans et al., 2007) and aviation disasters (Kaplanski & Levy, 2010), even appears to move stock markets.[103]

4.2.8.1. EQ and risk preferences

Recall the three parameters underlying risk preference, namely value function curvature, loss aversion and probability weighting. Each of these influences the willingness of a decision-maker to bear risk, with greater curvature, loss aversion and (usually) probability weighting all leading to less risk taking.[104] There has been evidence linking emotion to these risk preference parameters. For example, individuals who are subject to a negative mood have been shown to be willing to take on more risks than individuals who are in a good mood (DeSteno, Petty, Wegener, & Rucker, 2000; Forgas, 1995; Mano, 1992; Raghunathan & Pham, 1999).

Loewenstein and O'Donoghue (2005) suggest that loss aversion is a product of the affective (emotion) system. Dhar and Wertenbroch (2000) show that

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[103] At the level of the individual, Kliger and Levy (2003) find that weather impacts risk taking through mood. And Kramer and Weber (2011) document the role of seasonal affective disorder.

[104] Low values of the parameter of a single-parameter probability weighting function imply that the weight for the high-wealth outcome is for most probabilities levels less than the probability (hence inducing risk aversion), the exception being for low-probability events, hence the popularity of lottery tickets.

emotional forces can increase loss aversion. Thaler (1980) uses changes in health to show that loss aversion is more pronounced for emotional outcomes. Lerner, Small, and Loewenstein (2004) show that inducing emotions, specifically sadness and disgust, can affect the endowment effect (a tendency, related to loss aversion, to value an object more when one owns it) with disgust related to decreased loss aversion and sadness related to increased loss aversion.[105] Shiv, Loewenstein, Bechara, Damasio, and Damasio (2005) test whether dysfunction in neural systems relating to emotion influence decision-making. They find that individuals with brain lesions in regions related to emotional processing exhibited less loss aversion than healthy individuals, that is individuals who did not have any neurological dysfunctions.

Loewenstein and O'Donoghue (2005) develop a model that predicts the probability weighting function should be more S-shaped (small probabilities are overweighed and large probabilities are underweighted) when the affective system (emotion) is playing a strong role in decision making. There is evidence that supports this. Rottenstreich and Hsee (2001) find that probability weighting for affect-rich outcomes, including kisses, electric shocks, and vacations, is more S-shaped sensitive. Sunstein (2002, 2003) document that strong emotions can lead

[105] The endowment effect is used to describe the situation where the value of an object increases to a person once they own the object. It can be related to loss aversion because the loss associated with giving up an object that one owns is felt more strongly than the gain associated with receiving the object.

to probability insensitivity. Brandstaetter, Kuehberger and Schneider (2002) and Kliger and Levy (2008) show that emotion-laden contexts or negative mood can increase probability weighting.

On the other hand, Fehr-Duda, Epper, Bruhin and Schubert (2011) find good mood can increase the optimistic component of probability weighting. This is corroborated by other studies that find that positive affect has been related to individuals giving higher estimates of probabilities of success in risky situations (DeSteno et al., 2000; Johnson & Tversky, 1983; Nygren, Isen, Taylor, & Dulin, 1996). Note that these studies do not directly measure participants' EQ (or any other emotion-based metric). Charupat et al. (2013) however do directly measure EQ using the afore-mentioned I-PANAS-SF instrument, and find that probability weighting function curvature tends to be higher for those low in EQ.

Eckel et al. (2012) conduct a study using high school students and while they do not find a strong relationship between cognitive ability and risk aversion, they do find some support for emotional development and risk aversion.

4.2.8.2. EQ and time preferences

Epper et al. (2011) suggest that emotion may be a driver of time preferences. More specifically they speculate that hyperbolic discounting and an excessive preference for the present may be driven by visceral motives, akin to what is seen in addictive behaviors. Baumeister and Heatherton (1996) suggest that since the ability to delay gratification requires emotional resources that enable an individual to look beyond immediate situations and weigh possible consequences of impulsive behavior, there should be parallels between temporal discounting and emotional self-regulation.

The research available on EQ and time preferences indicates a positive relationship between EQ and patience. Individuals with high neuroticism (lower EQ) have been shown to report more procrastination and impulsive behavior (Lee, Kelly, & Edwards, 2006; Whiteside & Lynam, 2001) . Fisher and Montalto (2010) find that those taking the long view (implying higher EQ) save more. And Walther (2010) relates emotion to hyperbolic discounting. Wan, Downey, and Stough (2014) find a negative correlation between EQ and procrastination and a positive correlation between stress and procrastination.

Manning et al. (2014) investigate the influence of personality (measured using the “Big Five” model) on time preferences and on the neural activity engaged by intertemporal choice (using fMRI). They find that higher neuroticism (lower EQ) correlates positively with strong impatience in the short-term, and relatively less impatience when the same trade-off between delay and monetary amount is moved into the future (similar to time preference reversals). They also find no significant correlations between cognitive abilities and time sensitivity (impulsivity) and exponential discounting (pure impatience).

Hirsh et al. (2008) investigate delay discounting and interactions between neuroticism and cognitive ability. They find that greater neuroticism (decreased EQ) is associated with higher discounting rates, but only in individuals with higher cognitive ability scores.

4.2.9. Preference determinants

Putting IQ and EQ aside for the moment, there is abundant research investigating the determinants of risk taking and patience. As for risk taking, older people closer to retirement should and do take on less risk because they have less time to recover from adverse market outcomes (Ameriks & Zeldes, 2004), as do higher-income, high-net worth individuals because more of their wealth tends to be in usually safer human capital (Calvet & Sodini, 2014). Eckel et al. (2012) find that high school students who come from lower income homes are more risk averse. Gächter, Johnson, and Herrmann (2010) find that loss aversion increases in age, income, and wealth, and decreases in education.

Along the same lines, markers of security such as job seniority and being married lead to lower risk aversion (Agnew, Balduzzi, & Sunden, 2003). Holding such factors constant, males are more amenable to risk (Barsky, Juster, Kimball, & Shapiro, 1997)

There is also a host of rather more subtle determinants of risk preference, such as genetics (Barnea, Cronqvist, & Siegel, 2010; Cesarini, Johannesson, Lichtenstein, Sandewall, & Wallace, 2010); culture (Bruhin, Fehr-Duda, & Epper, 2010); recent experience (Tinsley, Dillon, & Cronin, 2012); school environment (Eckel et al., 2012); openness to advice and a planner mentality (Bhandari & Deaves, 2008); and expertise (von Gaudecker, van Soest, & Wengström, 2012).

In the realm of patience, various determinants are stressed including subjective beliefs, attitudes, cognitive biases and financial constraints (Brown, Ivković, & Weisbenner, 2015). Brown et al. (2015) use a sample of Croatian retirees and the decision to accept an immediate pension payment, or a stream of delayed payments. They find that an individual's patience is associated with youth, good health, higher life expectancy, parenthood, income and absence of liquidity constraints. Also impactful are such subtle determinants as nurture (Nguyen 2011); transparency (Mishra, Mishra, Rixom and Chatterjee 2013); and saving adequacy uncertainty (van Schie, Donkers and Dallaert 2012).

Tanaka et al. (2010), in a study whose methodology to elicit preferences is very similar to that employed in the present research, find that in Vietnam village income is related to risk and time preferences, with wealthier villages not only being more patient but also less risk- averse.

4.2.10. Gender

There have been significant differences found between genders when it comes to IQ, EQ, and risk and time preferences. Overall, women have been documented as being more risk averse than men (Barsky et al., 1997; Booth et al., 2014; Booth & Katic, 2012; Frederick, 2005; Schubert, Brown, Gysler, & Brachinger, 1999). Fehr-Duda, de Gennaro, and Schubert (2006) find that women appear more risk averse than men in specific circumstances due to differences in their probability weighting, not their value functions. They find that women tend to be less sensitive to probability changes than men and that they underestimate large probabilities of gains more strongly than men. Fehr-Duda, Epper, Bruhin, and Schubert (2011) find that pre-existing good mood is significantly associated with women's probability weights, whereas men appear to be immune to mood effects but instead apply more mechanical decision criteria.

While Dohmen et al. (2010) find that individuals with high cognitive ability take more risks in lottery experiments and are more patient, they also find that this relationship is somewhat weaker for females. In their study on CRT, risk and time preferences, Frederick (2005) finds that men have higher CRT scores than women, and that women's mistakes on the CRT tend to be of the intuitive variety more than men's mistakes. They also find that CRT scores are more highly correlated with risk preferences for men than for women; and that CRT scores are more highly correlated with time preferences for women than for men.[106] Oechssler et

[106] The relationship between CRT scores and patience in women is in line with the findings of Shoda et al. (1990) who find that patience of preschool girls is strongly related to their subsequent SAT scores (an indicator of cognitive ability), but not such relationship existed for boys.

al. (2009) echo the findings of Frederick (2005), in that they also find that CRT scores for males are higher than those of females.

4.3. Hypotheses

Extant research though in its infancy points in the direction of both IQ and EQ pushing preferences in the direction of rationality. The present study uniquely examines the role of IQ and EQ simultaneously. We conjecture that both matter: namely, both higher IQ and higher EQ should impel decision-makers in the direction of rational behavior. The following hypotheses are consistent with this conjecture:

Hypothesis 1: Higher IQ and higher EQ are associated with risk preferences that are closer to rational risk preferences. More specifically, we expect to see:

a) *High-IQ people are closer to risk neutrality (lower a^*).*
b) *High-EQ people are closer to risk neutrality (lower a^*).*
c) *High-IQ people are more neutral to losses (lower λ^*).*
d) *High-EQ people are more neutral to losses (lower λ^*).*
e) *High-IQ people have less probability weighting (lower γ^*).*
f) *High-EQ people have less probability weighting (lower γ^*).*

The second hypothesis concerns time preference:

Hypothesis 2: Higher IQ and higher EQ are associated with time preferences that are closer to rational time preferences. More specifically, we expect to see:

a) *High-IQ people are more present-indifferent (lower β^*).*
b) *High-EQ people are more present-indifferent (lower β^*).*
c) *High-IQ people have a lower rate of pure time preference (lower ρ).*

d) High-EQ people have a lower rate of pure time preference (lower ρ).

4.4. Experimental design

4.4.1. Basic setup

The present experiment was conducted at McMaster University on two days during 2014, with four sessions being held on the first day and three on the second. There were about 150 participants, with 146 being usable.[107] Subjects, recruited via advertisements and a mass e-mailing to all junior and senior undergraduate business students, were given a survey to fill out (in pen and paper) along with supporting question sets and instructions which were carefully written to explain how to answer the survey. These appear in Appendices 4.A., 4.B., and 4.C.

