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Junghan KIM
Singapore Management University, junghankim@smu.edu.sg

Arun LAKSHMANAN
State University of New York at Buffalo

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Do Animated Line Graphs Increase Risk Inferences?

Junghan Kim and Arun Lakshmanan

Abstract

This article shows that animated display of time-varying data (e.g., stock or commodity prices) enhances risk judgments. We outline a process whereby animated display enhances the visual salience of transitions in a trajectory (i.e., successive changes in data values), which leads to transitions being utilized more to form cognitive inferences about risk. In turn, this leads to inflated risk judgments. The studies reported in this article provide converging evidence via eye tracking (Study 1), serial mediation analyses (Studies 2 and 3), and experimental manipulations of transition salience (graph type; Study 3) and utilization of transitions (global trend; Study 4 and investment goals; Study 5) and, in the process, outline boundary conditions. The studies also demonstrate the effect of animated display on consequential investment decisions and behavior. This article adds to the literature on salience effects by disambiguating the role of inference making in how salience of stimuli causes biases in judgments. Broader implications for visual information processing, data visualization, financial decision making, and public policy are discussed.

Keywords

animation, data visualization, inferences, risk, salience

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Consumers and managers often make decisions based largely, or sometimes almost entirely, on visually presented time-varying data (e.g., stock prices, sales and profit figures, currency exchange rates). For example, retail investors see how the prices of stocks in their portfolio change over time to judge their financial risk. Similarly, commodity trading managers form expectations of market volatility based on temporal movement in spot or futures prices. Reflecting the prevalence of time-varying data in many domains, studies in the literature have examined how to effectively present this form of data (e.g., Duclos 2015; Henry 1995; Raghubir and Das 2010; Wallgren et al. 1996).

Notably, the literature has shown that graphical display systematically affects how people visually process data and infer meaning from it (e.g., Nenkov et al. 2009; Raghubir and Das 2010). Various aspects of graphical data display, such as the type of graph (e.g., bar/line graphs, box chart), colors, grids, and scales, affect visual information processing (Benbasat and Dexter 1985; Cleveland 1993; Duclos 2015; Zacks and Tversky 1999). However, researchers have predominantly examined this phenomenon for *static* forms of graphical data display. This gap is noteworthy given that animated display has emerged as a popular form of data visualization, especially given the development and maturing of multimedia technologies such as Java, JavaScript, and HTML5 (Fisher 2010).

Graphical tools for animated data display are now widely employed by major information providers. A brief observational study (N = 40) of major financial information providers (e.g., Bloomberg, Nasdaq.com), prominent media outlets (e.g., Fox Business, CNBC), and investing applications (e.g., Robinhood) indicated that most (76%) use animated graphics to present both real-time quotes and historical data (see Web Appendix A). Similarly, modern data visualization platforms (e.g., Tableau) also rely heavily on animated display to showcase data for consumer and business clients (Teal 2020).

Examining the role of animation in data visualization is particularly important in domains such as personal finance and trading, where visual formats and graphical interfaces are used extensively to convey the focal data (e.g., stock, commodity, foreign currency). As Raghubir and Das (1999) outline, in such domains individuals rarely have all the information needed to make a decision and so resort to making cognitive inferences on the basis of the available visual information. These inferences may sometimes relate to correlational beliefs about two

Junghan Kim is Assistant Professor of Marketing, Lee Kong Chian School of Business, Singapore Management University, Singapore (email: junghankim@smu.edu.sg). Arun Lakshmanan is Associate Professor of Marketing, School of Management, State University of New York at Buffalo, USA (email: alakshma@buffalo.edu).

variables (e.g., noise around a data string and risk; Raghubir and Das 2010) or the schemas and patterns that viewers impose on the available information (Raghubir and Das 1999, p. 67).

This propensity of individuals to make cognitive inferences opens up the potential for data visualization to systematically affect judgments about the underlying securities. The Securities and Exchange Commission (SEC) appears aware of this possibility. In 2018, the SEC recommended that investment advisers and dealers use "*charts*, *graphs*, tables, and *other graphics* or text features to explain the required information so long as the information does not, because of the *nature*, quantity, or *manner of presentation*, obscure or impede understanding of the information that must be included" (SEC 2018, p. 21553; emphasis added). Despite the widespread use of animation (e.g., Google Finance, MarketWatch, Microsoft Power BI, Tableau) and the high possibility of systematic effects on investors' data-based inferences, little to no research in marketing has examined how animated data display affects decision making. The current work aims to fill this gap.

Drawing on the literature on salience and its impact on judgments and decision making (Jarvenpaa 1990; Taylor and Thompson 1982), we propose and demonstrate that presenting data trajectories in an animated (vs. static) mode heightens risk judgments and alters attendant decision making. Specifically, animated presentation of time-varying data makes temporal transitions (i.e., how data values change from one point in time to the next) more salient, which in turn leads consumers to utilize such transitions in forming cognitive inferences about higher or lower levels of risk. In turn, these inferences systematically shape their judgments and decisions about investments.

Importantly, the current research investigates the role of animated display in contexts where the change in data values within a given trajectory implicates the probability of losing capital: commodity trading (pilot field study) and personal finance (Studies 1–5). Across six studies that include laboratory, online, and field experimentation, we show that the animated display effect is robust to variations in industry expertise, experience, age, gender, and other demographics. We also demonstrate how animated display shapes downstream consequential outcomes and thus uncover a robust, generalized phenomenon.

To recap briefly, the current research contributes to the literature in three ways: (1) identifying a novel, theoretically relevant, and managerially actionable antecedent of visual presentation effects; (2) disambiguating the process mechanism—in particular, the utilization of salient features in forming cognitive inferences; and (3) extending and demonstrating the effect of animated display on consequential downstream decisions and behavior.

Prior Literature and Theoretical Development

Graphical Display of Time-Varying Data

A time-varying data series conveys information that changes because of temporal updates in data values. As data values change from one point in a series to another, the transitions between individual data points also provide insight about the nature of the series (e.g., its trend, its pattern, the degree of noise surrounding such transitions).

Previous literature has suggested that graphical display forms a particularly effective way to represent time-varying data (e.g., Henry 1995; Wallgren et al. 1996). For example, when a stock's price history is visually presented in a line graph, summary information on temporal variations such as trend (e.g., increasing or decreasing), pattern (e.g., cyclical), and noise around the trend (e.g., volatility) are easily recognized by the user. Thus, graphical display offers a compact and easily discernible representation that helps us derive insights from the data (Hutchinson, Alba, and Eisenstein 2010).

Because the human visual system has highly developed skills of perceptual sense making (Kosslyn 1994), the effectiveness of graphical data display is often self-evident. In that regard, research in psychology has largely focused on basic phenomena related to perception and comprehension of graphs, such as pattern recognition, mapping, and interpretation (e.g., Carpenter and Shah 1998; Zacks and Tversky 1999). Further, decision and marketing researchers have focused on substantive impacts of graphical display on outcomes, such as risk assessment, stock investment, and budget allocation (e.g., Chua, Yates, and Shah 2006; Hutchinson, Alba, and Eisenstein 2010; Raghubir and Das 2010).

Although previous studies have examined various aspects of data visualization, the primary focus has been on static forms of graphical display. Notably, a few initial practitioner-driven investigations on animated data visualization have been conducted in computer science and information technology (e.g., Heer and Robertson 2007; Robertson et al. 2008). However, this line of research has left significant gaps. First, these studies primarily explore the effectiveness of specific visualization tools available at that time (e.g., DynaVis, Trendalyzer), but are largely silent on potential underlying theory. Second, they focus on basic graph comprehension outcomes (e.g., recall or recognition of data values or patterns), rather than process and consequences such as judgments and decision making. Figure 1 depicts some of the findings and gaps in the data visualization literature, and how the current research fills the gaps in the literature.

These gaps are noteworthy because emerging literature has shown unique consequences of dynamic display (e.g., Goldstein et al. 2014; Kim and Lakshmanan 2015; Roggeveen et al. 2015). For example, dynamic (vs. static) display modes (e.g., video presentation of product images, animated online ads) enhance consumers' involvement with the product (Roggeveen et al. 2015), shape impressions of ad design (Kim and Lakshmanan 2015), or, in some contexts, are seen as distracting and annoying (Goldstein et al. 2014). However, we are not aware of any prior studies that have systematically examined how *animated graphical* data display affects comprehension, judgments, and decision making. For instance, does animated data display simply grab more attention or distract viewers? Does it have an impact on basic graph comprehension? Does it

	Static Display	Animated Display
Perception and Comprehension	• **Carpenter and Shah (1998)** Integrative model for graph comprehension Graph comprehension consists of encoding the visual patterns, translating the depicted patterns into the associated conceptual or quantitative relations, and identifying the referents of the relations. • **Zacks and Tversky (1999)** Bar-line message correspondence Data presented in bars are described in terms of discrete data points and data presented in lines are interpreted in terms of relations between data points	• **Heer and Robertson (2007)** Animating transitions in data graphics using DynaVis Animated (vs. static) transitions between different types of graphs (e.g., bar, scatter plots, pie charts) enhances viewers' recognitions of data values represented in the graphs. • **Robertson et al. (2008)** Effectiveness of Trendalyzer in trend visualization Accuracy of data value recall is greater when the values are presented in multiple small charts (vs. one animated chart). **Research Gap**: *How animated display affects perception* • **Current Research** Animated (vs. static) display of time-varying data enhances the visual salience of temporal transitions in data values.
Judgment and Decision Making	• **Chua, Yates, and Shah (2006)** Pictures (vs. numbers) as driver of risk avoidance Graphical (vs. numerical) display enhances the perceived risk of less safe alternatives, thereby encouraging risk avoidance. • **Hutchinson, Alba, and Eisenstein (2010)** Difference-based heuristics Line graphs increase the use of changes in expenditures from one period to another in budget allocation decisions. • **Raghubir and Das (2010)** Run-length effect Stocks with longer run lengths are inferred as riskier than stocks with shorter run lengths.	**Research Gap**: *Why and how animated display guides judgment and decision making* • **Current Research** Enhanced visual salience of temporal transitions increases the extent to which transitions are utilized as a risk inferential cue. Further, greater utilization of transitions inflates risk judgments and alters downstream decision making (e.g., investment decision and behavior).

Figure 1. Relevant Findings and Gaps in the Data Visualization Literature.

change viewers' affective state? Does it have a systematic and/or unique effect on downstream judgments and decisions? The current research sheds light on these questions by integrating insights from the salience literature and cognitive inference making to lay out a process outlining when and why animated display affects data-based judgments and decision making.

Animated Display and Transition Salience

Salience as a stimulus characteristic refers to the availability of specific information (Lurie and Mason 2007; Taylor and Fiske 1978). The salience literature in different streams has identified various factors that could become salient, such as gender, race, and identity (Forehand, Deshpandé, and Reed 2002; Taylor and Fiske 1978). In the visual perception domain, the intensity of sensory features, such as brightness of a light or loudness of a tone, affects stimulus salience (Tversky 1977). With respect to data visualization, prior work explores how the use of visual elements such as color, size, and line thickness enhances the salience of spatial dimensions in geographical data (Hegarty, Canham, and Fabrikant 2010; Ozimec, Natter, and Reutterer 2010). Extending prior work, we identify animation as a salience-inducing mode of displaying time-varying data.

In its basic form, animation depicts a series of scenes that differ from each other temporally. For instance, a flip-book represents a basic form of animation that shows how a series of static images combine sequentially to form a dynamic visual: successive transitions between each page create a visual impression of moving images. As such, animation is a visual medium that dynamically depicts how a narrative evolves over time. We suggest that animated display of data values accomplishes something similar.

Imagine a line graph depicting how a stock's price has changed over the last month. In the animated version of this graph, stock price points are presented sequentially—with physical movement of the line—as the price trajectory unfolds. In this case, viewers visually trace transitions by seeing the prices physically appear by period. This unique aspect of animated display is especially well-suited to enhance the salience of the temporal dimension of data change. To elaborate, we propose that animated display of a data string draws viewers' attention in real time to the moment-to-moment unfolding of the data string. In doing so, it is uniquely able to enhance the salience of transitions between data points. Other, more static, ways of drawing attention to the graph (e.g., using visual elements such as color or arrows) are less likely to highlight the temporal variation of the data, particularly since the viewer sees the entire data string at once. Just as a three-dimensional (as opposed to strictly two-dimensional) representation of a scene uniquely enables identification of depth, animated display uniquely enables the detection of variability embedded in the stream of changing data values by making transitions salient.

Utilizing Temporal Transitions for Making Inferences About Risk

Prior literature proposes that heightening the salience of a particular stimulus aspect directs viewers' attention to it, and as a result, it exerts a prominent impact on subsequent judgments (Taylor and Fiske 1978). In our case, when animation unfolds the trajectory by period, transitions become more traceable and thus draw visual attention. Notably, the drawing of focused attention may not alone fully explain the downstream consequences of salience. Once a particular portion of a stimulus receives focused attention (say, due to its salience), the information contained in that portion is more likely to be disproportionately utilized in subsequent judgments (Taylor and Thompson 1982). For example, Raghubir and Das (2010) find that when stock prices are presented graphically, local maxima and minima appear more salient compared with the prices surrounding them, and this relative salience makes them more likely to be used to infer risk. Thus, the literature alludes to a sequential process in which salience shapes data-based judgments. Although stimulus salience occurs earlier in the overall process because of the focal features drawing differential attention, there is reason to expect an inferential process to follow, such that these visually salient features of the data are more heavily weighted in drawing meaning from the data.

Prior work has, to the best of our knowledge, not explicated the process role of utilizing salient features to form inferences. Indeed, recent research documents evidence that low-level visual attention metrics alone may not fully account for the effect of salience on subsequent judgments. For example, Duclos (2015) finds that graphically displaying a series of stock prices leads consumers to pay more attention to the recent price fluctuations to forecast a future price. However, the gaze duration on the recent price fluctuation does not mediate financial judgments, because such judgments involve "a variety of mental processes" (see Duclos 2015, p. 323). Similarly, McArthur and Ginsberg (1981) find that an individual whose visual appearance is more salient than others in a group draws longer fixations and is perceived as a causal agent in the social interaction. Yet, increased duration of attention to the salient individual does not directly mediate downstream causal attributions. To bridge the gap between salience-induced attention and downstream data-based inferences, we aim to theoretically disambiguate the utilization construct in the process.

We propose that enhanced salience of transitions increases the extent to which transitions are used as a diagnostic cue. Individuals often make judgments based on the given data instead of seeking all the information relevant to a judgment task (e.g., technical analysis in stock trading). In such cases, their judgments vary depending on which data features (e.g., overall trend, beginning/end, noise around a data string) they attend to and use to make judgments (Raghubir and Das 1999). In our case, when temporal transitions become more salient—because of animated unfolding (as opposed to all-at-once static display)—individuals are more likely to rely on these transitions to make risk judgments. Thus, we operationalize the utilization of transitions as the extent to which individuals base their risk judgments on changes in data values from one point in time to the next.

We further argue that greater utilization of transitions inflates downstream risk judgments. In financial investment, risk indicates the probability of losing capital (Duxbury and Summers 2018). Moreover, prior literature has documented that investors believe stock price volatility (i.e., the degree of change in stock prices over time) to be associated with risk (Raghubir and Das 2010). Volatility conceptually refers to a tendency to fluctuate from a stable outcome (Botner, Mishra, and Mishra 2020). Although volatility can signal both gain and loss in capital, the irregular nature of stock price sequences (i.e., random walks) makes it more strongly associated with downside risk (Pincus and Kalman 2004). Behavioral finance literature finds that when random sequences of stock prices are graphically presented, trajectories with greater price volatility correlate with greater risk judgments (Duxbury and Summers 2018). Work in consumer psychology also documents that retail investors infer greater risk from stocks with larger differences between the local maxima and minima—a proxy for the noise around a data trajectory (Raghubir and Das 2010).

Combining the preceding discussion on animated display, salience, and the utilization of transitions in judgment making, we formally hypothesize:

> **H_{1a}:** Risk judgments are greater when time-varying data are presented in an animated (vs. static) mode.
> **H_{1b}:** The salience of temporal transitions is greater when time-varying data are presented in an animated (vs. static) mode.
> **H_{1c}:** Temporal transitions are more likely to be utilized to infer risk when time-varying data are presented in an animated (vs. static) mode.
> **H_{1d}:** The impact of animated display on risk judgments is mediated by the salience and utilization of temporal transitions.

We examine these primary hypotheses regarding the animated display effect and underlying process in Studies 1 and 2 (see Figure 2 for our theoretical framework with associated studies).

Moderating Transition Salience

Our explication of the underlying process mechanism begins with the salience-inducing effect of animated display. For transitions to be disproportionately used as a meaningful inferential cue, it is necessary for animated display to make successive

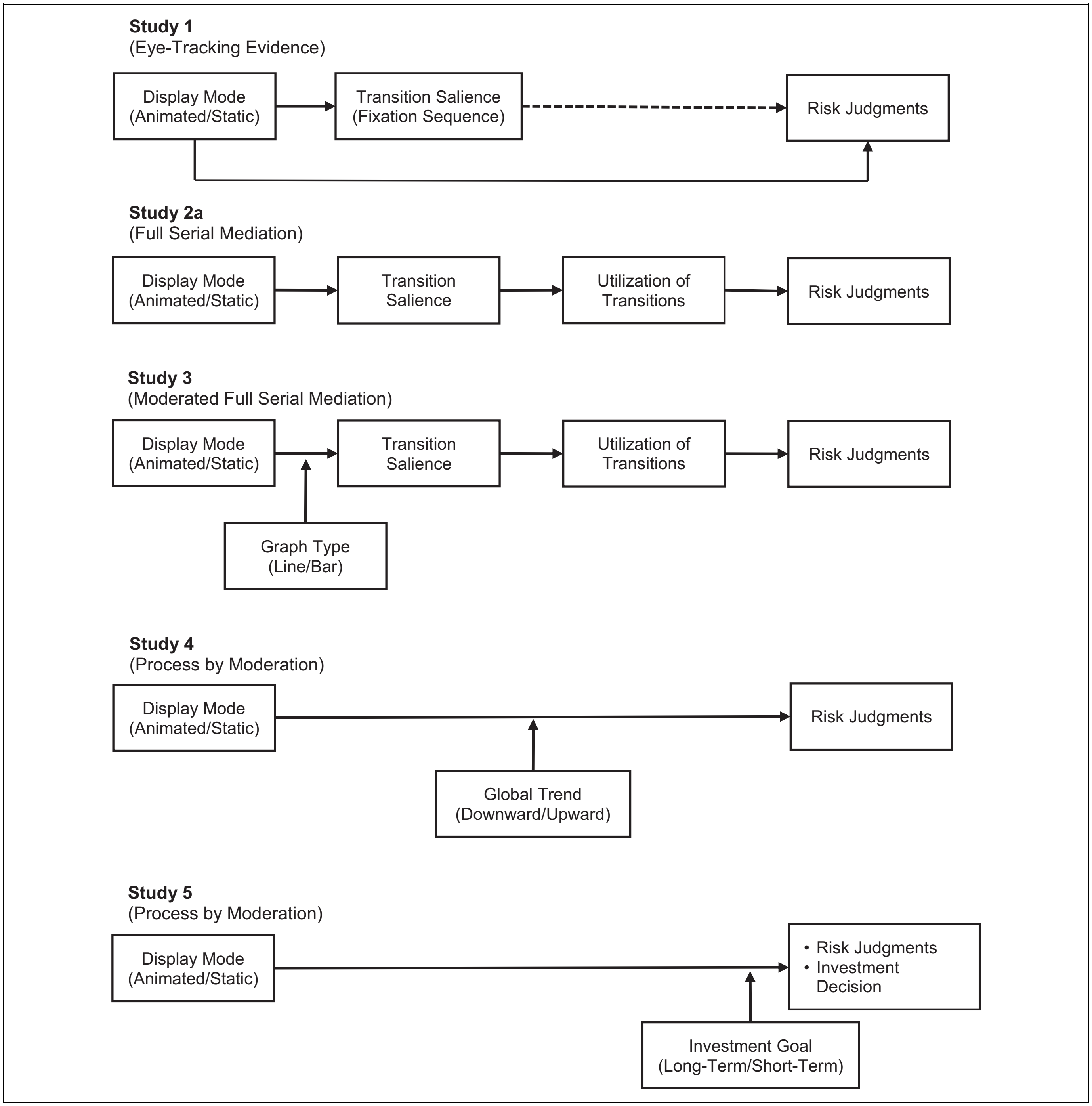


Figure 2. Theoretical framework with associated studies.

transitions visually stand out. Thus, if animated display does not enhance transition salience earlier in the perceptual process, the core effect should attenuate. We test this expectation by directly manipulating transition salience.

In graph comprehension, the type of representation (e.g., line vs. bar graphs) determines the extent to which specific insights can be discerned from a graph. For example, transitions in time-series information are easier to discern in line graphs, whereas the absolute values of discrete data points are easier to perceive in bar graphs (Hutchinson, Alba, and Eisenstein 2010; Zacks and Tversky 1999). This is because line graphs visually represent the connection between data points, whereas bar graphs visually separate each data point (Duclos 2015; Zacks and Tversky 1999).

When they are animated, line graphs—because they better represent continuity along the trajectory—should make transitions more salient, leading to greater utilization in inferring higher or lower levels of risk. Thus, the core animated display effect and its underlying process should manifest with line graphs. In contrast, though animated display physically unfolds each data point by period, in bar graphs each bar is not visibly and directly linked to the next. Each data point is represented as an independent bar visually rooted in the x-axis. Thus, because of the relative lack of continuity, successive data points in animated bar graphs are less likely to lead viewers to trace transitions, compared with line graphs. Consequent downstream process effects should therefore also attenuate. Stated formally,

> **H_2:** The effect of animated (vs. static) display on risk judgments through salience and utilization of transitions ($H_{1a–d}$) manifest with line graphs but attenuate with bar graphs.

We test H_2 by directly manipulating transition salience via the type of graphical representation in Study 3.

Contextualizing the Role of Transitions

Our theorizing also implies that transitions should inflate risk judgments when they serve as signals of the probability of loss. Thus, if the data string contains features that frame the context as one where the prospect of capital loss is low, the risk-inflating role of transitions should attenuate. We explore this moderation argument by recruiting global trends as such a "contextualizing" data feature.

A string of time-varying data may have multiple features, such as trend and the noise around the trend. While transitions happen moment to moment along the time-varying trajectory, global trends are represented as a holistic pattern (i.e., upward/downward patterns) across the entire trajectory. Such global trends are perceptually salient in and of themselves and are easily recognizable, as people's visual experience typically comes from a high-level recognition of the overall stimulus (principle of global precedence; Navon 1977). For these reasons, although animated display primarily increases transition salience, trends should remain salient irrespective of display mode (animated or static).