The survey consisted of 25 questions in 5 blocks. The 5 questions (in 2 blocks) designed to elicit risk and time preferences were actually question sets. There were four versions of the survey (the only difference being the positioning of the question blocks) in order to obviate ordering effects. In one version (i.e., the one shown in Appendix 4.A.), section A consisted of the 10 I-PANAS-SF questions; section B the 3 CRT questions; section C the 3 question sets eliciting the 3 risk-preference parameters; section D the 2 question sets eliciting the 2 time-preference parameters; and section E several demographic questions (concerning sex, age,

[107] All participants had taken at least basic courses in finance/economics and probability/statistics.

year (in university) and the number of courses potentially helpful for the exercise at hand previously completed or currently in progress).[108] It took virtually all subjects less than an hour to complete.

4.4.2. Elicitation of risk preference

The elicitation procedure follows closely Tanaka et al. (2010).[109] There were three question sets, each comprised of a series of paired prospects (A vs. B). Subjects were to choose for each pair the preferred prospect. Going down the rows of paired prospects, B always became relatively more attractive than A, and this was pointed out in the instructions. Thus, if at a certain row preference switched from A to B, it was clearly illogical for it to switch back later. There were then three possibilities: a subject could always prefer A; she could always prefer B; or at first, she could prefer A but further down at some row switch to a preference for B. We calculated certainty equivalents based on the switching rows. The first two question sets together yielded estimates of α and γ, while the third question set yielded estimates of λ.

[108] Specifically, the survey refers to courses in economics, finance, math and statistics.
[109] This in turn is based on the procedure of Holt and Laury (2002).

4.4.3. Elicitation of time preference

The elicitation procedure for the two time-preference parameters was similar to that for the risk-preference parameters.[110] Since there were only two parameters to be estimated, only two question sets were required. The first set specified choices between money to be received in one week vs. money to be received in two weeks, yielding an estimate of the (pure) rate of time preference. And the second set specified choices between money to be received "today" vs. money to be received in one week, yielding an estimate of present bias.[111]

4.4.4. Incentive compatibility

The risk- and time-preference questions were rendered incentive-compatible as follows. The subjects were made aware in the instructions that at the end of each session four students would be randomly selected. Two of the students were assigned to the risk- preference questions and two of the students were assigned to the time-preference questions. In the former case, there were 14 choices in the first question set, 14 more in the second (choices 15-28), and seven more in the third (29-35).[112] In the latter case, there were 18 choices in the first question set and

[110] There are critics of this sort of elicitation procedure. For example, it has been shown that time preference may be impacted by market conditions (Krupka & Stephens, 2013).

[111] More specifically, "today" meant that a student had to report to the office of one of the experimenters at the end of the day to collect payment. Such an approach is designed to equalize the "hassle factor" for immediate vs. deferred choices.

[112] One of the rows in the third question set is identical to the previous row, allowing for one check on inattentiveness.

17 more in the second (choices 19-35). Next each student randomly chose a card from a pack numbered '1' to '35.' The number chosen was then the row where payment was made per stated preference. For example, if in the case of a time-preference question, card 25 was chosen (corresponding to the seventh row of the second time-preference question set), a student who had chosen A would receive $100 today while a student who had chosen B would receive $110 in one week.

The risk-preference questions required a *third* level of randomness. While as in the case of the time-preference questions the first level dictated which students were eligible and the second level which choice was operative, the third level "played out" the random draw. Specifically, a card from a group numbered '1' to '10' was chosen by the subject, with high card numbers corresponding to high-payout probabilities. For example, for row 10 and given a subject choice of B, the card '10' awarded the subject $150 (because there was a 10% probability of the high payout) and all other cards awarded her $2.50.

4.5. Empirical findings

4.5.1. Characteristics of the data

Table 4.1 provides a key describing all variables, including demographic variables, cognitive ability (IQ) scores, emotional stability (EQ) scores, and estimated risk and time preference parameters, as well as descriptive statistics in Panel B and a correlation matrix in the Panel C. More females (56%) than males participated.

The average age of this undergraduate student sample is 21; they tend to be third-year students; and they have taken or are currently taking about 10 courses in economics, finance, math or statistics.

The average CRT score is 1.60, not surprisingly somewhat below the 2.18 found among MIT students and well above the 0.57 found among University of Toledo students (Frederick, 2005). Further details regarding the performance on the three CRT questions are available in Table 4.2. In line with the findings of Frederick (2005) and Oechssler et al. (2009) males score higher than females. Specifically, we find average scores of 1.89 for males and 1.60 for females[113]. The majority of the sample either answered the CRT questions correctly or with the intuitive response. One difference between our sample's CRT scores and what has been documented previously by Frederick (2005) and Oechssler et al. (2009) is that in our case we find that males' mistakes tend to be more of the intuitive variety than females', with the overall ratio of intuitive mistakes to other mistakes at 3.73 for males and 2.91 for females.

The average EQ is 2.73, quite close to the 2.42 level found by Charupat et al. (2013) using the same NA proxy. With the exception of loss aversion, the risk-preference parameters were on average also quite close to what has been documented elsewhere. The median values are α = .91, γ = .74, and λ = 1.04

[113] The difference in scores is statistically significant at the 1% level using both ANOVA and Welch tests.

compared to Tversky and Kahneman (1992) .88, .61, and 2.25. As for α and γ, it is important to note that there are estimates of α above unity (implying risk seeking) and of γ above unity (implying reverse-S-shaped probability weighting). As for λ, we find that values of λ below one (implying loss seeking) are almost as common as above one (i.e., loss aversion). For these reasons, regressions with α^*, γ^* and λ^* as dependent variables are more meaningful, as lower values of α^*, γ^* and λ^* unequivocally suggest greater rationality.

While the pure rate of time preference, ρ, is quite high – with a mean of 10% per week, our estimate of 0.08 is not dissimilar to what has been documented elsewhere (Tanaka et al., 2010).[114] Somewhat surprisingly, this sample lacks present bias in the aggregate.[115] While many do exhibit present bias, many others exhibit future bias, so on average there is neither present nor future bias. Thus, as above, the β^* regression is more meaningful than the corresponding β regression.

Correlations give us a sense of what we are likely to find when we perform regression analysis. Turning to Panel C of Table 4.1, a few salient tendencies are apparent. IQ and EQ are virtually uncorrelated, suggesting the 2 key psychometric variables are quite different constructs. High IQ is positively correlated with being male, and it is negatively correlated with the 3 risk-preference parameter deviations. EQ is uncorrelated with SEX (where SEX=1 for males), while it is

[114] For example, Tanaka et al. (2010) estimate $\rho = 0.078$.

[115] Hyperbolic or quasi-hyperbolic discounting is not always found (Meyer, 2013).

negatively correlated with weighting function curvature and present/future bias. Further, most of the parameter deviation pair-wise correlations are significant and positive, implying that rationality or irrationality is systematic. Finally, consistent with Charupat et al. (2013), EQ and PA are positively correlated.

4.5.2. IQ, EQ and time preferences

In Table 4.3 we present regression results for absolute deviation from one of present bias, β*, and in Table 4.4 for the pure rate of time preference, ρ. These two parameters are regressed on IQ, EQ, and positive affectivity (PA), as well as sex and other possible explanatory variables. As previously stated, our expectation for IQ and EQ is that the coefficients will be negative: higher IQ and EQ are expected to lead to more rational preferences, which should imply lower values of β* and ρ. In each of Tables 4.3 and 4.4 in Panel A, for each dependent variable, we present 2 full-sample regressions: first, with IQ, EQ and PA as dependent variables; and, second, with SEX, AGE, YEAR and EDU as additional potential explanatory variables.[116] Given the impact of sex elsewhere documented, Panel B reports the results of regressions are run with interaction terms for SEX, allowing us to test the difference in effects between males and females on each time preference

[116] Logically, one might expect that age, progress through university (YEAR) and relevant education (COURSES) are positively associated with rational preferences.

variable β* and ρ.[117] Finding significant differences between males and females in our sample we also report the results of the regressions for male and female subsamples separately in Panels C and D respectively.

Beginning with β*, for the interaction regression reported in Panel B of Table 4.3, EQ is negative and statistically significant at 10%, suggesting that in general EQ is negatively associated with present (or future) bias; this is as hypothesized.[118] The interaction regression also has a negative coefficient on AGE x SEX, indicating that the effect of AGE on β* is significantly different for males and females. In fact, in the all-female subsample all variables are insignificant except for age, which is anomalously positive and significant at 10% (whereas for males it is negative and insignificant). In the all-male subsample, EQ continues to be significant, at 5%.

Turning to the (pure) rate of time preference, ρ, as reported in Table 4.4 Panel A, in the full sample EQ is positively associated with lower rates of time preference, though the significance level is only 10%. Importantly, the interaction regressions of Panel B, tell us that EQ is negatively related to ρ, and that there is a

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[117] The interaction regressions have high variance inflation factors (VIFs), which can result in unstable regression solutions. To take care of this, we orthogonalized the interaction terms. Specifically, for each interaction term, the interaction is regressed on the two original variables, and the residuals are used as the new interaction variable. For example, the following regression is run to determine the variable to use for $IQ\ x\ SEX$, $SEX \times IQ = a + b_1 SEX + b_2 IQ + Residual$. The residual is used as the interaction term $IQ\ x\ SEX$ in the interaction regression.

[118] In Table 4.3, Panel A none of the coefficients for the 2 full-sample regressions on with β* are found to be significant.

significant difference in the effect of EQ on ρ for males and females. As in the case of β*, when we look at the subsample regressions, impact arises mostly from the male subsample, as EQ is significant at 1% in the expected direction for both regressions when women are excluded. None of the 3 psychometric measures matters however in the case of the female subsample.[119]

In sum, there is solid evidence that high-EQ males have lower values of both β* and ρ, in both cases suggesting greater rationality. On the other hand, the time-preference parameters for women exhibit no such sensitivity to any of the 3 psychometric measures.

4.5.3. IQ, EQ and risk preferences

In Tables 4.5, 4.6, and 4.7 we present similar regression results where the absolute deviations from one of value function curvature, α*, probability weighting, γ*, and loss aversion, λ*, are regressed on the same set of explanatory variables as above. Once again, our expectation for IQ and EQ is that their coefficients will be negative: higher IQ and EQ are anticipated to lead to more rational preferences, which in turn implies lower deviations of α, γ and λ from one.

Beginning with α*, IQ for the full sample (Panel A) and the interaction regressions (Panel B) has a negative impact on α*, with the level of significance at

[119] Anomalously, more educated people (in the less sense of having taken more relevant courses) are *less* rational (at 10% in both the full-sample and male-subsample regressions).

10%. The interpretation is that the higher one's cognitive ability the lower is the deviation of α from one. In other words, if risk neutrality is our gold standard for rationality, high-IQ subjects tend to be closer to this standard. While the interaction regressions do not indicate a significant difference for the effect of IQ on α*, it is interesting to note that the impact of IQ does show up in the male subsample, with IQ significant at 1% in both regressions, while it is insignificant in the female subsample, reminiscent of the two time-preference parameters previously discussed. The 2 emotion-based psychometric measures have no impact on α*.