As a generally salient data feature, global trends should come into play in risk inferences by framing the context of financial judgments. When a data string has a clear downward or upward trend, it provides a reference point (Raghubir and Das 1999). That is, the starting data point can serve as a reference point with which the current stock price is compared. Thus, when trend is downward (upward), the current price is lower (higher) than the reference point, leading investors to anticipate losses (gains) and so infer greater (lesser) risk.

Given that global trends asymmetrically set investors' expectations of outcomes, we expect these trends to contextualize the role of transitions in risk judgments. With a downward trend, losses are more likely, and so investors should remain sensitive to risk-diagnostic cues such as transitions in the data string (loss aversion; Kahneman and Tversky 1979). Therefore, for the downward trending stock, we expect animated display (vs. static display) to heighten risk judgments, as transitions are still a risk-relevant data feature. However, an upward trend establishes the context of a rising market, and in this environment, the prospect of losing capital is significantly reduced. Investors should therefore be generally less sensitive to risk-diagnostic cues such as transitions. Thus, for the upward trending stock, the impact of animated (vs. static) display on risk judgments would be mitigated. Formally,

> **H_3:** The effect of animated display on risk judgments is attenuated in the presence of a global upward trend (but not in the presence of a global downward trend).

H_3 outlines a condition in which salient transitions may be less likely to be utilized to heighten risk judgments because of the context established by global trends. In other words, the global trend data feature helps dissociate transition salience from downstream risk inferences. In doing so, H_3 helps indirectly explicate how transitions are utilized in inference making.

Moderating How Transitions Are Utilized

Further down the causal chain, theory suggests that transitions that have been made salient (on account of animated display) are more likely to be utilized to infer risk. Therefore, varying *how* transitions are utilized in the inference process should moderate the core effect of display. To minimize potential confounding with alternative data features, we test this expectation via contextual factors exogenous to the data, such as investment goals (H_4).

Our theory is that animated display inflates risk judgments because of beliefs that transitions are associated with risk. In other words, investors' belief that frequent changes in stock price are indicative of risk to investments drives the animated display effect. It follows therefore that decision contexts that highlight an opportunity for profits should moderate how transitions are utilized to form inferences about higher or lower levels of risk.

Prior work suggests that investors' investment goal can affect the meaning ascribed to daily changes in stock prices. For example, investors sometimes infer both risk and opportunity from investment instruments (Zhou and Pham 2004). Drawing on this insight, we propose that the meaning ascribed to price changes would differ depending on the investment goal (long- or short-term investing). Specifically, when forming their portfolio, long-term investors tend to seek instruments that are relatively more stable, that is, with less fluctuation over time (e.g., dividend stocks). This is because they generally wish to continue their investment in these instruments over longer durations. Therefore, multiple transitions in a stock's price should be associated with risk in long-term investors' beliefs. In contrast, short-term investors (e.g., day traders) tend to seek volatile instruments to maximize profits by taking advantage of price variations in a short period. Thus, they should relate short-term transitions not to risk, but to an opportunity to make higher returns.

Drawing on this notion, we expect the investment goal to moderate the effect of animated display by varying the meaning inferred from salient temporal transitions. Long-term investors should infer greater risk (H_{1a}). However, for short-term investors, because transitions represent more of an opportunity to make money, animated display should not discernibly inflate risk judgments.

> **H_4:** The effect of animated display on risk judgments is attenuated when investment goals reduce the association of transitions with risk (i.e., the effect will manifest for long-term but not for short-term investors).

We test H_3 and H_4 by introducing global trends and investment goal as moderators in Study 4 and Study 5, respectively. Table 1 summarizes our studies and main findings.

Pilot Field Evidence and Overview of Experiments

To obtain initial insights from an externally valid population, we conducted a pilot field study with 21 oil trading managers ($M_{trading\_experience}$ = 10.43 years, SD = 7.72) as our target sample. The experiment was followed by in-depth interviews with all participants (for full study details, see Web Appendix B). Over 70% were active traders. Participants were shown a line graph describing monthly spot prices of Brent oil in either animated or static mode. Then they reported their trading risk judgments on two items along seven-point scales (1 = "Not at all risky," and 7 = "Very risky"; 1 = "Safe," and 7 = "Unsafe"; r = .71; adapted from Raghubir and Das 2010). As we hypothesized, trading risk judgments were significantly greater in the animated (vs. static) mode ($M_{animated}$ = 5.90, SD = .77; M_{static} = 5.05, SD = .93; F(1, 19) = 5.14, p = .035). This finding should be interpreted with caution given the small sample size, but it supports our main hypothesis (H_{1a}).

Interestingly, in the postexperiment in-depth interviews, about half (43%) of the participants offered ideas on the impact of animated display on various aspects of time-varying data processing, such as attention capture, distraction, and pattern recognition. For example, the head of trading at a *Fortune* 500 firm noted, "Animation shows previous high and previous low and yearly highest and lowest comparison." However, our managerial sample was not clear about how animated display may affect their own interpretation and decision making, indicating a relative paucity in the understanding of its effect on their professional outcomes, which forms the objective for our main studies.

The basic experimental paradigm of the main studies involved showing participants a graph depicting a time-varying sequence of data values followed by a survey containing dependent measures, manipulation checks, and covariates (seven-point scale; for details on scale items, see Web Appendix C). For the graph stimuli, we used stock price data sets randomly generated around a predetermined mean and variance. Our focal price data followed no clear upward or downward trend over time, except in Study 4, where we manipulated the global trend (i.e., upward or downward).

We manipulated the display mode by varying the manner in which the focal data values were presented. In the animated condition, all data values were presented in a trajectory that unfolded dynamically as individual data points were sequentially traced on screen. The animation was triggered automatically after the stimulus screen was opened and took three to five seconds to unfold entirely. The graph animation unfolded once, and the completed graph remained visible until participants proceeded to the next screen. In the static graph condition, the same information was presented all at once without sequential unfolding. Unless otherwise noted, all other data features and graph properties were identical across display modes. All static versions of the stimuli and a link to the animated versions are provided in the Appendix.

Study 1: Underlying Process—Eye-Tracking Evidence

Study 1 tests whether animated display indeed enhances transition salience and, in doing so, affects data-based risk inferences (H_{1a} and H_{1b}). Per our theorizing, with animated display, transitions in the data would receive focused attention as evidence of their enhanced salience. To test this, we capture the sequence of participants' eye fixations as they viewed the focal data. We expect fixations to sequentially follow the movement of the trajectory when display is animated, whereas there should be no systematic fixation patterns with static display.

Moreover, we examine arousal as a potential alternative explanation. Seeing a spatially moving object is psychologically or physiologically arousing, which can be misinterpreted as the presence of threat or danger (Cian, Krishna, and Elder 2015). Thus, one could argue that animated data trajectory may heighten arousal, which in turn increases risk judgments. However, this rationale is also countered by prior work suggesting that heightened arousal can lead to diminished risk avoidance (e.g., lower willingness to pay for insurance; Mano 1994), a pattern opposite to our hypothesis. Thus, a priori, arousal is not likely to be a primary mechanism for the animated display effect. We nevertheless empirically test for it in Study 1 using pupil dilation as a direct physiological measure.

Stimuli, Design, and Procedure

Eighty-five undergraduate students (M_{age} = 21.46 years; 40% male) participated in a single-factor (display mode: animated/static) between-subjects laboratory experiment in exchange for course credit. Participants were told that they would make financial judgments and were given a brief overview of a fictitious company. They were then randomly assigned to review one of two (animated vs. static) stock price graphs (see the Appendix). The focal graph depicted 21-day stock prices (average monthly trading days in the United States) generated randomly around a predetermined mean and variance (for details,

Table 1. Summary of Studies and Main Findings.

Pilot Field Study: Evidence from Oil Trading Experts (N = 21; M_{age} = 38.14 years; 90% male; oil trading managers)

	Animated Display (n = 10)	Static Display (n = 11)
Risk judgments	5.90 (.77)	5.05 (.93)
Belief about speculation	4.60 (1.65)	4.45 (1.51)
Belief about hedging	5.80 (1.81)	5.82 (1.17)
Trading experience (in years)	10.70 (7.36)	10.18 (8.38)

Main findings:

- Presenting crude oil price history in an animated (vs. static) graph leads to greater risk judgments.

Study 1: Underlying Process—Eye-Tracking Evidence (N = 85; M_{age} = 21.46 years; 40% male; students)

	Animated Display (n = 43)	Static Display (n = 42)
Risk judgments	5.23 (.84)	4.80 (.96)
Number of fixation sequences	5.19 (1.75)	2.12 (.92)
Fixation duration (in seconds)	11.50 (5.97)	9.62 (7.49)
Pupil diameters (in millimeters)	4.46 (.81)	4.55 (.96)

Main findings:

- Animated (vs. static) display enhances the salience of transitions in stock prices—evidenced by the number of fixation sequences following the animated trajectory.
- Presenting monthly stock prices in an animated (vs. static) graph leads to greater risk judgments.

Study 2a: Serial Mediation (N = 190; M_{age} = 35.46 years; 67% male; MTurk)

	Animated Display (n = 93)	Static Display (n = 97)
Risk judgments	5.56 (1.08)	5.21 (1.24)
Transition salience	5.93 (.89)	5.62 (1.06)
Utilization of transitions	5.76 (1.08)	5.42 (1.13)
Frequency of price change	11.23 (7.36)	11.35 (11.21)
Range of price change	19.41 (8.27)	19.24 (8.89)
Arousal	3.84 (1.31)	3.82 (1.26)
Involvement with stock investment	4.73 (1.69)	4.58 (1.57)
Stock trading experience	2.71 (1.56)	2.77 (1.37)

Main findings:

- Animated (vs. static) display enhances the salience of transitions in stock prices, which in turn leads to greater utilization of the transitions and, consequently, increases risk judgments.

Study 2b: Arousal Effect of Animation Speed (N = 165; M_{age} = 21.51 years; 43% male; students; six participants who skipped the stimulus page were excluded)

	Three-Second Animated (n = 54)	Ten-Second Animated (n = 51)	Static (n = 54)
Risk judgments	5.27 (1.13)	5.17 (1.02)	4.74 (.99)
Frequency of price change	8.70 (4.49)	9.55 (7.25)	8.37 (4.84)
Range of price change	20.48 (6.00)	20.10 (6.30)	19.11 (5.49)
Arousal	3.39 (1.32)	3.32 (1.25)	3.75 (1.13)

Main findings:

- Animated (vs. static) display of stock prices increases risk judgments both in the three-second and ten-second animated modes without any differences in arousal.

Study 3: Manipulating Transition Salience—Graph Type (N = 335; M_{age} = 36.55 years; 52% male; MTurk)

	Animated Line Graph (n = 81)	Static Line Graph (n = 85)	Animated Bar Graph (n = 82)	Static Bar Graph (n = 87)
Risk judgments	5.28 (1.43)	4.78 (1.22)	4.41 (1.39)	4.70 (1.39)
Transition salience	5.84 (.93)	5.45 (1.01)	5.49 (.88)	5.52 (.94)
Utilization of transitions	5.88 (1.04)	5.52 (1.08)	5.38 (1.13)	5.59 (1.09)

Main finding

- Animated (vs. static) display of stock prices increases risk judgments through salience and utilization of transitions when the focal data are presented in line graphs. However, the core effect and its underlying process do not manifest when the same data are presented in bar graphs.

(continued)

Table 1. (continued)

Study 4: Contextualizing the Role of Transitions in Risk Judgments—Global Trend (N = 208; M_{age} = 21.09 years; 34% male; students; five participants who failed an attention check and four participants who did not view or follow the experiment instruction were excluded)

	Animated Downward Trend (n = 49)	Static Downward Trend (n = 49)	Animated Upward Trend (n = 51)	Static Upward Trend (n = 50)
Risk judgments	5.87 (1.04)	5.41 (.99)	4.02 (1.15)	4.27 (1.17)
Range of price change	21.65 (5.64)	21.96 (5.94)	22.22 (5.90)	23.52 (5.59)

Main findings:

- Animated (vs. static) display of stock prices increases risk judgments when global trend is downward, but the effect is mitigated when global trend is upward.

Study 5: Moderating How Transitions Are Utilized—Investment Goal (N = 216; M_{age} = 35.05 years; 59% male; Prolific Academic; three participants who did not view the investment goal manipulation were excluded)

	Animated Long-Term Goal (n = 55)	Static; Long-Term Goal (n = 53)	Animated; Short-Term Goal(n = 51)	Static; Short-Term Goal (n = 54)
Risk judgments	5.51 (1.13)	4.73 (1.39)	5.24 (1.16)	5.25 (1.10)
Investment decision—amount willing to invest ($)	2,414.69 (2,686.82)	4,712.26 (4,307.70)	5,373.45 (5,387.58)	5,129.72 (4,917.32)
Stock trading experience	3.31 (1.17)	3.17 (1.16)	3.22 (1.14)	3.02 (.98)
Financial literacy	2.60 (.78)	2.68 (.58)	2.37 (.94)	2.67 (.61)

Main findings:

- Animated (vs. static) display of stock prices increases risk judgments for long-term investors, but not for short-term investors.
- The amount that long-term investors are willing to invest is lower in the animated (vs. static) display mode, whereas there is no difference between the two display modes in the amount that short-term investors are willing to invest.

Notes: Values are means with standard deviation in parentheses.

see Web Appendix D). The display mode was manipulated as outlined in the previous section.

While participants reviewed the graph, a screen-based eye tracker (Tobii Pro X2-60) captured their eye movement (i.e., they did not need to wear any additional apparatus). After viewing the graph, participants reported risk judgments relating to buying the focal stock (1 = "Not at all risky," and 7 = "Very risky"; 1 = "Safe," and 7 = "Unsafe"; r = .57; adapted from Raghubir and Das 2010). Manipulation check measures (r = .83) and demographics were collected thereafter.

Results

We created seven rectangular areas of interest (AOIs) to test our theorizing (see Web Appendix E). These AOIs were positioned contiguously every three time periods (with no space in between and no overlap) so as to capture the 20 paths linking each of the 21 stock price points to one another. For analysis, we specifically focus on identifying successive patterns in fixation sequences to test whether participants' gaze points fixate systematically on the data trajectory that unfolds following the order of the AOIs (i.e., test whether the animated display indeed enhances the salience of temporal transitions). We examined gaze points fixated on the AOIs during the first five seconds for both static and animated display modes because it took five seconds from the first moment of exposure for the entire animated trajectory to unfold.

We also measured the total duration of fixations within AOIs to capture overall attention. Further, to test for arousal, we measured dilations of participants' right and left pupils (Bradley et al. 2008). To enable proper comparison, we captured the pupil dilations for the first five seconds of graph exposure for both static and animated display modes.

Salience—number of fixation sequences. Following prior eye-tracking research (e.g., Eraslan, Yesilada, and Harper 2015), we counted fixation sequences that follow the order of AOIs. Our dependent variable ranges in value from 1 to 7 (given seven consecutive AOIs), with a greater number reflective of more attention directed to temporal transitions. Because the dependent variable was count data, we conducted a Poisson regression with display mode (animated/static) as the independent variable. Consistent with our prediction, the effect of the display mode on the number of fixation sequences was significant (Wald χ^2 (1) = 50.96, $p < .001$). Specifically, the number of fixation sequences that follow the order of AOIs was greater in the animated (vs. static) mode ($M_{animated}$ = 5.19, SD = 1.75; M_{static} = 2.12, SD = .92). Further, a one-way analysis of variance (ANOVA) on fixation durations showed no significant effect for display mode ($M_{animated}$ = 11.50, SD = 5.97; M_{static} = 9.62, SD = 7.49; F(1, 83) = 1.64, p = .204; reported in seconds), indicating that animation did not affect the overall amount of attention (for details on amount of attention as an alternative explanation, see Web Appendix F).

Survey measures. A one-way ANOVA on manipulation check measures revealed that the focal graph was perceived as being more animated when it was animated than when it was static ($M_{animated} = 4.91$, SD = 1.90; $M_{static} = 1.82$, SD = 1.35; $F(1, 83) = 74.28$, $p < .001$). Moreover, a one-way ANOVA on risk judgments revealed a significant main effect for display mode ($F(1, 83) = 4.93$, $p = .029$). Supporting H_{1a}, participants' stock risk judgments were greater in the animated mode than in the static mode ($M_{animated} = 5.23$, SD = .84; $M_{static} = 4.80$, SD = .96).

Arousal—pupil dilation. Another one-way ANOVA on pupil dilation revealed no main effect for display mode ($M_{animated} = 4.46$, SD = .81; $M_{static} = 4.55$, SD = .96; $F(1, 83) = 2.00$, $p = .659$; reported in millimeters) thereby ruling out arousal as an alternative explanation.

Discussion

In Study 1, eye-tracking data lends physiological support that animated display enhances the salience of temporal transitions (evidenced by the number of fixation sequences following the animated trajectory). Study 1 also replicates the core animated display effect: risk judgments are greater when the focal data trajectory is animated (vs. static). Moreover, results show that animated display does not affect the amount of attention devoted or arousal, helping rule them out as potential process constructs.

Importantly, in Study 1 we found that the effect of display mode on risk judgments was not directly mediated by the number of fixation sequences (b = .1064, SE = .2090, 95% confidence interval [CI] = [−.2887, .5371]). This result supports prior research as well as our expectation that an inference-making process may more completely explain the effect of animated display on downstream risk judgments. To further explore the full causal chain, which involves cognitive inferences, we test a serial process in Study 2a where we examine how enhanced salience caused by animated display leads to greater utilization of temporal transitions and, consequently, the heightening of risk judgments. Study 2b further investigates the role of arousal as an alternative explanation (via manipulation of animation speed).

Study 2a: Underlying Process—Serial Mediation

Study 2a explores the proposed full causal chain: animated (vs. static) display heightens risk judgments (H_{1a}) by enhancing transition salience (H_{1b}), which leads to greater utilization of transitions in forming inferences about higher or lower levels of risk (H_{1c}). We test this process hypothesis (H_{1d}) using a serial mediation analysis. We also test for competing process accounts related to basic comprehension of variability and arousal.

Method

One hundred ninety individuals from Amazon Mechanical Turk (MTurk; $M_{age} = 35.46$ years; 67% male) participated in a single-factor (display mode: animated/static) between-subjects experiment. Participants were randomly assigned to review one of two (animated vs. static) monthly stock price graphs of a fictitious NASDAQ company, called Pegatrans (abbreviated PEGA). The stock price data used in Study 1 were presented in line form. In the animated mode, all data values were presented in a shaded trajectory for one second and then became more clearly visible as the trajectory was sequentially traced with animation. Thus, in both display modes participants were able to recognize the overall trajectory at the time they were exposed to the graph. This method formed an experimental control for the potential effect of uncertainty-induced arousal.

After reviewing the graph, participants reported risk judgments (r = .71) followed by salience and utilization of transitions, our two mediating variables. We measured the salience of transitions using five items ("daily changes in the PEGA stock price were:" "salient," "vivid," noticeable," "visible," and "clear") measured on seven-point scales (1 = "Not at all," and 7 = "Very" or "Highly"; α = .85). These scale items were adapted from prior salience literature for our visual context (see Web Appendix C).

Next, in keeping with the overarching cognitive-inference based conceptualization (Raghubir and Das 1999) we aimed to directly capture the utilization-of-transitions construct via participants' self-report. In a separate pretest (N = 99), individuals were shown the stock price graph used in Study 2a and were asked to describe particular aspects of the data that they had considered in their decision to invest. Unaided open-response protocols revealed that approximately 60% utilized temporal transitions as a basis for judgment. We reviewed the protocols and selected phrases reflecting the definition of temporal transitions (i.e., changes in data values from one point in time to the next). Using these phrases, we developed a four-item scale measuring utilization of transitions ("I rated the risk of the PEGA stock based on:" "daily changes in the stock price," "how the stock price varied one day to the next," "how often the stock price changed on a daily basis," and "how much the stock price rose and fell from day to day"; 1 = "Strongly disagree," and 7 = "Strongly agree"; α = .87). Items were worded to capture the degree to which participants relied on transitions in forming their risk judgments. Convergent and discriminant validity was verified using factor analyses (for details, see Web Appendix G).

Subsequently, participants reported the frequency of price changes ("How many times do you think the stock price rose and fell in the graph?") along with the highest and lowest prices they saw. The difference between these prices formed the recalled price range. These two measures (i.e., frequency and range of price changes) captured comprehension of overall variability of the focal data. Next, participants reported their arousal at the time of viewing the graph (α = .85), manipulation check measures for the display mode (r = .82), involvement with stock investment (α = .95), and prior stock trading experience (on a frequency response scale). Finally, they provided demographic information.

Results

Manipulation check. As expected, the animated display group perceived the focal graph as being more animated ($M_{animated}$ = 4.97, SD = 2.14; M_{static} = 2.56, SD = 1.86; F(1, 188) = 68.85, $p < .001$).

Risk judgments. A one-way ANOVA revealed that participants' stock risk judgments were greater in the animated (vs. static) mode ($M_{animated}$ = 5.56, SD = 1.08; M_{static} = 5.21, SD = 1.24; F(1, 188) = 4.26, p = .04). Involvement with stock investments ($M_{animated}$ = 4.73, SD = 1.69; M_{static} = 4.58, SD = 1.57; F(1, 188) = .39, p = .536) and stock trading experience ($M_{animated}$ = 2.71, SD = 1.56; M_{static} = 2.77, SD = 1.37; F(1, 188) = .09, p = .765) were not significantly different across display modes. Including them as covariates does not change the core effect.

Transition salience. A one-way ANOVA revealed a significant main effect for display mode (F(1, 188) = 4.67, p = .032). As expected, transition salience was greater in the animated (vs. static) mode ($M_{animated}$ = 5.93, SD = .89; M_{static} = 5.62, SD = 1.06).

Utilization of transitions. A one-way ANOVA on the utilization of transitions also showed a significant main effect for display mode (F(1, 188) = 4.45, p = .036). Specifically, participants were more likely to rely on temporal transitions to make risk judgments when the focal stock price data were presented in the animated (vs. static) mode ($M_{animated}$ = 5.76, SD = 1.08; M_{static} = 5.42, SD = 1.13).