Turning to γ*, in the full sample both IQ and EQ are negative and significant at 5% when only the 3 psychometric variables are included as independent variables. When all variables are included, however, both IQ and EQ cease to be significant, with much of the explanatory power moving to SEX: specifically, males are more rational at 1%. Additionally, older people are more rational (at 10%). In the interaction regressions IQ (at 10%), PA (at 10%) and SEX (at 1%) are negative and significant, and interestingly the interaction term SEX x IQ has a negative, significant coefficient at 5% and EQ x SEX has a positive and significant coefficient at 5%. In the male subsample, IQ is negative and significant at 1%. Moreover, high-PA subjects are also more rational at close to 1% significance. As for the female subsample, here EQ plays its expected role, with significance at 5%.

Finally, IQ is negatively associated with λ^* and once again this operates primarily through the male subsample. As evidence, IQ is significantly negative at 5% in the 3-psychometric-measure full-sample regression, and in the interaction regressions IQ, PA x SEX and SEX are each negative and significant at 5%, 10% and 5% respectively. While the interaction regressions do not show a significant difference between males and females, for IQ and EQ in the male-subsample regressions, IQ is significant at 1-5%, while high-PA individuals are more rational at 5%. As before, the 3 psychometric measures have no impact in the female subsample.

In sum, IQ is the dominant psychometric measure impacting risk preferences but only for males. High-IQ males have α, γ and λ values closer to their rational levels (i.e., unity). For γ and λ, those with high PA are also more rational. For females, only in the case of probability weighting does either IQ or EQ enter the picture, with high-EQ females having less probability weighting. These findings are in line with the findings of Frederick (2005) and Dohmen et al. (2010), who find that individuals with high cognitive ability have risk preferences more in line with rationality and that the relationship is weaker for females than for males. Fehr-Duda et al. (2011) find that probability weights for females are more related to mood effects, whereas males in their sample tend to apply rational decision criteria (e.g., expected value maximization), and in our case, we find a significant association between EQ and probability weighting for females.

4.5.4. Rational risk preferences

As has been found in past research, a substantial minority of the subjects have risk preferences approximating rationality (i.e., EUT-type behavior). Specifically, in our sample a far from negligible percentage of subjects have estimates of α, γ and λ that fall close to unity for each parameter. By far the most common set of choices for the three risk- preference question sets was the seventh choice for the first question set, the first choice (or choice 15 overall) for the second question set (i.e., always B), and the second choice (or choice 30 overall) for the third. In fact, 25 of 146 subjects (or 17%) answered these questions in the exact same fashion. In all three cases unity falls within their choice intervals. It is notable that this percentage is quite comparable to the results of Bruhin et al (2010) and Charupat et al. (2013), who find that for 20% and 29% of subjects, respectively, rationality could not be rejected.

We next categorize individuals as having risk preferences in line with expected utility theory (EUT) or prospect theory (PT). Since utility curvature is arguably appropriate for both EUT and PT, we focus on the values of λ and γ. More specifically, if individuals have estimates of both λ and γ within 10% of unity we assign them to the EUT category. Individuals with γ below unity by 10% or more and λ above unity by 10% or more are categorized as PT. Individuals who do not conform to either EUT or PT behavior are categorized as 'Other'.

Table 4.8 reports the results of the categorizations of individuals as one of the three risk preference types. Of 146 subjects, 32 (22%) are labelled as EUT, 56 (38%) as PT, and 58 (40%) as Other. Panel B of Table 4.8 reports the results of an ANOVA test, with the null hypothesis that the means for IQ, EQ, PA, SEX, AGE, YEAR, and EDU are equal across the three risk preference categories. We reject the null for the means of IQ, EQ, PA, and SEX. Individuals categorized as EUT have higher average IQ, EQ, and PA values than those categorized as PT or Other. While those categorized as PT have the lowest average IQ values.

Probably it is more interesting to focus on pairwise comparisons of differences between means for each of the three risk preference categories (these are reported in Panel C of Table 4.8). For the difference in means between EUT and PT we find that average IQ is significantly higher for EUT individuals at 1% significance. We also find that the difference between EUT and PT for SEX is positive, significant at 1%. If we refer back to Panel A of Table 4.8 we can see that there are significantly more males than females with EUT preferences and more females than males with PT preferences. More specifically, 31% of males exhibit EUT preferences and only 15% of females do. And 46% of females exhibit PT preferences, whereas only 28% of males do. Individuals who demonstrate EUT type preferences have significantly higher average EQ and PA scores, at 5% and 1 % respectively, than Other individuals. And individuals who demonstrate PT preference have significantly higher average PA (at 5%) than Other individuals.

4.5.5. Males vs. females

A salient observation above was that there was a large difference between males and females in the sensitivity of their time- and risk-preference parameters to IQ and EQ. In this section, we explore central tendencies rather than sensitivities. Table 4.9 presents sample means by sex for preference parameter deviations and psychometric variables. Additionally, we present p-values of differences between means with and without the assumption of common variance. In all cases the p-values are nearly identical, so we will concentrate on the ANOVA F-test which assumes common variance. Some notable patterns emerge.

In this sample, men have substantially higher IQ scores as proxied by CRT, with a mean of 1.89 vs. 1.38 for females (p-val = .003).[120] They also have slighter higher EQs: 2.82 vs. 2.67 (p-val = .091). But there is no difference on the third psychometric measure, PA. In the case of risk preferences men are more rational: for all three parameter deviations the female-vs.-male differential is positive, and it is strongly statistically significant for both probability weighting and loss aversion. Specifically, γ^* is .237 for males vs. .367 for females (p-val=.001), while λ^* is .519 for males vs. 1.007 for females (p-val=.007). On the other hand, there is

[120] Of course, we are not suggesting that males are "smarter" than females. We only claim that *in our sample* males performed significantly better on the CRT which seems to be correlated with some aspects of cognitive ability. This is similar to the findings reported by Frederick (2005) and Oechssler et al. (2009).

no significant difference between sexes when it comes to the time-preference parameters.

4.5.6. Risk and time preferences

As mentioned in the literature review, there is a strand of literature that investigates the relationship between risk and time preferences for individuals. Their main finding is that there is a correlation between risk and time preferences. In Table 4.10 we report the results of testing whether including risk preference deviation parameters (α^*, γ^*, λ^*) would change the results of time preference regressions that have β^* and ρ as the dependent variables. We run full-sample and interaction regressions with time preference parameters as the dependent variables and α^*, γ^*, λ^*, IQ, EQ, PA, SEX, YEAR, AGE, and EDU as the independent variables. For both β^* and ρ, EQ is negative and significant. It is important to note that EQ remains a significant factor in predicting time preferences even after controlling for risk preferences. This supports suggestions that the correlation between risk and time preferences found in previous studies might be driven by a third factor (Epper et al., 2011).

4.5.7. Discussion

In sum, EQ appears to be the dominant force in the realm of time preference. High-EQ males have less present or future bias and lower rates of time preference. On the other hand, IQ is front and center for risk preference, with high-IQ males having parameter values closer to their rational levels. It is not clear why these sensitivities are not apparent for females (except in the case of probability distortion and EQ).

The results for EQ predicting time preferences remain robust even after controlling for risk preference parameters. It is interesting to note that Epper et al. (2011) find a link between probability weights and discount weights, and suggest that there may be a third factor driving both types of departure from standard predictions. Nevertheless, we continue to find negative correlations between both EQ and γ^* and EQ and β^* even after controlling for SEX, YEAR, AGE, and EDU.

The evidence presented here suggests that it is often the case that the same people who fall short of rationality (or who are subject to bias) in one way also fall short in other ways as well. Along these lines, van der Heijden, Klein, Müller, and Potters (2012) find that those influenced by framing are more impatient. And Epper et al (2011) find that those who distort probabilities also tend to be present-biased.

4.6. Conclusion

To recap, both cognitive ability (IQ) and emotional balance (EQ) impact preferences. If we take expected utility theory as the hallmark of normative decision-making when people face risk, those with higher levels of IQ have preferences that are more rational than those with low levels of IQ. This operates almost entirely in the male subsample. EQ seems to matter for probability weighting in the case of women. As for time preference, again more consistent with rationality, high-EQ males are less subject to present (or future) bias. And high-EQ males are also more patient in that they tend to have lower rates of time preference.

A unique contribution is that EQ plays a role that is about as meaningful as IQ when it comes to explaining preferences. This suggests that the growing research (which has been previously cited) on the impact of cognitive ability, while important, is perhaps omitting an equally important determinant of preferences. Indeed, it has been suggested that EQ is a more important determinant of whether someone should be a "do-it-yourselfer" in the investment realm than financial sophistication, and the results presented here buttress this notion.[121]

[121] See Deaves (2006).

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Tables

Table 4.1.
Variable Definitions, Descriptive Statistics and Correlations

Panel A is a key describing the variables computed from subject responses collected in the experiment, this includes demographic variables, cognitive ability (IQ), emotional stability (EQ) and risk and time preference parameters. Panel B reports descriptive statistics of the variables. Panel C provides correlations.

Panel A: Definition of Variables

IQ	A measure of cognitive ability. IQ is measured based on the response to the 3-question Cognitive Reflection Test (CRT) and the value of this variable can range from 0-3; where 3 indicates that a participant has answered all three questions correctly. A higher IQ value implies higher cognitive ability.
EQ	A measure of emotional balance. EQ is 5 minus the average response to 5 Negative Affectivity (NA) questions from I-PANAS-SF. A 5-point Likert scale is used for these questions. A higher value implies higher emotional balance.
PA	A measure of positive emotions. PA is the average response to the 5 Positive Affectivity (PA) questions from I-PANAS-SF. A 5-point Likert scale is used for these questions. A higher value implies a higher tendency to experience positive emotions.
SEX	An indicator variable set to 1 if the participant is male and 0 if female.
AGE	Participant age (in years).
YR	The number of years of postsecondary education completed by the participant.
EDU	Number of relevant courses (including finance, economics, statistics, and probability) that the participant has completed or is currently enrolled in.
α	Risk preference parameter. Measures the concavity/convexity of prospect theory's value function for a participant in the positive/negative domain. α is estimated for each participant based on their responses to two questions in which participants are asked to choose between a series of paired prospects.
α^*	$\lvert 1-\alpha \rvert$.
γ	Risk preference parameter. Measures the probabilistic insensitivity of Prelec's 1998 single parameter probability weighting function for a participant in the positive/negative domain. γ is estimated for each participant based on their responses to the same two questions used to estimate α.
γ^*	$\lvert 1-\gamma \rvert$.
λ	Risk preference parameter. Measures loss aversion. Estimated using the estimates of α and γ along with a question set from the survey.
λ^*	$\lvert 1-\lambda \rvert$.
β	Time preference parameter. β measures present bias using the general time function estimated by Tanaka, Camerer, and Nguyen (2010). This parameter is estimated for each participant using the estimated value of ρ and the response to a question set where the participant makes a choice between money to be received today and money to be received in one week.
β^*	$\lvert 1-\beta \rvert$.
ρ	Time preference parameter. ρ measures the pure rate of time preference. This parameter is estimated using a question set where the choice is between money to be received in one week and money to be received in two weeks. A higher ρ implies a higher deviation from rationality.