Serial mediation. To test our proposed causal chain (animated display → salience of transitions → utilization of transitions → risk judgments), we conducted a serial mediation analysis, with risk judgments as the dependent variable, display mode (coded 1 for animated display and 0 for static display) as the independent variable, and the salience and utilization of transitions as mediators, based on 5,000 bootstrap samples (Hayes 2018, model 6). First, animated display significantly enhanced transition salience ($b_{display}$ = .31, SE = .14, t(188) = 2.16, p = .032). Next, transition salience had a positive, significant effect on the utilization of transitions, after controlling for display mode ($b_{salience}$ = .52, SE = .07, t(187) = 7.08, p = .000). Furthermore, the utilization of transitions had a significant effect on risk judgments ($b_{utilization}$ = .38, SE = .08, t(186) = 4.79, p = .000). Finally, the effect of display mode on risk judgments became nonsignificant when both salience and utilization of transitions were entered into the regression model ($b_{display}$ = .20, SE = .16, t(186) = 1.24, p = .217). Importantly, in support of H_{1d}, the bias-corrected CI of the indirect effects through transition salience and then to utilization on risk judgments excluded zero, which confirmed a significant serial mediation ($b_{indirect}$ = .0608, SE = .0374, 95% CI = [.0040, .1482]). Other than this significant causal chain, all other causal chains in the regression model yielded CIs including zero.

We conducted an additional mediation analysis with transition salience alone as a mediator. The results revealed that transition salience mediates the effect of animated display on risk judgments ($b_{indirect\_salience}$ = .0839, SE = .0474, 95% CI = [.0049, .1924]). However, when we added the utilization of transitions into the model, the mediation effect via transition salience became nonsignificant ($b_{indirect\_salience}$ = .0231, SE = .0391, 95% CI = [−.0488, .1138]). Further, we compared the model that includes salience as a single mediator with our proposed serial mediation model that includes both mediators. Importantly, adding utilization as a second mediator significantly improved the overall model fit over the single mediator model (R^2_{change} = .1017, F(1, 186) = 22.95, $p < .001$). This result establishes that the utilization of transitions has a place as a unique process construct connecting salience to risk judgments. Alternative mediation analyses using participants' comprehension of frequency and range as well as arousal as process variables revealed no evidence for their mediational role (for details, see Web Appendix H).

Discussion

Study 2a yields support for the proposed full causal chain (H_{1d}): enhanced salience of transitions caused by animated display leads to greater utilization of transitions in forming risk inferences and, consequently, increases risk judgments. Moreover, the data do not support competing accounts of variability comprehension and arousal.

Study 2b: Arousal Effect of Animation Speed

To further explore the arousal explanation, we manipulated animation speed, which is known to affect arousal level. Sundar and Kalyanaraman (2004) show that fast (vs. slow) animation leads to greater arousal. Thus, if arousal drives the animated display effect, when animation is significantly slower (i.e., ten seconds) than our baseline animated display (i.e., three seconds), the core effect should be mitigated.

Method

One hundred sixty-five undergraduate students (M_{age} = 21.51 years; 43% male) participated in a single-factor (display mode: three-second animated, ten-second animated, or static) between-subjects laboratory experiment in exchange for course credit. Six participants who skipped the stimulus page were excluded from the analysis. Participants were given the same cover story as in Study 2a and were then randomly assigned to one of the three display mode conditions. We used the stock price data used in previous studies. The display mode was manipulated in the same way as in previous studies, but in the ten-second animated condition, the entire trajectory took ten seconds to unfold (for stimuli, see the Appendix). After reviewing the graph, participants reported risk judgments (r = .66) and the frequency and range of stock price changes they saw in the focal graph. Next, participants reported their arousal at the time of viewing the graph (α = .89) and manipulation check measures for the display mode (r = .81), followed by demographic information.

Results

Manipulation check. Both the three-second ($M_{\text{three-sec. animated}}$ = 4.38, SD = 2.06; M_{static} = 2.19, SD = 1.44; t(156) = 6.37, $p <$ .001) and ten-second ($M_{\text{ten-sec. animated}}$ = 4.91, SD = 1.81; M_{static} = 2.19, SD = 1.44; t(156) = 7.80, $p <$ .001) animated (vs. static) display groups perceived the focal graph as being more animated.

Risk judgments. A one-way ANOVA on risk judgments revealed a significant main effect for display mode (F(2, 156) = 3.81, p = .024). Planned contrasts showed that risk judgments were greater in the three-second animated (vs. static) mode ($M_{\text{three-sec. animated}}$ = 5.27, SD = 1.13; M_{static} = 4.74, SD = .99; t(156) = 2.61, p = .01; replication of H_{1a}). In addition, participants exposed to the ten-second animated display rated the focal stock as riskier than those exposed to the static display ($M_{\text{ten-sec. animated}}$ = 5.17, SD = 1.02; M_{static} = 4.74, SD = .99; t(156) = 2.07, p = .04). There were no differences between the three- and ten-second animated groups (t(156) = .50, p = .621). Lastly, participants' arousal ($M_{\text{three-sec. animated}}$ = 3.39, SD = 1.32; $M_{\text{ten-sec. animated}}$ = 3.32, SD = 1.25; M_{static} = 3.75, SD = 1.13; F(2, 156) = 1.89, p = .155), comprehensions of the frequency ($M_{\text{three-sec. animated}}$ = 8.70, SD = 4.49; $M_{\text{ten-sec. animated}}$ = 9.55, SD = 7.25; M_{static} = 8.37, SD = 4.84; F(2, 156) = .61, p = .546) and range ($M_{\text{three-sec. animated}}$ = 20.48, SD = 6.00; $M_{\text{ten-sec. animated}}$ = 20.10, SD = 6.30; M_{static} = 19.11, SD = 5.49; F(2, 156) = .77, p = .467) of stock price changes were not significantly different across three display modes.

Discussion

Taken together, these findings indicate that animated display increases risk judgments and that potential differences in arousal do not explain this effect. In combination with the pupil dilation evidence from Study 1, the experimental results from Study 2b suggest that arousal may not be a primary driver of the animated display effect. In the next study, we further test the salience-based cognitive inference account by experimentally manipulating transition salience in time-varying data (operationalized via the type of graphical representation).

Study 3: Manipulating Transition Salience—Graph Type

Study 3 aims to directly manipulate transition salience via the type of graphical representation (i.e., line vs. bar graphs; H_2). Also, we test our full hypothesized process again using moderated serial mediation analysis.

Stimuli, Design, and Procedure

Three hundred thirty-five individuals from MTurk (M_{age} = 36.55 years; 52% male) participated in a 2 (graph type: line/bar) × 2 (display mode: animated/static) between-subjects experiment. We followed the same procedure as in Study 2a. Stock price data used in previous studies were presented either in line (i.e., baseline condition) or bar graphs (see Appendix). We manipulated the display mode in the same manner as in previous studies. After reviewing the graph, participants reported risk judgments (r = .71) followed by salience (α = .83) and utilization (α = .86) of transitions, using the same measures as in Study 2a. Finally, participants responded to manipulation check measures for display mode (r = .85) and provided demographic information.

Results

Manipulation check. A 2 (graph type) × 2 (display mode) ANOVA on the manipulation check measures for display mode revealed a significant main effect for display mode (M_{animated} = 4.35, SD = 2.16; M_{static} = 3.28, SD = 2.36; F(1, 313) = 18.31, $p <$ .001), indicating that our display mode manipulation was successful. The main effect for graph type was also significant (M_{line} = 4.17, SD = 2.31; M_{bar} = 3.43, SD = 2.31; F(1, 313) = 8.73, p = .003). Eighteen participants did not answer the manipulation check questions. No significant interaction effect emerged.

Risk judgments. A two-way ANOVA revealed a significant main effect for graph type (M_{line} = 5.02, SD = 1.35; M_{bar} = 4.56, SD = 1.39; F(1, 331) = 10.24, p = .002), no main effect for display mode (p = .47), and a significant two-way interaction (F(1, 331) = 7.26, p = .007). Planned contrasts revealed that within the line graph condition, risk judgments were greater when the focal stock price data were presented in the animated (vs. static) mode (M_{animated} = 5.28, SD = 1.43; M_{static} = 4.78, SD = 1.22; F(1, 331) = 5.53, p = .019; replication of H_{1a}). However, in the bar graph condition, risk judgments were equivalent across the two display modes (M_{animated} = 4.41, SD = 1.39; M_{static} = 4.70, SD = 1.39; F(1, 331) = 1.78, p = .183).

Transition salience. A two-way ANOVA on transition salience (i.e., the manipulated process construct) revealed no main effects for graph type (p = .18) and display mode (p = .083) but a significant two-way interaction (F(1, 331) = 4.29, p = .039). As expected, within the line graph condition, transition salience was greater in the animated (vs. static) mode (M_{animated} = 5.84, SD = .93; M_{static} = 5.45, SD = 1.01; F(1, 331) = 7.08, p = .008; replication of H_{1b}), whereas in the bar graph condition, it was equivalent across display modes (M_{animated} = 5.49, SD = .88; M_{static} = 5.52, SD = .94; F(1, 331) = .04, p = .836).

Utilization of transitions. A two-way ANOVA on utilization of transitions revealed no main effects for graph type (p = .081) and display mode (p = .533). Critically, the two-way interaction was significant (F(1, 331) = 5.75, p = .017). As expected, within the line graph condition, utilization of transitions was greater in the animated (vs. static) mode (M_{animated} = 5.88, SD = 1.04; M_{static} = 5.52, SD = 1.08; F(1, 331) = 4.40, p = .037; replication of H_{1c}), whereas in the bar graph condition, it was equivalent across display modes (M_{animated} = 5.38, SD = 1.13; M_{static} = 5.59, SD = 1.09; F(1, 331) = 1.50, p = .222).

Moderated serial mediation. To test how graph type (line vs. bar) moderates our proposed process, we conducted a moderated serial mediation analysis, with risk judgments as the dependent variable, display mode (coded as 1 for animated and 0 for static display) as the independent variable, graph type (coded as 1 for bar and 0 for line) as the moderator, and the salience and utilization of transitions as the mediators, based on 5,000 bootstrap samples (Hayes 2018, model 83). A significant interaction between graph type and display mode emerged on transition salience ($b_{graph \times display} = -.43$, SE = .21, t(331) = −2.07, $p = .039$), and transition salience had a positive, significant effect on the utilization of transitions, after controlling for display mode ($b_{salience} = .58$, SE = .05, t(332) = 10.62, $p < .001$). Furthermore, the utilization of transitions had a significant effect on risk judgments ($b_{utilization} = .45$, SE = .07, t(331) = 6.11, $p < .001$). Finally, the conditional indirect effect of display mode on risk judgments, through the salience and utilization of transitions, was significant in the line graph condition ($b_{line\_indirect} = .10$, SE = .05, 95% CI = [.0217, .2071], replication of H_{1d}) but not significant in the bar graph condition ($b_{bar\_indirect} = -.01$, SE = .04, 95% CI = [−.0829, .0634]).

Discussion

Study 3 provides converging evidence for our proposed process by visually manipulating transition salience. Specifically, when the focal data are presented in line graphs, animated display enhances the salience of transitions, leading to greater utilization and, consequently, increasing risk judgments. However, the core effect and its underlying process do not manifest when the same data are presented in bar graphs. This finding suggests that temporal transitions should stand out in the earlier, perception stage to be further utilized in the subsequent inferential process.

Study 4: Contextualizing the Role of Transitions in Risk Judgments—Global Trend

Study 4 tests H_3, namely, that the overall trend of the stock graph will frame inferences such that when transitions are made salient by animated display, the inference of higher risk will be made only under certain conditions (i.e., a downward global trend).

Stimuli and Pilot Study

We manipulated global trends by rearranging the stock price data used in Studies 1 through 3 in descending and ascending orders while maintaining the same price fluctuations (i.e., both the downward and upward stocks had the same run length [1.3]; for stimuli, see Appendix). In doing so, we made the stock price data used in Study 4 clearly have either a downward slope (−.7) or an upward slope (.7), compared with the baseline, which has a virtually flat slope (.1). A pretest also confirmed that the slopes of the downward and upward trending stock data were perceived as being more downward and upward than the baseline stock data, respectively (both $p < .001$; for details, see Web Appendix I).