Panel B: Descriptive Statistics

	Mean	Median	Minimum	Maximum	SD	Observations
IQ	1.603	2	0	3	1.047	146
EQ	2.733	2.8	0.8	3.8	0.543	146
PA	3.364	3.4	1.4	4.8	0.598	146
SEX	0.438	0	0	1	0.498	146
AGE	21.007	21	19	25	1.054	146
YR	2.949	3	2	6	0.756	146
EDU	10.048	9	1	29	4.211	146
α	0.858	0.907	0.033	1.614	0.342	146
α*	0.293	0.209	0.006	0.967	0.226	146
γ	0.747	0.735	0.028	1.500	0.302	146
γ*	0.310	0.273	0.003	0.972	0.243	146
λ	1.602	1.043	0.084	6.934	1.206	145
λ*	0.793	0.506	0.009	5.934	1.089	145
β	1.023	1.002	0.871	1.567	0.084	146
β*	0.039	0.010	0.000	0.567	0.078	146
ρ	0.099	0.054	0.001	0.454	0.114	146

Panel C: Correlations

	IQ	EQ	PA	SEX	AGE	YR	EDU	α	α*	γ	γ*	λ	λ*	β	β*	ρ
IQ	1.00															
EQ	-0.05	1.00														
PA	-0.12	**0.31** ***	1.00													
SEX	**0.25** ***	0.13	-0.05	1.00												
AGE	0.01	0.05	-0.02	0.03	1.00											
YR	0.03	-0.06	0.04	-0.04	0.55 ***	1.00										
EDU	0.08	0.01	0.02	-0.09	0.10	0.17 **	1.00									
α	0.13	0.13	-0.01	0.12	-0.01	-0.01	0.18 **	1.00								
α *	**-0.17** **	-0.06	0.06	-0.12	-0.09	-0.06	-0.10	**-0.66** ***	1.00							
γ	**0.22** ***	**0.20** **	0.10	**0.26** ***	0.17 **	0.05	0.07	**0.58** ***	-0.52 ***	1.00						
γ*	**-0.17** **	**-0.18** **	-0.13	**-0.26** ***	-0.16*	-0.05	-0.11	**-0.62** ***	**0.48** ***	**-0.92** ***	1.00					
λ	**-0.16** *	0.05	0.08	**-0.21** ***	-0.03	-0.07	-0.10	0.02	**0.27** ***	**-0.22** ***	**0.20** **	1.00				
λ *	**-0.12** **	0.02	0.02	**-0.22** ***	-0.05	-0.08	-0.10	-0.08	**0.37** ***	**-0.29** ***	**0.27** ***	**0.94** ***	1.00			
β	0.05	-0.07	0.11	-0.10	0.11	0.07	-0.04	-0.09	0.10	-0.02	0.03	-0.01	0.00	1.00		
β*	0.00	**-0.22** ***	0.07	-0.05	0.11	**0.17** **	0.08	**-0.15** *	**0.14** *	-0.07	0.08	-0.03	0.00	**0.81** ***	1.00	
ρ	-0.08	-0.14	0.05	0.01	0.09	0.12	0.16	-0.05	0.13	0.00	0.00	-0.04	0.00	**0.43** ***	**0.67** ***	1.00

Table 4.2.
Distribution of Answers to the Cognitive Reflection Test (CRT)

Panel A provides the distribution of responses to the three CRT questions administered in the experiment. Correct is the number of correct responses to each of the three CRT questions, intuitive mistakes are incorrect responses of the intuitive nature, other mistakes are any other incorrect answers. Panel B and Panel C report the distribution of responses for males and females respectively. Panel D reports the average CRT scores, as well as ratios of intuitive to other mistakes. Average intuitive to other mistakes is an average of the intuitive to other mistakes ratios for each of the three questions. Overall intuitive to other mistakes is a ratio of the total number of intuitive mistakes to the total number of other mistakes for the three questions combined. The full CRT question set is available in Appendix 4.A: Experimental Survey.

Panel A: All Responses

	Correct		**Intuitive Mistakes**		**Other Mistakes**		**Ratio of Intuitive to Other Mistakes**	**Total Responses**
Question	**N**	**%**	**N**	**%**	**N**	**%**		
Bat and Ball	81	55%	58	40%	7	5%	8.29	146
Widgets	59	40%	70	48%	17	12%	4.12	146
Lily Pads	94	64%	27	18%	25	17%	1.08	146

Panel B: Male Responses

	Correct		**Intuitive Mistakes**		**Other Mistakes**		**Ratio of Intuitive to Other Mistakes**	**Total Responses**
Question	N	%	N	%	N	%		
Bat and Ball	40	27%	23	16%	1	1%	23.00	64
Widgets	30	21%	29	20%	5	3%	5.80	64
Lily Pads	51	35%	4	3%	9	6%	0.44	64

Panel C: Female Responses

Question	Correct N	Correct %	Intuitive Mistakes N	Intuitive Mistakes %	Other Mistakes N	Other Mistakes %	Ratio of Intuitive to Other Mistakes	Total Responses
Bat and Ball	41	28%	35	24%	6	6%	5.83	82
Widgets	29	20%	41	28%	12	12%	3.42	82
Lily Pads	43	29%	23	16%	16	11%	1.44	82

Panel D: Average CRT Scores

	Average CRT Score	Average Intuitive to Other Mistakes	Overall Intuitive to Other Mistakes
All Responses	1.60	4.49	3.16
Male	1.89	9.75	3.73
Female	1.40	3.56	2.91

Table 4.3.
Time Preference - Present Bias (β*) Regressions

Linear regression estimates for dependent variable beta deviation, β* are shown below. The explanatory variables include cognitive ability (IQ), emotional stability (EQ), positive affectivity (PA), SEX (male = 1), AGE, YEAR, and EDU. Panel A reports the full-sample regressions. Panel B reports interaction regressions with orthogonalized interaction terms based on SEX. Given the impact of SEX, Panel C and Panel D repeat the linear regressions for males and female subsamples respectively. t-Statistics are displayed under the coefficient estimates. The White test indicates p-values for a test of the null of homoscedasticity in regression errors. As a result of this test, HCSE indicates whether standard errors are corrected for heteroscedasticity. See Panel A of Table 1 for variable definitions. Significant at * 10%, ** 5%, and *** 1%.

Panel A: Beta deviation (β*) full-sample regressions

Const.	IQ	EQ	PA	SEX	AGE	YEAR	EDU		N	White Test	HCSE
0.076	0.000	-0.037	0.019					0.043	146	0.003	Yes
1.02	0.00	-1.57	1.42								
-0.087	0.000	-0.036	0.018	0.000	0.006	0.008	0.001	0.041	146	0.009	Yes
-0.69	-0.08	-1.57	1.38	0.008	0.73	1.00	.69				

Panel B: Beta deviation (β*) interaction regressions

Const.	IQ	IQ × SEX	EQ	EQ × SEX	PA	PA × SEX	SEX	AGE	AGE × SEX	YEAR	YEAR × SEX	EDU	EDU × SEX		N	White Test	HCSE
0.076	0.07	0.00	-0.04	-0.02	0.02	0.03	0.00							0.04	146	0.000	Yes
1.02	0.83	0.28	-1.60	-0.55	1.48	0.96	-0.14										
-0.05	0.00	0.02	**-0.04**	-0.02	0.02	0.03	0.00	0.00	**-0.04**	0.01	0.01	0.00	0.00	0.08	146	0.000	Yes
-0.44	0.13	1.28	**-1.69**	-0.47	1.52	0.92	0.03	0.37	**-2.17**	1.61	0.69	.69	0.08				
			*						**								

Interaction terms are orthogonalized.

Panel C: Beta deviation (β*) male subsample regressions

Const.	IQ	EQ	PA	AGE	YEAR	EDU		N	White Test	HCSE
0.022	0.016	**-0.055**	0.042				0.097	64	0.003	Yes
0.30	0.96	**-2.13**	1.30							
		**								
0.243	0.014	**-0.049**	0.038	-0.014	0.021	0.001	0.077	64	0.006	Yes
1.54	0.95	**-2.21**	1.31	-1.21	1.52	.57				
		**								

Panel D: Beta deviation (β*) female subsample regressions

Const.	IQ	EQ	PA	AGE	YEAR	EDU		N	White Test	HCSE
0.105	-0.006	-0.032	0.009				0.014	82	0.003	Yes
1.01	-0.83	-0.93	0.72							
-0.444	-0.007	-0.031	0.009	**0.025**	0.008	0.001	0.097	82	0.006	Yes
-2.01	-0.99	-1.02	0.79	**1.82**	0.73	.44				
				*						

Table 4.4.
Time Preference – Pure Rate of Time Preference (ρ) Regressions

Linear regression estimates for dependent variable beta deviation, ρ are shown below. The explanatory variables include cognitive ability (IQ), emotional stability (EQ), positive affectivity (PA), SEX (male = 1), AGE, YEAR, and EDU. Panel A reports the full-sample regressions. Panel B reports interaction regressions with orthogonalized interaction terms based on SEX. Given the impact of SEX, Panel C and Panel D repeat the linear regressions for males and female subsamples respectively. t-Statistics are displayed under the coefficient estimates. The White test indicates p-values for a test of the null of homoscedasticity in regression errors. As a result of this test, HCSE indicates whether standard errors are corrected for heteroscedasticity. See Panel A of Table 1 for variable definitions. Significant at * 10%, ** 5%, and *** 1%.

Panel A: Rho (ρ) full-sample regressions

Const.	IQ	EQ	PA	SEX	AGE	YEAR	EDU		N	White Test	HCSE
0.152	-0.009	**-0.032**	0.015					0.009	146	0.420	No
2.27	-1.00	**-1.76**	0.90								
		*									
-0.035	-0.013	**-0.035**	0.015	0.020	0.006	0.009	0.005	0.028	146	0.458	No
-0.16	-1.40	**-1.89**	0.90	1.00	0.54	0.58	2.01				
		*					**				

Panel B: Rho (ρ) interaction regressions

Const.	IQ	IQ × SEX	EQ	EQ × SEX	PA	PA × SEX	SEX	AGE	AGE × SEX	YEAR	YEAR × SEX	EDU	EDU × SEX		N	White Test	HCSE
0.13	-0.01	0.02	**-0.04**	**-0.11**	0.02	0.03	0.01							0.04	146	0.003	Yes
2.01	-0.74	1.15	**-2.06**	**-2.70**	1.33	0.74	0.72										
			**	**													
-0.10	-0.01	0.02	**-0.04**	**-0.10**	0.02	0.03	0.01	-0.02	-0.02	0.01	-0.01	0.00	0.00	0.07	146	0.156	No
-0.54	-1.04	1.29	**-1.73**	**-2.24**	1.29	0.79	0.76	-1.22	-1.22	0.78	-0.21	1.47	-0.64				
			*	**													

Interaction terms are orthogonalized.

Panel C: Rho (ρ) male subsample regressions

Const.	IQ	EQ	PA	AGE	YEAR	EDU		N	White Test	HCSE
0.275	0.007	**-0.110**	0.037				0.140	64	0.420	No
2.67	0.49	**-3.63**	1.49							
		***								
0.302	0.006	**-0.108**	0.036	-0.003	0.008	0.002	0.101	64	0.623	No
0.96	0.39	**-3.41**	1.41	-0.19	0.31	0.57				
		***								

Panel D: Rho (ρ) female subsample regressions

Const.	IQ	EQ	PA	AGE	YEAR	EDU		N	White Test	HCSE
0.089	-0.016	-0.003	0.012				-0.015	82	0.420	No
1.03	-1.26	-0.14	0.50							
-0.450	-0.018	-0.004	0.010	0.022	0.014	**0.006**	0.058	82	0.623	No
-1.51	-1.55	-0.18	0.44	1.51	0.71	**1.83**				
						*				

Table 4.5.
Risk Preference – Alpha Deviation (α*) Regressions

Linear regression estimates for dependent variable alpha deviation, α* are shown below. The explanatory variables include cognitive ability (IQ), emotional stability (EQ), positive affectivity (PA), SEX (male = 1), AGE, YEAR, and EDU. Panel A reports the full-sample regressions. Panel B reports interaction regressions with orthogonalized interaction terms based on SEX. Given the impact of SEX, Panel C and Panel D repeat the linear regressions for males and female subsamples respectively. t-Statistics are displayed under the coefficient estimates. The White test indicates p-values for a test of the null of homoscedasticity in regression errors. As a result of this test, HCSE indicates whether standard errors are corrected for heteroscedasticity. See Panel A of Table 1 for variable definitions. Significant at * 10%, ** 5%, and *** 1%.

Panel A: Alpha deviation (α*) full-sample regressions

Const.	IQ	EQ	PA	SEX	AGE	YEAR	EDU		N	White Test	HCSE
0.361	**-0.036**	-0.032	0.023					0.016	146	0.060	Yes
2.48	**-1.95**	-0.83	0.69								
	*										
0.637	-0.031	-0.027	0.022	-0.034	-0.010	-0.012	-0.005	0.006	146	0.211	No
1.50	-1.64	-0.72	0.66	-0.86	-0.45	-0.41	-0.99				

Panel B: Alpha deviation (α*) interaction regressions

Const.	IQ	IQ × SEX	EQ	EQ × SEX	PA	PA × SEX	SEX	AGE	AGE × SEX	YEAR	YEAR × SEX	EDU	EDU × SEX		N	White Test	HCSE
0.38	**-0.04**	-0.06	-0.02	-0.01	0.01	-0.10	-0.03							0.002	146	0.000	Yes
2.72	**-1.85**	-1.37	-0.52	-0.13	0.37	-1.53	-0.79										
	*																
0.84	**-0.04**	-0.06	-0.02	0.01	0.01	**-0.11**	-0.03	-0.02	-0.06	0.00	0.05	-0.02	-0.06	0.004	146	0.000	Yes
2.35	**-1.84**	-1.54	-0.39	0.11	0.34	**-1.80**	-0.87	-1.07	-1.46	0.11	0.85	-1.07	-1.46				
	*					*											

Interaction terms are orthogonalized.

Panel C: Alpha deviation (α*) male subsample regressions

Const.	IQ	EQ	PA	AGE	YEAR	EDU		N	White Test	HCSE
0.615 3.40	**-0.071** **-2.26** **	-0.027 -0.57	-0.042 -1.14				0.074	64	0.060	Yes
1.510 2.67	**-0.074** **-2.73** ***	-0.011 -0.19	-0.051 -1.12	-0.047 -1.55	0.029 0.65	-0.001 -0.20	0.076	64	0.143	No

Panel D: Alpha deviation (α*) female subsample regressions

Const.	IQ	EQ	PA	AGE	YEAR	EDU		N	White Test	HCSE
0.204 1.04	-0.016 -0.62	-0.018 -0.32	0.053 1.06				-0.018	82	0.060	Yes
0.082 0.13	-0.013 -0.49	-0.019 -0.37	0.058 1.19	0.011 0.35	-0.020 -0.48	-0.006 -0.94	-0.039	82	0.143	No

Table 4.6.
Risk Preference – Gamma deviation (γ*) Regressions

Linear regression estimates for dependent variable gamma deviation, γ* are shown below. The explanatory variables include cognitive ability (IQ), emotional stability (EQ), positive affectivity (PA), SEX (male = 1), AGE, YEAR, and EDU. Panel A reports the full-sample regressions. Panel B reports interaction regressions with orthogonalized interaction terms based on SEX. Given the impact of SEX, Panel C and Panel D repeat the linear regressions for males and female subsamples respectively. t-Statistics are displayed under the coefficient estimates. The White test indicates p-values for a test of the null of homoscedasticity in regression errors. As a result of this test, HCSE indicates whether standard errors are corrected for heteroscedasticity. See Panel A of Table 1 for variable definitions. Significant at * 10%, ** 5%, and *** 1%.

Panel A: Gamma deviation (γ*) full-sample regressions

Const.	IQ	EQ	PA	SEX	AGE	YEAR	EDU		N	White Test	HCSE
0.722	**-0.044**	**-0.077**	-0.039					0.058	146	0.662	No
5.23	**-2.33**	**-2.02**	-1.14								
	**	**									
1.569	-0.030	-0.050	-0.050	**-0.110**	**-0.041**	0.021	-0.007	0.116	146	0.072	Yes
3.75	-1.49	-1.53	-1.52	**-2.75**	**-1.90**	0.65	-1.59				
				***	*						

Panel B: – Gamma deviation (γ*) interaction regressions

Const.	IQ	IQ × SEX	EQ	EQ × SEX	PA	PA × SEX	SEX	AGE	AGE × SEX	YEAR	YEAR × SEX	EDU	EDU × SEX		N	White Test	HCSE
0.76	**-0.04**	**-0.08**	-0.05	**0.13**	**-0.06**	-0.07	**-0.11**							0.116	146	0.048	Yes
6.77	**-1.97**	**-2.15**	-1.56	**2.17**	**-1.91**	-1.04	**-2.61**										
	*	**		**	*		***										
1.65	**-0.04**	**-0.08**	-0.04	**0.14**	**-0.07**	-0.07	-0.11	**-0.04**	0.02	0.02	0.01	-0.01	0.00	0.201	146	0.000	Yes
4.29	**-1.84**	**-2.10**	-1.32	**2.22**	**-2.10**	-1.14	-2.71	**-2.16**	0.40	0.52	0.09	-1.50	-0.59				
	*	**		**	**			*									

Interaction terms are orthogonalized.

Panel C: Gamma deviation (γ*) male subsample regressions

Const.	IQ	EQ	PA	AGE	YEAR	EDU		N	White Test	HCSE
0.615	**-0.086**	0.042	**-0.101**				0.131	64	0.662	No
3.35	**-3.27**	0.78	**-2.29**							
	***		*							
1.377	**-0.084**	0.052	**-0.108**	-0.035	0.019	-0.009	0.240	64	0.592	No
2.54	**-3.22**	0.96	**-2.48**	-1.22	0.45	-1.52				
	***		**							

Panel D Gamma deviation (γ*) female subsample regressions

Const.	IQ	EQ	PA	AGE	YEAR	EDU		N	White Test	HCSE
0.738	-0.009	**-0.092**	-0.033				0.023	82	0.662	No
3.90	-0.34	**-1.78**	-0.67							
		*								
1.799	-0.008	-0.086	-0.036	-0.051	0.014	-0.004	0.095	82	0.592	No
2.67	-0.28	-1.64	-0.72	-1.57	0.31	-0.61				

Table 4.7.
Risk Preference – Lambda deviation (λ*) Regressions

Linear regression estimates for dependent variable lambda deviation, λ* are shown below. The explanatory variables include cognitive ability (IQ), emotional stability (EQ), positive affectivity (PA), SEX (male = 1), AGE, YEAR, and EDU. Panel A reports the full-sample regressions. Panel B reports interaction regressions with orthogonalized interaction terms based on SEX. Given the impact of SEX, Panel C and Panel D repeat the linear regressions for males and female subsamples respectively. t-Statistics are displayed under the coefficient estimates. The White test indicates p-values for a test of the null of homoscedasticity in regression errors. As a result of this test, HCSE indicates whether standard errors are corrected for heteroscedasticity. See Panel A of Table 1 for variable definitions. Significant at * 10%, ** 5%, and *** 1%.

Panel A: Lambda deviation (λ*) full-sample regressions

Const.	IQ	EQ	PA	SEX	AGE	YEAR	EDU		N	White Test	HCSE
1.109	**-0.205**	0.013	-0.007					0.018	146	0.512	No
1.75	**-2.38**	0.08	-0.04								
	**										
1.596	-0.141	0.075	-0.022	**-0.455**	0.001	-0.093	-0.027	0.043	146	0.783	No
0.79	-1.60	0.43	-0.14	**-2.43**	0.01	-0.66	-1.24				
				**							

Panel B: Lambda deviation (λ*) interaction regressions

Const.	IQ	IQ × SEX	EQ	EQ × SEX	PA	PA × SEX	SEX	AGE	AGE × SEX	YEAR	YEAR × SEX	EDU	EDU × SEX		N	White Test	HCSE
1.21	**-0.18**	-0.08	0.09	0.23	-0.05	-0.44	**-0.41**							0.039	146	0.035	Yes
1.91	**-2.00**	-0.41	0.48	0.61	-0.33	-1.36	**-2.21**										
	**						**										
3.41	**-0.17**	-0.11	0.07	0.33	-0.05	**-0.53**	**-0.42**	-0.09	-0.11	-0.02	0.71	-0.02	0.01	0.061	146	0.348	No
2.14	**-2.56**	-0.87	0.35	1.04	-0.31	**-1.77**	**-2.54**	-1.06	-0.61	-0.20	3.27	-1.14	0.34				
	**					*	**				***						

Interaction terms are orthogonalized.