Next, we conducted a pilot study with 174 MTurk participants ($M_{age} = 35.72$ years; 63% male) to explore how animated display affects the salience of transitions and global trends. Per our theorizing, we expect animated display to enhance transition salience for both downward and upward trending stocks. However, as a global feature, trend should be salient irrespective of display mode and serve to contextualize the role of transitions. Consistent with our expectations, a two-way ANOVA with global trends and display mode as independent factors revealed a significant main effect for display mode ($M_{animated} = 5.65$, SD = .82; $M_{static} = 5.32$, SD = 1.17; F(1, 170) = 4.46, $p = .036$) on transition salience. No other significant main or interaction effects emerged. On the other hand, trend salience was not significantly different across all conditions ($p = .307$; for details, see Web Appendix J).

Main Study

Two hundred eight undergraduate students ($M_{age} = 21.09$ years; 34% male) participated in an online experiment in exchange for course credit. They were randomly assigned to one of four conditions following a 2 (global trend: downward/upward) × 2 (display mode: animated/static) between-subjects design. Five participants who failed an attention check and four participants who did not view or follow the instructions were excluded from the analysis.

After participants reviewed the graph stimuli, we measured their risk judgments using the two items measured on seven-point scales as in previous studies (r = .72). Next, participants reported the range of stock price changes they saw, followed by manipulation check measures for display mode (r = .81) and global trend (r = .99) and finally demographic information.

Results

Manipulation checks. An ANOVA revealed a significant main effect for global trend ($M_{downward} = 1.31$, SD = .69; $M_{upward} = 6.40$, SD = .93; F(1, 195) = 1,895.17, $p < .001$). No other effects emerged, indicating that our global trend manipulation was successful. The display mode manipulation was also successful with only the main effect significant ($M_{animated} = 5.20$, SD = 1.75; $M_{static} = 1.66$, SD = 1.31; F(1, 195) = 259.81, $p < .001$).

Risk judgments. A two-way ANOVA on risk judgments revealed a significant main effect for global trend ($M_{downward} = 5.64$, SD = 1.03; $M_{upward} = 4.14$, SD = 1.16; F(1, 195) = 93.05, $p < .001$), no main effect for display mode ($p = .501$), and a significant two-way interaction (F(1, 195) = 5.26, $p = .023$). As expected, when the global trend was downward, risk judgments were greater in the animated (vs. static) mode ($M_{animated} = 5.87$, SD = 1.04; $M_{static} = 5.41$, SD = .99; F(1, 195) = 4.34, $p = .039$), whereas risk judgments were equivalent across the two display modes when the global trend was upward ($M_{animated} = 4.02$, SD = 1.15; $M_{static} = 4.27$, SD = 1.17; F(1, 195) = 1.49, $p = .224$). In addition, there were no differences in recalled stock price range ($M_{range} = 22.34$, SD = 5.77) across all conditions ($p = .39$).

Discussion

Study 4 provides empirical support for H_3 and, in the process, shows that global trend contextualizes how transitions—made salient through animated display—are utilized for inference making. We find that although animation makes transitions salient, the risk-inflating effect of these salient transitions manifests only when risk-related inference-making is warranted, that is, when the overall trend is downward. When prices are generally upward trending, the prospect of capital loss is dramatically lowered, and in such an environment, salient transitions do not lead to inferences of higher risk. The dissociation of transition salience from risk judgments bolsters our theorizing that a higher-level (possibly cognitive) inference-making process is implicated in how stimulus factors cause systematic variations in downstream judgments.

This process evidence by moderation should be interpreted with caution because transition salience was not directly measured in the main study. In addition, our experimental manipulation does not directly and independently manipulate the utilization-of-transitions construct. Since the global trend manipulation we use is itself a data feature, it combines with animated display to jointly shape how transitions are used. In Study 5, we address this concern by employing contextual manipulations that are exogenous to the data string and that directly affect how transitions are used to form judgments.

Study 5: Moderating How Transitions Are Utilized—Investment Goal

The purpose of Study 5 is twofold. First, we empirically test the role of investment goals (H_4). Second, we explore how animated display shapes downstream investment decisions and behavior. The behavioral finance literature has found that individuals' risk judgments predict their investment decisions (e.g., buy–sell ratios, willingness to invest). For example, when individual investors perceive assets to be risky, they both are less likely to buy these assets and also trade them at lower prices, thereby driving aggregate asset prices downward (Hoffmann, Post, and Pennings 2015; Huber, Palan, and Zeisberger 2019). Drawing on this insight from behavioral finance, we expect that the amounts that participants are willing to invest will reflect the opposite pattern for risk judgments.

Stimuli, Design, and Procedure

Two hundred sixteen ($M_{age} = 35.05$ years; 59% male) individual investors were recruited from Prolific Academic. On average, participants traded stocks on a quarterly basis and also currently held a retirement plan. They were randomly assigned to one of four conditions following a 2 (investment goal: long-term/short-term investing) $\times$ 2 (display mode: animated/static) between-subjects factorial design. Three participants who did not view the investment goal manipulation were excluded from the analysis.

Participants were told that they would be asked to make financial judgments based on market information. They were then asked to imagine themselves as long-term or short-term investors and were given an investment goal to keep in mind during the experiment. Adapting past work (Zhou and Pham 2004), for the long-term investing group, we informed participants that long-term investors intend to maintain long-term profits by avoiding short-term stock price fluctuations, whereas for the short-term investing group, we informed participants that short-term investors intend to make immediate profits by taking advantage of stock price fluctuations. Next, we provided participants with a brief overview of a fictitious NASDAQ company. Stock price data used in previous studies were presented in line graph form. We manipulated the display mode in the same manner as in previous studies.

After reviewing the graph, participants reported their judgments of stock risk (two items; $r = .72$). Then, participants were asked to imagine that they had $25,000 for their portfolio and to indicate the amount they wished to invest in the focal stock. Following this, they responded to manipulation check measures for display mode ($r = .80$) and investment goal. We also measured participants' trading experience (on a frequency response scale) and financial literacy (Lusardi and Mitchell 2007). Finally, participants provided demographic information.

To assess the validity of our investment goal manipulation, we conducted a separate posttest with 123 MTurk participants ($M_{age} = 34.85$ years; 63% male). Participants were given the same investment goal manipulation and asked to describe their general thoughts on how they interpret daily changes in stock prices. Two independent coders classified thought protocols and reconciled disputes through discussion. Overall, 40% of the interpretations were related to risk, while 31% related to opportunity. Other interpretations were related to supply and demand (12%), normal market phenomenon (5%), market up and down (3%), firm performance (2%), trading volume (2%), and trend (2%). Lastly, 3% provided no clear interpretations.

We observed that risk-related interpretations (e.g., volatility, instability, uncertainty, unsteady flow of cash, massive loss) and opportunity-related interpretations (e.g., good deal, potential for earnings, making quick money, cashing out to make the most profit) differed significantly depending on the investment goal. Within the long-term group, 66% inferred meanings related to risk, whereas 3% inferred opportunity. Importantly, risk-related meanings were more prominent than all other meanings combined ($\chi^2 = 30.20$, $p < .001$). In contrast, within the short-term group, 55% inferred opportunity, whereas 17% inferred risk. In this group, opportunity-related meanings were more prominent than all other meanings combined ($\chi^2 = 38.73$, $p < .001$). Taken together, the posttest results confirm that our investment goal manipulation indeed varied the meaning ascribed to the daily changes observed in stock prices.

Results

Manipulation checks. Participants in the long-term investing group focused more on reducing risk from stock price movements (M_{long} = 5.10, SD = 1.77; M_{short} = 3.24, SD = 1.97; F(1, 209) = 52.45, $p < .001$), whereas those in the short-term investing group focused more on taking advantage of stock price movements (M_{long} = 3.03, SD = 1.92; M_{short} = 5.35, SD = 1.61; F(1, 209) = 91.00, $p < .001$), suggesting that our investment goal manipulation was successful. In addition, the display mode manipulation was also successful: participants in the animated (vs. static) display mode perceived the focal graph as being more animated ($M_{animated}$ = 4.62, SD = 2.26; M_{static} = 2.03, SD = 1.70; F(1, 209) = 88.88, $p < .001$). No other significant main or interaction effects emerged (all $p > .09$).

Risk judgments. A two-way ANOVA revealed a significant effect for display mode ($M_{animated}$ = 5.38, SD = 1.15; M_{static} = 4.99, SD = 1.27; F(1, 209) = 5.45, $p = .021$), no main effect for investment goal ($p > .4$), and a significant two-way interaction (F(1, 209) = 5.87, $p = .016$). Within the long-term investing group, risk judgments were greater in the animated (vs. static) mode ($M_{animated}$ = 5.51, SD = 1.13; M_{static} = 4.73, SD = 1.39; F(1, 209) = 11.41, $p = .001$), whereas within the short-term group, risk judgments were equivalent ($M_{animated}$ = 5.24, SD = 1.16; M_{static} = 5.25, SD = 1.10; F(1, 209) = .01, $p = .938$). In addition, participants' trading experience ($M_{trading\_experience}$ = 3.18, SD = 1.11, $p = .587$) and their level of financial literacy ($M_{literacy}$ = 2.58, SD = .75, $p = .129$) were not significantly different across all conditions. Including these variables as covariates does not change the core effect.

Amount willing to invest. Because of the skewness of the data, we log-transformed the amount the participant was willing to invest, but we report results in untransformed units. A two-way ANOVA revealed significant main effects for investment goal (M_{long} = \$3,542.20, SD = \$3,740.69; M_{short} = \$5,248.10, SD = \$5,127.60; F(1, 209) = 8.44, $p = .004$) and display mode ($M_{animated}$ = \$3,838.25, SD = \$4,443.06; M_{static} = \$4,922.94, SD = \$4,608.37; F(1, 209) = 4.92, $p = .028$). Furthermore, the two-way interaction between investment goal and display mode was significant (F(1, 209) = 3.98, $p = .047$). Planned contrasts showed that within the long-term investing group, participants were willing to invest significantly lesser amounts in the animated (vs. static) display mode ($M_{animated}$ = \$2,414.69, SD = \$2,686.82; M_{static} = \$4,712.26, SD = \$4,307.70; F(1, 209) = 9.24, $p = .003$), whereas within the short-term investing group, there was no significant difference between the two display modes ($M_{animated}$ = \$5,373.45, SD = \$5,387.58; M_{static} = \$5,129.72, SD = \$4,917.32; F(1, 209) = .05, $p = .829$).

Discussion

Using manipulation of the investment goal, Study 5 provides additional evidence for our theory by moderating how transitions are utilized to form risk judgments. Results show that for long-term investors who infer risk from the transitions in stock prices, animated display inflates risk judgments. Reflecting their risk judgments, it reduces the amount that they are willing to invest. However, for short-term investors, who might infer opportunity from the same transitions, animated display does not increase risk judgments. In fact, we find that short-term investors invest more in the given stock, regardless of display mode, compared with long-term investors; this pattern is consistent with our manipulation.

To further explore the effect of animated display on consequential decision making, we conducted a follow-up study that examines how an individual investor characteristic, elaboration on potential outcomes (EPO; Nenkov, Inman, and Hulland 2008), interacts with animated display to affect incentivized investment behavior.