Panel C: Lambda deviation (λ*) male subsample regressions

Const.	IQ	EQ	PA	AGE	YEAR	EDU		N	White Test	HCSE
1.283	**-0.228**	0.241	**-0.304**				0.082	64	0.512	No
2.08	**-2.59**	1.33	**-2.06**							
	**		**							
3.385	**-0.235**	0.293	**-0.351**	-0.141	**0.346**	-0.012	0.140	64	0.957	No
1.89	**-2.72**	1.63	**-2.42**	-1.48	**2.46**	-0.63				
	***		**		**					

Panel D: Lambda deviation (λ*) female subsample regressions

Const.	IQ	EQ	PA	AGE	YEAR	EDU		N	White Test	HCSE
0.716	-0.151	0.010	0.139				-0.018	82	0.512	No
0.74	-1.10	0.04	0.55							
2.632	-0.128	-0.040	0.178	-0.031	-0.357	-0.022	0.003	82	0.957	No
0.77	-0.94	-0.15	0.70	-0.19	-1.61	-0.63				

Table 4.8.
Risk Preferences – EUT, PT, and Other

Individuals are categorized as having risk preferences in line with expected utility theory (EUT), prospect theory (PT), and other. Individuals whose estimates of both λ and γ are within 10% of unity are labelled as EUT, while those with estimates of γ 10% below unity and λ 10% above unity are labelled as PT. Individuals who do not conform to EUT or PT are categorized as Other. Panel A provides a summary of observations categorized as EUT, PT, or Other. Panel B reports the results of and ANOVA test with the null hypothesis that the means for IQ, EQ, PA, SEX, AGE, YEAR, and EDU are equal across risk preference categories. Panel C reports the pairwise comparison among the means for IQ, EQ, PA, and SEX.

Panel A: Number of observations labelled as EUT, PT, and Other

	Observations	Males	Females
EUT	32	20	12
PT	56	18	38
Other	58	26	32

Panel B: ANOVA test

	Mean			ANOVA Test		
	EUT	PT	OTHER	F Value	Pr > F	
IQ	1.875	1.339	1.707	3.240	0.042	**
EQ	2.913	2.711	2.655	2.440	0.091	*
PA	3.625	3.405	3.179	6.380	0.002	***
SEX	0.625	0.321	0.448	3.960	0.021	**
AGE	21.188	20.839	21.069	1.280	0.280	
YEAR	3.000	2.830	3.034	1.140	0.324	
EDU	10.813	9.500	10.155	1.020	0.363	

Significant at * 10%, ** 5%, and *** 1%.

Panel C: Pairwise difference in means – Tukey's test

	Difference Between Means		
	EUT – PT	EUT – Other	PT - Other
IQ	**0.536*** **	0.168	-0.368
EQ	0.202	**0.257** **	0.056
PA	0.220	**0.466*** **	**0.226** **
SEX	**0.304*** **	0.177	-0.127

Significant at * 10%, ** 5%, and *** 1%.

Table 4.9.
Male vs. female differences

This table presents sample means by SEX for preference parameter deviations and psychometric variables. The p-values for both the ANOVA F-test and Welch test are reported.

	Male	Female	ANOVA	Welch
IQ	**1.891**	**1.378**	**.003*** **	**.003*** **
EQ	**2.819**	**2.666**	**.091***	**.082***
PA	3.331	3.389	.565	.564
α*	0.264	0.315	.171	.161
γ*	**0.237**	**0.367**	**.001*** **	**.001*** **
λ*	**0.519**	**1.007**	**.007*** **	**.004*** **
β*	0.035	0.041	.573	.572
ρ	0.100	0.096	.829	.829

Significant at * 10%, ** 5%, and *** 1%.

Table 4.10.
Risk and time preference regressions

Linear regression estimates for dependent variable beta deviation (β^*), and ρ are shown below. The explanatory variables include alpha deviation (α^*), gamma deviation (γ^*), lambda deviation (λ^*), cognitive ability (IQ), emotional stability (EQ), positive affectivity (PA), SEX (male = 1), AGE, YEAR, and EDU. Panel A reports the full-sample regressions for β^*. Panel B reports interaction regressions for $\beta^*$with orthogonalized interaction terms based on SEX. Panel C and Panel D report the same regressions for ρ. The White test indicates p-values for a test of the null of homoscedasticity in regression errors. As a result of this test, HCSE indicates whether standard errors are corrected for heteroscedasticity. See Panel A of Table 1 for variable definitions. Significant at * 10%, ** 5%, and *** 1%

Panel A: Present Bias (β^*) Full-sample Regressions

Const.	α^*	γ^*	λ^*	IQ	EQ	PA	SEX	AGE	YEAR	EDU		N	White Test	HCSE
0.06	0.05	0.00	0.00	0.00	**-0.03**	0.02					0.041	146	0.197	No
1.26	1.48	0.02	-0.50	0.18	**-2.81** ***	1.56								
-0.13	0.05	0.01	-0.002	0.001	**-0.03**	0.02	0.001	0.007	0.008	0.001	0.043	146	0.470	No
-0.85	1.53	0.24	-0.38	0.15	**-2.72** ***	1.53	0.10	0.99	0.78	0.70				

Panel B: Present Bias (β^*) Interaction Regressions

Const.	α^*	α^* x SEX	γ^*	γ^* x SEX	λ^*	λ^* x SEX	IQ	IQ × SEX	EQ	EQ × SEX	PA	PA × SEX	SEX	AGE	AGE × SEX	YEAR	YEAR × SEX	EDU	EDU × SEX		N
0.05	0.05	**-0.14**	0.00	0.01	0.00	**0.03**	0.00	0.02	**-0.04**	-0.03	0.02	0.04	0.00							0.062	146
0.69	1.08	**-1.95** *	0.13	0.28	-0.38	**2.32** **	0.45	1.32	**-1.77** *	-0.78	1.44	1.21	-0.03								
-0.08	0.04	**-0.14**	0.02	0.00	0.00	**0.02**	0.00	0.02	**-0.04**	-0.03	0.02	0.04	0.00	0.00	**-0.04**	0.01	0.01	-0.02	0.01	0.103	146
-0.67	0.99	**-2.07** *	0.82	-0.06	0.03	**1.67** *	0.31	1.37	**-1.85** *	-0.79	1.54	1.20	0.39	0.44	**-2.27** **	1.41	0.40	-1.14	0.34		

Interaction terms are orthogonalized.
White tests of interaction regressions have p-values < 0.001, standard errors are corrected for heteroscedasticity.

Panel C: Pure rate of time preference (ρ) Full-sample Regressions

Const.	α*	γ*	λ*	IQ	EQ	PA	SEX	AGE	YEAR	EDU		N	White Test	HCSE
0.16	**0.09**	-0.05	-0.01	-0.01	**-0.03**	0.01					0.011	146	0.145	No
2.23	**1.77**	-1.12	-0.55	-0.99	**-1.79**	0.65								
	*				*									
-0.04	**0.09**	-0.03	-0.002	-0.01	**-0.03**	0.01	0.02	0.01	0.01	**0.005**	0.030	146	0.143	No
-0.16	**1.81**	-0.70	-0.24	-1.22	**-1.83**	0.67	0.88	0.49	0.69	**2.04**				
	*				*					**				

Panel D: Pure rate of time preference (ρ) Interaction Regressions

Const.	α*	α* x SEX	γ*	γ* x SEX	λ*	λ* x SEX	IQ	IQ × SEX	EQ	EQ × SEX	PA	PA × SEX	SEX	AGE	AGE × SEX	YEAR	YEAR × SEX	EDU	EDU × SEX		N
0.14	0.07	**-0.19**	-0.03	0.00	0.00	**0.05**	-0.01	0.03	**-0.04**	**-0.12**	0.02	0.04	0.01							0.055	146
1.72	1.17	**-1.86**	-0.67	-0.04	-0.25	**2.05**	-0.65	1.20	**-1.88**	**-2.49**	1.20	1.06	0.64								
		*				**			*	**											
-0.10	0.06	**-0.20**	-0.02	-0.02	0.00	0.05	-0.01	0.03	**-0.04**	**-0.12**	0.02	0.04	0.02	0.01	-0.02	0.01	-0.02	**0.005**	0.00	0.084	146
-0.42	1.30	**-1.81**	-0.39	-0.17	0.26	1.63	-0.79	1.27	**-2.19**	**-2.88**	1.20	1.19	0.99	0.69	-0.90	0.31	-0.60	**1.98**	-0.89		
		*							*	**								**			

Interaction terms are orthogonalized.
White tests of interaction regressions have p-values < 0.001, standard errors are corrected for heteroscedasticity.

Appendix 4.A. Experimental Survey

SURVEY ANSWER SHEET (S1)

Sect.	No.	Question	Answer	Answer unit
A	**1**	Thinking about yourself and how you normally feel, to what extent do you generally feel UPSET?		**1-5 scale** **1 = NEVER** **5 = ALWAYS**
A	**2**	Thinking about yourself and how you normally feel, to what extent do you generally feel HOSTILE?		**As above**
A	**3**	Thinking about yourself and how you normally feel, to what extent do you generally feel ALERT?		**As above**
A	**4**	Thinking about yourself and how you normally feel, to what extent do you generally feel ASHAMED?		**As above**
A	**5**	Thinking about yourself and how you normally feel, to what extent do you generally feel INSPIRED?		**As above**
A	**6**	Thinking about yourself and how you normally feel, to what extent do you generally feel NERVOUS?		**As above**
A	**7**	Thinking about yourself and how you normally feel, to what extent do you generally feel DETERMINED?		**As above**
A	**8**	Thinking about yourself and how you normally feel, to what extent do you generally feel ATTENTIVE?		**As above**
A	**9**	Thinking about yourself and how you normally feel, to what extent do you generally feel AFRAID?		**As above**
A	**10**	Thinking about yourself and how you normally feel, to what extent do you generally feel ACTIVE?		**As above**
B	**1**	A bat and ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost?		**Cents**
B	**2**	If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?		**Minutes**
B	**3**	In a lake there is a patch of lily pads. Every day the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?		**Days**

SURVEY ANSWER SHEET cont.