Prior literature has proposed that high-EPO individuals have a stronger tendency than low-EPO individuals to generate a variety of potential consequences and evaluate the importance of these consequences before making decisions (see Nenkov, Inman, and Hulland 2008). Moreover, low-EPO (vs. high-EPO) investors are more susceptible to information presentation effects (Nenkov et al. 2009). Therefore, we expect that susceptibility to the animated display effect varies depending on individuals' chronic tendency to engage in predecision elaboration on potential outcomes. In the follow-up study, we examined this with the actual number of dollars participants decided to invest based on the reward structure in the cover story (for full study details, including incentivized decision structure, see Web Appendix K). Results revealed a significant interaction between display mode and EPO ($b_{display \times EPO}$ = .18, SE = .08, t(184) = 2.19, $p = .03$) on the amounts invested by participants when they made the focal investment decision. Specifically, low-EPO individuals (the EPO scale of 3.72 and below) invested significantly lesser money in the animated (vs. static) display mode (b = −.36, SE = .18, t(184) = −1.97, $p = .05$). However, the amount that high-EPO individuals (the EPO scale above 3.72) invested was not significantly different in the two display modes (animated vs. static).

In general, high-EPO investors were less affected by the animated display, but, interestingly, animated display appears to have helped low-EPO investors make equally self-regulated decisions, compared with high-EPO investors. This finding has significant public policy implications in that animated display offers a way to effectively debias investors who may be predisposed to riskier decision making.

General Discussion

Theoretically, the current research contributes to the extant literature in several aspects. First, we extend prior research on visual representations and data-based inferences (e.g., Hutchinson, Alba, and Eisenstein 2010; Nenkov et al. 2009) by uncovering animated display as a new determinant. We demonstrate that animation systematically draws viewers' attention to specific time-varying features of the data (e.g., transitions). This drawing of attention to transitions leads to unique downstream inferences pertaining to risk. Importantly, animation naturally causes this phenomenon by unfolding data values in a moment-to-moment manner, independent of other statistical or visual properties of the data string.

To further examine the unique effect of animation (as opposed to other methods of drawing attention, e.g., arrow glyphs), we conducted a single-factor (display mode: animated, static, or static with arrows pointing at each transition in a data string) between-subjects online experiment (for stimuli and full study details, see Web Appendix L). We found that risk judgments were greater for the animated group when compared with the static group ($M_{animated} = 5.28$, SD = 1.18; $M_{static} = 4.70$, SD = 1.38; $t(207) = 2.46$, $p = .015$) as well as when compared with the static-with-arrows group ($M_{static\ with\ arrows} = 4.68$, SD = 1.60; $t(207) = 2.53$, $p = .012$). There were no differences between the two static display modes ($t(207) = .05$, $p = .958$). This finding underscores that the *dynamic* nature of animation uniquely enhances the temporal variations in the data, something even the use of arrows explicitly pointing to data transitions in a static display does not appear to achieve.

Previous marketing research has explored salience effects on visual processing of data (e.g., Duclos 2015; Raghubir and Das 2010) by changing features inherent to a data string, such as run length or start and end points. We extend this line of work by demonstrating that animation causes unique effects while holding all other statistical as well as visual properties of the data string constant.

We also contribute to the larger literature on salience effects (e.g., Jarvenpaa 1990; Taylor and Fiske 1978). By theoretically disambiguating the role of cognitive inference making in how salient features come to drive downstream judgments, this research enriches theories on salience effects. To explain why salience affects downstream judgments, prior research has mainly focused on the upstream determinant of the salience effect, namely, attentional mechanisms. Although some theoretical discussions have alluded to a cognitive process in which specific portions of the data to which attention is paid are *utilized* in judgments (see Lurie and Mason 2007), this utilization construct has generally not been incorporated into underlying process explanations nor empirically tested. This paper fills that gap by connecting salience-induced visual processing and corresponding cognitive inferences within a single framework. Using the financial decision-making context, the current research connects low-level visual processing stimulus factors (i.e., animated display, salience of transitions) to higher-order inference making processes (i.e., utilization of transitions, inferences of risk) and finally to downstream consequences (i.e., investment decisions).

The studies reported here employ two approaches to empirically outline this serial process. We first measure the salience and utilization of transitions using eye-tracking technology (in Study 1) and participants' self-report (in Studies 2a and 3; transition salience is both manipulated and measured using graph type in Study 3). Second, we moderate the utilization construct by contextualizing the role of transitions using global trends in Study 4 and investment goals in Study 5. The overall evidence not only supports the serial causal chain, but also helps disambiguate cognitive inferences (i.e., utilization) as an important part of the underlying process beyond perceptual salience. Thus, this work is the first to empirically examine and delineate the process, from the operative attentional level via subsequent inferences to judgments and decision making.

Third, we provide converging evidence with different populations (field managers, individual investors, online panels, and undergraduate students) and contexts: oil trading (pilot field study) and personal finance (Studies 1–5). The animated display effect is robust to variations in industry expertise, experience, age, gender, and other demographics. For example, in our studies, individuals' trading experience (pilot field study, $p > .8$; Study 2a, $p > .7$; Study 5, $p > .8$) or level of financial literacy (Study 5, $p > .6$) did not moderate the core effect. To further examine generalizability, we conducted a study (N = 93) involving foreign currency exchange. Results showed that consumers judged the risk in exchanging foreign currency as higher when exchange rates were presented in animated (vs. static) mode ($M_{animated} = 4.16$, SD = 1.07; $M_{static} = 3.62$, SD = 1.33; $F(1, 85) = 4.43$, $p = .038$; for full study details, see Web Appendix M). The overall preponderance of evidence points to a robust and generalizable effect across multiple domains of financial decision making as well as across populations.

With the advancement of multimedia technology, firms and consumers, with minimal effort, are able to use animation to effectively visualize time-varying data (Heer and Robertson 2007). However, as we show in this work, animation is a subtle but powerful mode of data display that can systematically affect judgments and decision making. Therefore, this work offers broad implications that are substantively important for major stakeholders in the modern economy, namely, consumers, industry, and regulators.

According to a recent report (Market Reports World 2018), the rapidly growing data visualization software market is expected to reach a value of $7.76 billion by 2023. Moreover, a major field adopting data visualization software is banking and financial services. Given that numerous financial service providers (e.g., Plus500, Robinhood, Saxo Markets) employ graphical dashboards with interactive or animated visualizations, our finding urges caution for retail investors, who often make investment decisions based on readily accessible graphs of market data. Modern data visualization tools are efficient because their representations are perceptually intuitive. However, such tools can potentially lead to biased portfolio management to the extent that they rely on animated visualization. Specifically, the enhanced risk sensitivity elicited by animated display may lead consumers to forgo investment opportunities that might otherwise yield solid returns. This implication is critical from a consumer welfare perspective since foregone earnings can detrimentally affect consumers' financial planning in the long run.

On the other hand, animated display may also prevent retail investors from making reckless investment decisions by moderating their risk sentiments. Retail investors are often risk tolerant and actively follow market trends (Pett 2014) as was reflected by the recent retail speculation in GameStop and AMC stocks. Notably, as in the follow-up experiment to Study 5, animated display can debias retail investors who elaborate less on the potential outcomes of their investment decisions. This finding has important public policy implications in that animated display can be utilized as an effective intervention that helps retail investors more thoroughly assess the value of a stock instrument, instead of simply speculating on future returns. Related to this implication, since 2013 the SEC's Market Structure Analytics website has offered interactive visualization tools to promote retail investors' understanding of market metrics (www.sec.gov/marketstructure/index.html).

On a forward-looking note, while our salience-based framework reflects a visual information processing perspective, frameworks based on mental imagery (see Roggeveen et al. 2015) might also be useful in exploring the effectiveness of animated visual communication. Further, insights from Study 4 point to interesting future directions involving the role of visual processing style (global vs. local). One conjecture is that global trends shape inferences when they encompass the entire data string. In some of our experiments, visual trends did not cover the entire data set (see pilot study stimuli), suggesting potential perceptual thresholds for global (or local) processing, a rich area for future research.

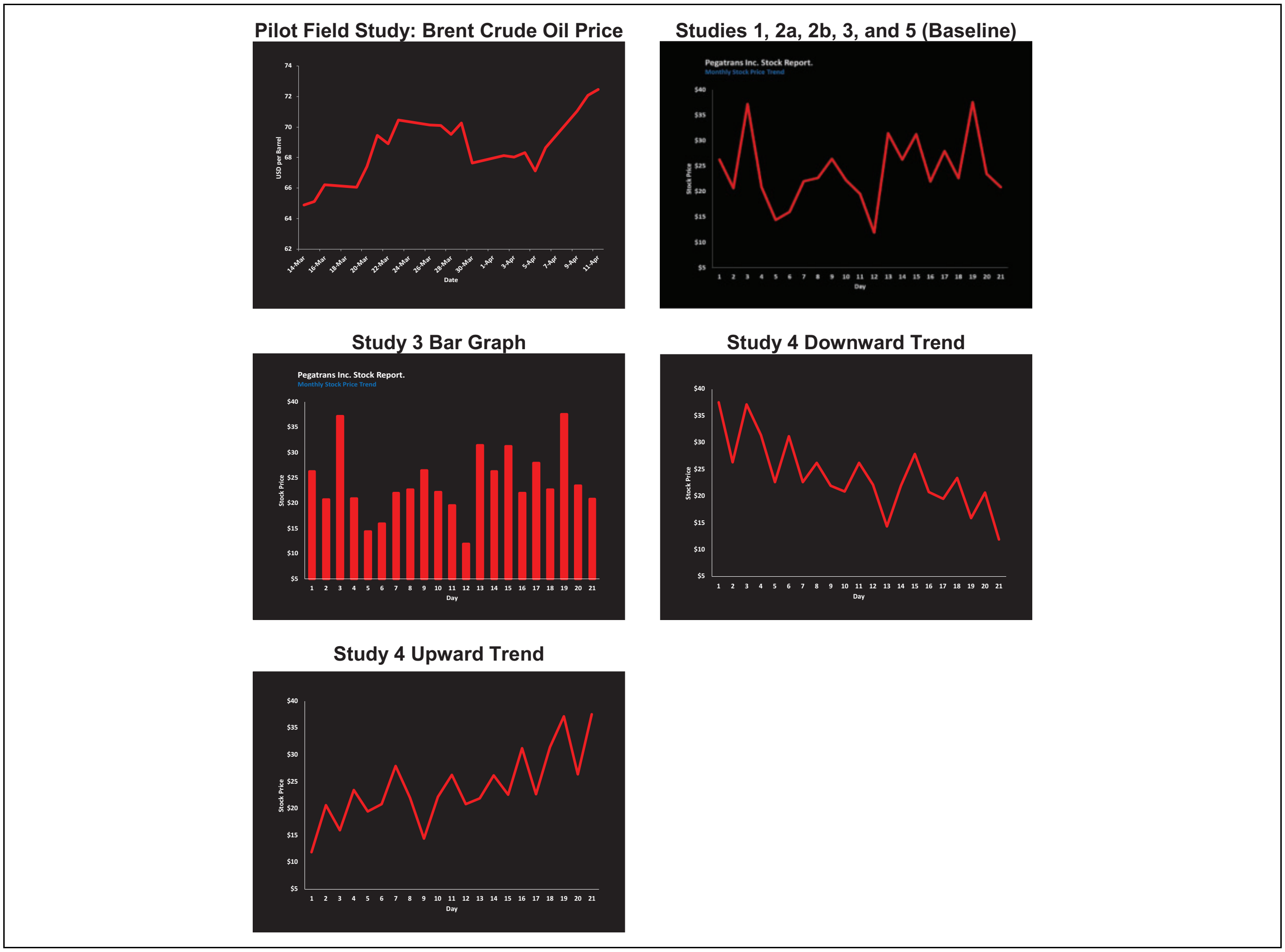
In addition, more ecologically relevant manipulations and measures can further develop this line of work. One example would be how financial products associated with different goal orientations (e.g., retirement accounts vs. individual stock accounts; Zhou and Pham 2004) interact. We also note that inter-item correlations of our risk measures sometimes tended to be at the lower end of the spectrum; secondary measures such as asset allocation or portfolio diversification decisions could also be incorporated into future work.