C	**QN SET1**	When you had to choose between Option A and Option B, did you always choose A, always choose B, or switch from A to B beginning at a particular choice?		**Choice number or A = always A or B = always B**
C	**QN SET 2**	When you had to choose between Option A and Option B, did you always choose A, always choose B, or switch from A to B beginning at a particular choice?		**Choice number or A = always A or B = always B**
C	**QN SET 3**	When you had to choose between Option A and Option B, did you always choose A, always choose B, or switch from A to B beginning at a particular choice?		**Choice number or A = always A or B = always B**
D	**QN SET 1**	When you had to choose between Option A and Option B, did you always choose A, always choose B, or switch from A to B beginning at a particular choice?		**Choice number or A = always A or B = always B**
D	**QN SET 2**	When you had to choose between Option A and Option B, did you always choose A, always choose B, or switch from A to B beginning at a particular choice?		**Choice number or A = always A or B = always B**
E	**1**	What is your sex?		**M = male or F = female**
E	**2**	What is your age?		**Years**
E	**3**	How many years of post-secondary school education have you completed?		**Number of years**
E	**4**	How many economics and finance courses have you successfully completed at the university level?		**Number of courses**
E	**5**	How many economics and finance courses are you currently enrolled in?		**Number of courses**
E	**6**	How many probability and statistics courses have you successfully completed at the university level?		**Number of courses**
E	**7**	How many probability and statistics courses are you currently enrolled in?		**Number of courses**

Appendix 4.B. Experimental Question Sets

SECTION C: QUESTION SET 1 Choose between Option A and Option B

	Option A					Option B					Prefer A or B?
	Cash	with prob		Cash	with prob	Cash	with prob		Cash	with prob	
Choice 1	$20	30%	or	$5	70%	$34.00	10%	or	$2.50	90%	
Choice 2	$20	30%	or	$5	70%	$37.50	10%	or	$2.50	90%	
Choice 3	$20	30%	or	$5	70%	$41.50	10%	or	$2.50	90%	
Choice 4	$20	30%	or	$5	70%	$46.50	10%	or	$2.50	90%	
Choice 5	$20	30%	or	$5	70%	$53.00	10%	or	$2.50	90%	
Choice 6	$20	30%	or	$5	70%	$62.50	10%	or	$2.50	90%	
Choice 7	$20	30%	or	$5	70%	$75.00	10%	or	$2.50	90%	
Choice 8	$20	30%	or	$5	70%	$92.50	10%	or	$2.50	90%	
Choice 9	$20	30%	or	$5	70%	$110.00	10%	or	$2.50	90%	
Choice 10	$20	30%	or	$5	70%	$150.00	10%	or	$2.50	90%	
Choice 11	$20	30%	or	$5	70%	$200.00	10%	or	$2.50	90%	
Choice 12	$20	30%	or	$5	70%	$300.00	10%	or	$2.50	90%	
Choice 13	$20	30%	or	$5	70%	$500.00	10%	or	$2.50	90%	
Choice 14	$20	30%	or	$5	70%	$850.00	10%	or	$2.50	90%	

SECTION C: QUESTION SET 2 Choose between Option A and Option B

	Option A					Option B					Prefer A or B?
	Cash	with prob		Cash	with prob	Cash	with prob		Cash	with prob	
Choice 15	$20	90%	or	$15	10%	$27.00	70%	or	$2.50	30%	
Choice 16	$20	90%	or	$15	10%	$28.00	70%	or	$2.50	30%	
Choice 17	$20	90%	or	$15	10%	$29.00	70%	or	$2.50	30%	
Choice 18	$20	90%	or	$15	10%	$30.00	70%	or	$2.50	30%	
Choice 19	$20	90%	or	$15	10%	$31.00	70%	or	$2.50	30%	
Choice 20	$20	90%	or	$15	10%	$32.50	70%	or	$2.50	30%	
Choice 21	$20	90%	or	$15	10%	$34.00	70%	or	$2.50	30%	
Choice 22	$20	90%	or	$15	10%	$36.00	70%	or	$2.50	30%	
Choice 23	$20	90%	or	$15	10%	$38.50	70%	or	$2.50	30%	
Choice 24	$20	90%	or	$15	10%	$41.50	70%	or	$2.50	30%	
Choice 25	$20	90%	or	$15	10%	$45.00	70%	or	$2.50	30%	
Choice 26	$20	90%	or	$15	10%	$50.00	70%	or	$2.50	30%	
Choice 27	$20	90%	or	$15	10%	$55.00	70%	or	$2.50	30%	
Choice 28	$20	90%	or	$15	10%	$65.00	70%	or	$2.50	30%	

SECTION C: QUESTION SET 3 Choose between Option A and Option B

	Option A					Option B					Prefer A or B?
	Cash	with prob		Cash	with prob	Cash	with prob		Cash	with prob	
Choice 29	$12.50	50%	or	($2.00)	50%	$15.00	50%	or	$(10.50)	50%	
Choice 30	$2.00	50%	or	($2.00)	50%	$15.00	50%	or	$(10.50)	50%	
Choice 31	$0.50	50%	or	($2.00)	50%	$15.00	50%	or	$(10.50)	50%	
Choice 32	$0.50	50%	or	($2.00)	50%	$15.00	50%	or	$(8.00)	50%	
Choice 33	$0.50	50%	or	($2.00)	50%	$15.00	50%	or	$(8.00)	50%	
Choice 34	$0.50	50%	or	($2.00)	50%	$15.00	50%	or	$(7.00)	50%	
Choice 35	$0.50	50%	or	($2.00)	50%	$15.00	50%	or	$(5.50)	50%	

SECTION D: QUESTION SET 1 Choose between Option A and Option B

	What would you rather have?		Prefer A or B?
	Option A	Option B	
Choice 1	$100 in one week	$100.25 in 2 weeks	
Choice 2	$100 in one week	$100.50 in 2 weeks	
Choice 3	$100 in one week	$101 in 2 weeks	
Choice 4	$100 in one week	$102 in 2 weeks	
Choice 5	$100 in one week	$103 in 2 weeks	
Choice 6	$100 in one week	$104 in 2 weeks	
Choice 7	$100 in one week	$105 in 2 weeks	
Choice 8	$100 in one week	$106 in 2 weeks	
Choice 9	$100 in one week	$108 in 2 weeks	
Choice 10	$100 in one week	$110 in 2 weeks	
Choice 11	$100 in one week	$112 in 2 weeks	
Choice 12	$100 in one week	$114 in 2 weeks	
Choice 13	$100 in one week	$117 in 2 weeks	
Choice 14	$100 in one week	$120 in 2 weeks	
Choice 15	$100 in one week	$125 in 2 weeks	
Choice 16	$100 in one week	$130 in 2 weeks	
Choice 17	$100 in one week	$140 in 2 weeks	
Choice 18	$100 in one week	$150 in 2 weeks	

SECTION D: QUESTION SET 2 Choose between Option A and Option B

	What would you rather have?		Prefer A or B?
	Option A	Option B	
Choice 19	$100 today	$101 in one week	
Choice 20	$100 today	$102 in one week	
Choice 21	$100 today	$103 in one week	
Choice 22	$100 today	$104 in one week	
Choice 23	$100 today	$105 in one week	
Choice 24	$100 today	$107.50 in one week	
Choice 25	$100 today	$110 in one week	
Choice 26	$100 today	$115 in one week	
Choice 27	$100 today	$120 in one week	
Choice 28	$100 today	$125 in one week	
Choice 29	$100 today	$130 in one week	
Choice 30	$100 today	$135 in one week	
Choice 31	$100 today	$140 in one week	
Choice 32	$100 today	$145 in one week	
Choice 33	$100 today	$150 in one week	
Choice 34	$100 today	$160 in one week	
Choice 35	$100 today	$170 in one week	

Appendix 4.C. Survey Instructions

1. Thank you for attending this survey session. Your participation will be of great benefit to us in our research into financial decision-making. You will be paid a $15 participation fee. Proper, careful completion of this survey, which consists of 25 questions, should take no more than 45 minutes. During this session, there is to be no use of electronic devices such as computers and phones. All phones should be turned off (not just set to vibrate). And there should be no communication of any kind with other participants. The only aids allowed are writing utensils, scrap paper and (if you wish) a calculator.

2. The 25 questions of this survey appear in 5 sections, Section A to Section E. The 3 questions of Section C and the 2 questions of Section D are actually closely-related question sets, and are described carefully below. The remaining questions are self-explanatory and require little explanation.

3. The two components of financial decision-making that we will explore in this session are called risk preference and time preference. Your risk preference is how comfortable you are with risk taking. Your time preference reveals how much you wish to be compensated for receiving money later rather than sooner. Risk preference is investigated in Section C and time preference is addressed in Section D. There are no correct or incorrect answers to these questions since answers are based on personal preferences.

4. All answers should be clearly written **in pen** in the appropriate answer boxes on the two-sided **SURVEY ANSWER SHEET** provided. Please pay careful attention to the units (e.g., years, cents, etc.). **The questions must be done in order.** Also, after writing in an answer, please do not go back and change it as you move to later questions. If, however, you were confused and erroneously wrote an answer and wish to *immediately* change it before moving to the next question, raise your hand and an experimenter will initial the change.

5. The rest of these instructions guide you through the survey. Please read the description of each section before you answer the questions of that section.

6. The 13 questions in Sections A and B explore your personality/mood.

7. **Section A:** This section has 10 questions. Think about yourself, and how you normally feel. You are asked to say how often you feel a certain way. Please answer these questions to the best of your ability using a 5-point scale. If you always feel a certain way '5' should be your answer. If you never feel that

way '1' should be your answer. Frequency of feelings between these extremes should be answered with '4' or '3' or '2,' with higher numbers reflecting higher frequency.

8. **Section B:** The 3 items in this section vary in difficulty. Try to answer as best you can. Please pay careful attention to the units.

9. **Section C:** The 3 question sets of Section C explore your risk preference. Refer to page 1 of the two-sided **QUESTION SET SHEET**. Let's make sure you understand these question sets and the choices that you need to make.

10. Begin with **Section C: Question Set 1**. First look at this question set and then read the description below. You have to make 14 choices – sounds like a lot of work but it's actually much simpler than it sounds. Consider Choice 1. You have to choose between 2 options, A and B. These options are both gambles. If you choose A, you have a 30% chance of getting $20 and a 70% chance of receiving $5. Or you could choose Option B. If you choose B, you have a 10% chance of getting $34 and a 90% chance of receiving $2.50. Do you prefer Option A or Option B? Remember there is no right answer. It's just a matter of personal preference.

11. Before choosing it is important to know that your answer is not merely hypothetical. Four students will be randomly selected at the end of this session, and will (if they so choose) be allowed to participate in either a Risk Preference Game or a Time Preference Game. The 2 students who are selected to participate in the Risk Preference Game will have one of their Section C choices determine an **actual** payment made to them (as will be described in detail later). Since you don't know in advance which row (choice) may matter, you are of course well advised to answer all questions by using your true preferences.

12. Now go ahead and make your choice. You should write your answer (A or B) in the last column of Choice 1 of the QUESTION SET SHEET.

13. Suppose you prefer Option A for Choice 1. Now go to Choice 2. Notice Option A does not change. The only thing about Option B that changes is the high-cash outcome, which is now $37.50 instead of $34. Obviously Option B is more attractive than it was before. Since you chose Option A for Choice 1 there is a chance that you will switch preference, now preferring Option B to Option A. Suppose instead you continue to prefer Option A. Then go on to Choice 3. Once gain the only thing that changes is that Option B becomes more attractive, creating the possibility that you might switch preference

from A to B. The pattern now becomes clear. As you move down the rows (choices), Option B looks better and better and assuming you initially preferred A there may come a particular row (say row 9 or Choice 9) where you first prefer B. After that point, it is only logical that you will continue to prefer B because B continues to become more attractive. You should now be able to fill in 'A' or 'B' in all the QUESTION SET SHEET rows for this question set (C-1).

14. Turning to the SURVEY ANSWER SHEET, locate the relevant answer box for C-1. You are prompted that there are three possibilities. You might always prefer Option A to Option B – in which case you write 'A' in the answer box. Or you might always prefer Option B to Option A – in which case you write 'B' in the answer box. Or you might first prefer Option A but then at a certain point switch to Option B. If this switch occurs at Choice 9, you would write '9' in the answer box. Now answer according to what you wrote on the QUESTION SET SHEET.

15. Note that for the rest of the questions of Section C and for both of the Section D questions the same pattern will hold. Specifically, as you move down the rows (choices) Option B will become more and more attractive relative to Option A. This means that there will be three possibilities: you might always prefer A; you might always prefer B; or you might first prefer A but then switch preference to B at a particular row (choice).

16. The next question set -- **Section C: Question Set 2** – is similar in structure, and so it requires little further explanation. While the cash outcomes and probabilities are different, it remains true that the only thing that changes from row to row (choice to choice) is one of the Option B cash outcomes, with as before B becoming increasingly attractive as you move down the rows (choices). Note that the row (choice) numbering continues from the previous question. Please look at Section C: Question Set 2, make your choices, and provide your answer on the SURVEY ANSWER SHEET according to your preference.

17. The final question set of this section, **Section C: Question Set 3**, is again quite similar except for one important difference. The difference is that in all cases one of the cash outcomes is negative. For example, consider Choice 29. Selecting Option A means you are accepting a gamble with a 50% chance of receiving $12.50 and a 50% chance of **losing** $2. Accepting Option B on the other hand means you are accepting a gamble with a 50% chance of receiving $15 and a 50% chance of **losing** $10.50. As one moves down the rows (choices) a single cash outcome from one of the options (either from Option A

or Option B) changes. Still, as before, as you move down the rows (choices), B becomes increasingly more attractive relative to A. Please look at Section C: Question Set 3 now, make your choices, and provide your answer on the SURVEY ANSWER SHEET according to your preference.

18. As was said earlier, 2 students will be randomly selected to participate in the Risk Preference Game (if they so desire). This will be done as follows. All students will be at numbered desks (say, 1-50 if there are 50 students participating in a session). At the end we will ask a student in attendance to blindly select 2 cards from a deck of numbered cards. The students whose desk numbers come up will be able to participate in the Risk Preference Game. (The identical procedure will be used for the Time Preference Game.) If they choose to participate, these 2 students will be able to receive a payment from one of the rows (choices) in Section C according to their stated preferences and a draw from the relevant probability distribution. More specifically, after these students are selected, they will be asked to choose one of 35 cards which are numbered 1 to 35. Their card selection will then signify which row (i.e., Choices 1-35) they will receive payments from. Suppose one of these 2 students selects card #20, and for this row (Choice 20) she expressed a preference for Option B over Option A. Then she gets to "play" Option B. Using a random device she will receive $32.50 with a 70% probability and $2.50 with a 30% probability. Note that the students participating in the game will receive both their Risk Preference Game payment and their $15 participation fee. As stated earlier, since you don't know in advance which row (choice) may matter, you are of course well advised to answer all questions by using your true preferences.

19. **One thing that needs to be stressed is that the students who are randomly chosen to participate in the Risk Preference Game have the option to decline**. (The same is true with the Time Preference game, but in reality it would always be unwise to decline participation in this case because all outcomes are positive.) With this in mind note that if cards #29-35 are chosen then these students may face negative payments. In other words, they may **lose money**. Note that since 7 of 35 rows (20%) *potentially* lead to losses, and when these rows are selected losses occur 50% of the time, this implies that one should expect that **losses will on average happen 10% (20% * 50%) of the time**. But it is important to understand that the worst negative outcome is -$10.50. So if even if this occurs, the worst that can happen is the student in question will end up with $4.50, which is the participation fee minus the worst possible outcome ($15.00 - $10.50 = $4.50). Still, if a student is fearful of such negative events he/she may simply decline to participate. **This is a private decision and will not occur with other students witnessing it.**

20. **Section D:** These 2 question sets explore your time preference. Refer to page 2 of the two-sided QUESTION SET SHEET. Let's make sure you understand these question sets and the choices that you need to make.

21. As before it is important to take your choices seriously because they are not merely hypothetical. Again, as previously noted, 2 of the 4 students randomly selected at the end of each the session will be allowed to participate in the Time Preference Game. This means their Section D choices will be paid out to them, again based on a random selection of the 35 choices (rows) making up the two Section D question sets.

22. Like Section C, you have to express a preference for Option A vs. Option B over a series of choices. Also like Section C, as you move down the rows (choices) Option B becomes relatively more attractive vs. Option A. Note that the choices are simpler in the sense that no gambles are involved. In all cases you have to express a preference for $x received today or at some future time vs. $y received at a more distant future time. It's as simple as that.

23. Begin with **Section D: Question Set 1**, Choice 1. The choice is between $100 received in one week (Option A) vs. $100.25 received in 2 weeks (Option B). Say you prefer Option A. As you continue down the rows (choices) notice that Option B becomes increasingly more attractive. This is because in the case of Option B you receive more and more money in 2 weeks. As a result at some point you may switch from Option A to Option B. When this happens you know that you will continue to prefer B as you move down the rows (choices).

24. To clarify payment timing for those choosing to participate in the Time Preference Game, if you are due to receive a payment today you can pick it up between 4:00pm and 4:30pm today in DSB/303. If a payment is specified as "in one week" this means payment is made one week from today between 4:00pm and 4:30pm in DSB/303, while if a future payment is specified as "in 2 weeks" this means payment is made two weeks from today between 4:00pm and 4:30pm in DSB/303.

25. Turning to the SURVEY ANSWER SHEET you will notice that once again there are 3 possibilities. You might always prefer A to B – in which case you write 'A' in the answer box. Or you might always prefer B to A – in which case you write 'B' in the answer box. Or you might first prefer A but then at a certain point switch to B. If this switch occurs at Choice 4, you would write '4' in the answer box. Please look at Section D: Question Set 1 again, make

your choices, and provide your answer on the SURVEY ANSWER SHEET according to your preference.

26. **Section D: Question Set 2** operates in a similar fashion. Option A always entails receiving $100 today. Option B involves receiving more than $100 in one week. Since this amount increases as you go down the rows (choices) Option B (as elsewhere) becomes more and more attractive. Please look at this question set, make your choices, and provide your answer on the SURVEY ANSWER SHEET according to your preference.

27. **Section E:** We end with some basic demographic questions on your gender, age and educational background. Please answer these 7 questions of Section E now.

28. You have now finished the survey. Please check that you have answered all questions, and that your printing can be read. While you wait for everyone else to finish the survey, we kindly ask you to remain silent and to not use any electronic devices (such as phones or computers).

Chapter Five: *Conclusion*

This thesis uses three essays to answer questions in the areas of (i) corporate governance, specifically the intersection of ownership structure characteristics and firm-specific information in stock prices; and (ii) behavioral finance particularly investor decision-making.

In the first essay of this thesis, entitled *Ownership structure and stock price synchronicity in Canada: ownership concentration, family ownership and multiple large controlling shareholders*, a unique dataset of the largest controlling shareholders of Canadian companies listed on the Toronto Stock Exchange during 2000-2012 is used to examine the effects of the size of a firm's largest shareholder (in terms of voting rights held), family ownership, and multiple large controlling shareholders on the amount of firm-specific information in stock prices, measured using synchronicity. The use of the unique dataset, together with the distinction between family and non-family firms, provides new insights into the effects of ownership structure on firms' stock price information.

I find evidence of a significant, non-linear relationship between the size of the largest shareholder and stock price informativeness. Specifically, price informativeness increases as concentration is increasing for values of ownership concentration below 26% and above 62%, indicating incentive alignment. While, between 26% and 62% ownership concentration, price informativeness is decreasing, indicating entrenchment. Using propensity score matching (PSM) to isolate the effect of family firms on synchronicity, I find no evidence of a significant difference in price informativeness for matched pairs of family and non-family firms. Finally, I find evidence of a positive relationship between firms with multiple large controlling shareholders and stock price informativeness.

This study provides several contributions to the literature. First, the Canadian environment presents an opportunity to investigate a setting where ownership structure characteristics share similarities to studies that find evidence supporting entrenchment theory, while maintaining corporate governance mechanisms and strong shareholder protections that are in line with studies that support incentive alignment. Second, testing the effect of family firms on stock price synchronicity has, to my knowledge, not yet been addressed by the literature. And third, considering whether the largest controlling shareholder in a firm is alone, contributes to the literature on multiple controlling shareholders, corporate governance and financial markets.

The second essay, entitled *An experimental analysis of path-dependent financial behaviors and investor characteristics,* is co-authored work with Dr. Richard Deaves (McMaster University) and Dr. Brian Kluger (University of Cincinnati). We investigate the relationship between path-dependent behaviors (i.e., the disposition effect, house money effect and break-even effect) and investor characteristics (e.g., overconfidence and emotional stability) using experimental trading sessions. The experimental assets are designed such that there is a high likelihood of observing *both* cases where relative prices change but wealth remains constant, and cases where wealth changes but relative prices are unchanged, permitting us to disentangle the path-dependent behaviors.

Our main finding is that the majority of our subjects exhibit path-dependent biases and given our design, we are able to investigate in an unambiguous comprehensive fashion whether the tendency of an individual to exhibit a particular behavior makes it more or less likely that they will exhibit another behavior. To our knowledge this is an innovation and we do find correlations among the biases. Subjects prone to the disposition effect are more likely to also be prone to the breakeven effect, and less likely to display the house money effect. We also find that the house money effect is negatively correlated with the breakeven effect. These correlations hint at the possibility that common psychological factors may drive all the path-dependent behaviors.

While we do not include treatments to manipulate psychological variables, we do measure overconfidence, regret and negative affect using questionnaire instruments. Though this exercise can only be viewed as exploratory several patterns do emerge. Broadly speaking, though precise mechanisms remain murky, the existence of psychological bias (overconfidence and negative affect) leads to more bias in financial decision-making. Further, consistent with expectations, overconfidence (impacting disposition effect) and negative affect (impacting house money effect) appear to contribute to the existence of disposition effect and wealth effects.

The third essay, entitled *Cognitive Ability, Emotional Stability and Risk and Time Preferences: An Experimental Analysis,* is co-authored work with Dr. Lucy Ackert (Kennesaw State University), Dr. Richard Deaves (McMaster University) and Dr. Quang Nguyen (Middlesex University). In this essay, we report the results of an experiment designed to uniquely explore whether *both* cognitive ability (IQ) and emotional stability (EQ) impact risk preference and time preference in financial decision-making.

We find that, both cognitive ability (IQ) and emotional stability (EQ) impact preferences. If we take expected utility theory as the hallmark of normative decision-making when people face risk, those with higher levels of IQ have preferences that are more rational than those with low levels of IQ. This operates almost entirely in the male subsample. EQ seems to matter for probability weighting in the case of women. As for time preference, again more consistent with rationality, high-EQ males are less subject to present (or future) bias. And high-EQ males are also more patient in that they tend to have lower rates of time preference.

The unique contribution is that EQ plays a role that is about as meaningful as IQ when it comes to explaining preferences. This suggests that the growing research (which has been previously cited) on the impact of cognitive ability, while important, is perhaps omitting an equally important determinant of preferences.