Lastly, future research can explore the effects of animated display in different risk domains. For example, Han et al. (2012) find that communicating health risk estimates with animation increases subjective uncertainty about the risk. Future work can test how animated display interacts with risk types (e.g., health risk), as animation may trigger different psychological mechanisms depending on the focal domain.

To sum up, as our environment becomes more saturated with digital inputs, a more nuanced understanding of dynamic forms of display, such as animation, offers a theoretically interesting and substantively relevant lens for future research and practical, consumer-focused interventions.

Appendix

Stimuli



Notes: All animated versions of the stimuli are provided at https://sites.google.com/view/animatedstimuli.

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ORCID iD

Junghan Kim https://orcid.org/0000-0001-8818-5123

References

Benbasat, Izak and A.S. Dexter (1985), "An Experimental Evaluation of Graphical and Color-Enhanced Information Presentation," *Management Science*, 31 (11), 1348–64.

Botner, Keith A., Arul Mishra, and Himanshu Mishra (2020), "The Influence of the Phonetic Elements of a Name on Risk Assessment," *Journal of Consumer Research*, 47 (1), 128–45.

Bradley, Margaret M., Laura Miccoli, Miguel A. Escrig, and Peter J. Lang (2008), "The Pupil as a Measure of Emotional Arousal and Autonomic Activation," *Psychophysiology*, 45 (4), 602–07.

Carpenter, Patricia A. and Priti Shah (1998), "A Model of the Perceptual and Conceptual Processes in Graph Comprehension," *Journal of Experimental Psychology: Applied*, 4 (2), 75–100.

Chua, Hannah Faye, J. Frank Yates, and Priti Shah (2006), "Risk Avoidance: Graphs Versus Numbers," *Memory and Cognition*, 34 (2), 399–410.

Cian, Luca, Aradhna Krishna, and Ryan S. Elder (2015), "A Sign of Things to Come: Behavioral Change Through Dynamic Iconography," *Journal of Consumer Research*, 41 (6), 1426–46.

Cleveland, William S. (1993), "A Model for Studying Display Methods of Statistical Graphics," *Journal of Computational and Statistical Graphics*, 2 (4), 323–64.

Duclos, Rod (2015), "The Psychology of Investment Behavior: (De)biasing Financial Decision-Making One Graph at a Time," *Journal of Consumer Psychology*, 25 (2), 317–25.

Duxbury, Darren and Barbara Summers (2018), "On Perceptions of Financial Volatility in Price Sequences," *The European Journal of Finance*, 24 (7–8), 521–43.

Eraslan, Sukru, Yeliz Yesilada, and Simon Harper (2015), "Eye Tracking Scanpath Analysis Techniques on Web Pages: A Survey, Evaluation and Comparison," *Journal of Eye Movement Research*, 9 (1), 1–19.

Fisher, Danyel (2010), "Animation for Visualization: Opportunities and Drawbacks," in *Beautiful Visualization: Looking at Data Through the Eyes of Experts*, Julie Steele and Noah Iliinsky, eds. Sebastopol, CA: O'Reilly, 329–51.

Forehand, Mark R., Rohit Deshpandé, and Americus Reed II (2002), "Identity Salience and the Influence of Differential Activation of the Social Self-Schema on Advertising Response," *Journal of Applied Psychology*, 87 (6), 1086–99.

Goldstein, Daniel G., Siddharth Suri, R. Preston McAfee, Matthew Ekstrand-Abueg, and Fernando Diaz (2014), "The Economic and Cognitive Costs of Annoying Display Advertisements," *Journal of Marketing Research*, 51 (6), 742–52.

Han, Paul K.J., William M.P. Klein, Bill Killam, Tom Lehman, Holly Massett, and Andrew N. Freedman (2012), "Representing Randomness in the Communication of Individualized Cancer Risk Estimates: Effects on Cancer Risk Perceptions, Worry, and Subjective Uncertainty About Risk," *Patient Education and Counseling*, 86 (1), 106–13.

Hayes, Andrew F. (2018), *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*, 2nd ed. New York: Guilford.

Heer, Jeffrey and George Robertson (2007), "Animated Transitions in Statistical Data Graphics," *Visualization and Computer Graphics, IEEE Transactions*, 13 (6), 1240–47.

Hegarty, Mary, Matt S. Canham, and Sara I. Fabrikant (2010), "Thinking About the Weather: How Display Salience and Knowledge Affect Performance in a Graphic Inference Task," *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 36 (1), 37–53.

Henry, Gary T. (1995), *Graphing Data: Techniques for Display and Analysis*. Thousand Oaks, CA: Sage Publications.

Hoffmann, Arvid O.I., Thomas Post, and Joost M.E. Pennings (2015), "How Investor Perceptions Drive Actual Trading and Risk-Taking Behavior," *Journal of Behavioral Finance*, 16 (1), 94–103.

Huber, Jürgen, Stefan Palan, and Stefan Zeisberger (2019), "Does Investor Risk Perception Drive Asset Prices in Markets? Experimental Evidence," *Journal of Banking and Finance*, 108, 105635.

Hutchinson, J. Wesley, Joseph W. Alba, and Eric M. Eisenstein (2010), "Heuristics and Biases in Data-Based Decision Making: Effects of Experience, Training, and Graphical Data Displays," *Journal of Marketing Research*, 47 (4) 627–42.

Jarvenpaa, Sirkka L. (1990), "Graphic Displays in Decision Making—the Visual Salience Effect," *Journal of Behavioral Decision Making*, 3 (4), 247–62.

Kahneman, Daniel and Amos Tversky (1979), "Prospect Theory: An Analysis of Decision Under Risk," *Econometrica*, 47 (2), 263–92.

Kim, Junghan and Arun Lakshmanan (2015), "How Kinetic Property Shapes Novelty Perceptions," *Journal of Marketing*, 79 (6), 94–111.

Kosslyn, Stephen M. (1994), *Elements of Graph Design*. New York: W.H. Freeman.

Lurie, Nicholas H. and Charlotte H. Mason (2007), "Visual Representation: Implications for Decision Making," *Journal of Marketing*, 71 (1), 160–77.

Lusardi, Annamaria and Olivia S. Mitchell (2007), "Financial Literacy and Retirement Preparedness: Evidence and Implications for Financial Education," *Business Economics*, 42 (1), 35–44.

Mano, Haim (1994), "Risk-Taking, Framing Effects, and Affect," *Organizational Behavior and Human Decision Processes*, 57 (1), 38–58.

Market Reports World (2018), "Global Data Visualization Market—Segmented by Organizational Department, Delivery Mode, Industry Vertical (BFSI, IT & Telecommunication, Retail/E-Commerce, Education, Manufacturing, Government) and Region—Growth, Trends and Forecasts (2018–2023)," Market Reports World (February 8).

McArthur, Leslie Zebrowitz and Elise Ginsberg (1981), "Causal Attribution to Salient Stimuli: An Investigation of Visual Fixation Mediators," *Personality and Social Psychology Bulletin*, 7 (4), 547–53.

Navon, David (1977), "Forest Before Trees: The Precedence of Global Features in Visual Perception," *Cognitive Psychology*, 9 (3), 353–83.

Nenkov, Gergana Y., J. Jeffrey Inman, and John Hulland (2008), "Considering the Future: The Conceptualization and Measurement of Elaboration on Potential Outcomes," *Journal of Consumer Research*, 35 (1), 126–41.

Nenkov, Gergana Y., J. Jeffrey Inman, John Hulland, and Maureen Morrin (2009), "The Impact of Outcome Elaboration on Susceptibility to Contextual and Presentation Biases," *Journal of Marketing Research*, 46 (6), 764–76.

Ozimec, Ana-Marija, Martin Natter, and Thomas Reutterer (2010), "Geographical Information Systems-Based Marketing Decisions: Effects of Alternative Visualizations on Decision Quality," *Journal of Marketing*, 74 (6), 94–110.

Pett, David (2014), "Why Retail Investors Almost Always Get Burned," *Financial Post* (May 9).

Pincus, Steve and Rudolf E. Kalman (2004), "Irregularity, Volatility, Risk, and Financial Market Time Series," *Proceedings of the National Academy of Sciences*, 101 (38), 13709–14.

Raghubir, Priya and Sanjiv R. Das (1999), "The Psychology of Financial Decision-Making: A Case for Theory Driven Experimental Enquiry," *Financial Analysts Journal*, 55 (6), 56–79.

Raghubir, Priya and Sanjiv R. Das (2010), "The Long and Short of It: Why Are Stocks with Shorter Runs Preferred?" *Journal of Consumer Research*, 36 (6), 964–82.

Robertson, George, Roland Fernandez, Danyel Fisher, Bongshin Lee, and John Stasko (2008), "Effectiveness of Animation in Trend Visualization," *Visualization and Computer Graphics, IEEE Transactions*, 14 (6), 1325–32.

Roggeveen, Anne L., Dhruv Grewal, Claudia Townsend, and R. Krishnan (2015), "The Impact of Dynamic Presentation Format on Consumer Preferences for Hedonic Products and Services," *Journal of Marketing*, 79 (6), 34–49.

Securities and Exchange Commission (2018), "17 CFR Parts 240, 249, 275 and 279—Amendments to Form ADV; Required Disclosures in Retail Communications and Restrictions on the Use of Certain Names or Titles," 83 *Federal Register* 90, 21416–571.

Sundar, S. Shyam and Sriram Kalyanaraman (2004), "Arousal, Memory, and Impression-Formation Effects of Animation Speed in Web Advertising," *Journal of Advertising*, 33 (1), 7–17.

Taylor, Shelley E. and Susan T. Fiske (1978), "Salience, Attention, and Attribution: Top of the Head Phenomena," *Advances in Experimental Social Psychology*, 11, 249–88.

Taylor, Shelley E. and Suzanne C. Thompson (1982). "Stalking the Elusive Vividness Effect," *Psychological Review*, 89 (2), 155–81.

Teal, Scott (2020), "Creating Animated Data Visualizations with Tableau Public," (February 24), https://public.tableau.com/en-us/s/blog/2020/02/creating-animated-data-visualizations-tableau-public.

Tversky, Amos (1977) "Features of Similarity," *Psychological Review*, 84 (4), 327–52.

Wallgren, Anders, Britt Wallgren, Rolf Persson, Ulf Jorner, and Jan-Aage Haaland (1996), *Graphing Statistics and Data: Creating Better Charts*. Newbury Park, CA: Sage Publications.

Zacks, Jeff and Barbara Tversky (1999), "Bars and Lines: A Study of Graphic Communication," *Memory and Cognition*, 27 (6), 1073–79.

Zhou, Rongrong and Michel Tuan Pham (2004), "Promotion and Prevention Across Mental Accounts: When Financial Products Dictate Consumers' Investment Goals," *Journal of Consumer Research*, 31 (1), 125–35.