Disclosure Processing Costs, Investors' Information Choice, and Equity Market Outcomes: A Review

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Abstract

This paper reviews the literature examining how costs to monitoring, acquiring, and analyzing firm disclosures – collectively, "disclosure processing costs" – affect investor information choices, trades, and market outcomes. When investors face disclosure processing costs, learning from a disclosure is an active economic choice, and investors expect to be compensated for their costly processing activities. We review the analytical and empirical literature on sources of processing costs and how these costs affect price informativeness, responsiveness, liquidity, volatility, and volume within rational equilibria. We also discuss studies of the feedback effects of investors' processing costs on managers' choices about disclosure and corporate actions. We conclude that disclosure processing costs, and likely information frictions more broadly, have implications for a wide array of accounting research and phenomena, but we are only just beginning to understand their effects.

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1. Introduction

This review focuses on the frictions to investors using firm disclosures. In particular, we review the literature examining how costs to monitoring, acquiring, and analyzing firm disclosures – collectively, "disclosure processing costs" – affect investor information choices, trades, and market outcomes.

Many studies assume that firms' disclosures are public and, thus, that investors costlessly transform the information from disclosures into prices. This assumption is often unrealistic though; just as it takes effort to read this article, it can be costly to acquire and understand firms' disclosures. When investors face disclosure processing costs, learning from a disclosure is an active economic choice similar to that of acquiring private information, and investors expect to be compensated for their costly processing activities (Grossman & Stiglitz 1980). Disclosure processing costs can affect price informativeness, responsiveness, liquidity, volatility, and volume within rational equilibria, inhibit the efficient flow of disclosure information into prices, and have implications for a broad array of accounting research.

While the idea that disclosure processing costs affect pricing has existed for decades (e.g., Ball 1992), the literature on processing costs has surged in recent years. The objectives of this review are to provide an analytical primer for thinking about how disclosure processing costs affect equity markets, organize and critique existing empirical work, highlight links in seemingly disparate literatures, and provide guidance for future research. Our review of the frictions affecting investors' disclosure usage complements prior reviews on the frictions affecting firms' disclosure production (Healy & Palepu 2001; Beyer et al. 2010).

Figure 1 provides an overview of the paper. Section 2 discusses conceptual underpinnings and Sections 3 through 6 discuss primarily empirical literature. For brevity, we limit our scope in several ways. First, we focus on the costs of processing firm disclosures as opposed to information from sources outside the firm. Second, we focus on equity investors' trading decisions, but note that processing costs likely also affect other stakeholders and decision contexts. Third, while disclosure processing costs very likely affect cost of capital (e.g., Merton 1987; Easley & O'Hara 2004), for brevity we exclude cost of capital when discussing market outcomes. Fourth, we limit our focus to U.S. markets. Fifth, while psychological biases can affect disclosure processing, we focus primarily on processing costs and choices within rational paradigms. Finally, given our collective expertise, we do not review experimental literature.

Conceptual underpinnings

The literature identifies three steps to processing a disclosure for use in a trading decision, where "disclosure" refers to a specific signal from a firm report or communication. An investor must: (i) learn that the disclosure exists; (ii) obtain the report and extract the disclosure; and (iii) analyze the implications of the disclosure for firm value. Each of these steps is costly, and we refer to those costs as: (i) awareness costs; (ii) acquisition costs; and (iii) integration costs.[1] Just as in Grossman & Stiglitz (1980), the presence of any processing cost means that prices cannot be fully informative because, if investors' costly information is immediately revealed in prices, then nobody would process the disclosure to begin with. For similar reasons, processing costs can also affect price responsiveness, liquidity, volatility, and trading volume.

While most existing analytical theory on processing costs comes from classic rational models such as Grossman & Stiglitz (1980), Verrecchia (1982a), and Kyle (1989), two other types of models are relevant. First, "behavioral models" (as defined in Section 2) were among the first to

[1] Many of the papers discussed in this review use different labels to describe these three processing costs. As discussed in Section 2, we use labels that we believe lie most closely at the intersection of the various literatures discussed throughout this paper, but readers are free to substitute their own terminology.

explicitly consider awareness frictions; i.e., that it is costly to monitor whether a manager has released a report or included a disclosure within a larger report (e.g., DellaVigna & Pollet 2009; Hirshleifer et al. 2011). Second, "rational inattention" models explicitly incorporate the realistic assumption that processing capacity is a limited resource, whether it be a human sacrificing leisure for work or an institution buying increasingly expensive labor and technology (e.g. Sims 2003; Veldkamp 2011). Capacity constraints mean that disclosure processing has an opportunity cost, so investors must allocate their capacity across disclosures and other activities. Rational inattention models can likely be adapted to consider awareness frictions and, more broadly, can bridge the gap between classic models and behavioral models while adhering to traditional rationality requirements.

One insight emerging from the analytical literature is that disclosure processing costs can provide rational explanations for many market phenomena that may otherwise appear anomalous. For example, post-earnings announcement drift, accruals mispricing, and portfolio under-diversification can all be generated by rational models with disclosure processing costs. However, most analytical insights come from studies examining private information, and it is possible that unforeseen differences exist for processing firm disclosures. Also, analytical studies typically examine awareness, acquisition, and integration costs in isolation from one another, and it is likely that interactive or substitutive effects would generate more complex predictions. We conclude that the analytical literature on disclosure processing costs is at an early stage of development.

Empirical research

Section 3 transitions from theory to empirics with descriptive analyses of data frequently used in empirical research.[2] We examine how proxies for disclosure processing and market outcomes covary with one source of variation in processing costs: the number of other firms announcing earnings on the same day (Hirshleifer et al. 2009). Busy earnings days strain investor resources and increase the opportunity cost of processing a particular firm's disclosure. Our analyses replicate and extend existing work, and provide descriptive evidence that: (i) disclosure processing is costly even for sophisticated market participants; and (ii) capacity constraints force investors to optimize across disclosures.

Section 4 reviews the empirical literature on how disclosure processing costs affect investor information choices, trades, and market outcomes. Several takeaways emerge. First, disclosure processing costs and capacity constraints affect all types of investors, big and small, and a broad array of market outcomes. Second, the mechanisms for how and why processing costs affect market outcomes are not well understood, in part because the underlying theory (analytical or otherwise) is still relatively early. Third, empirical studies struggle to isolate the effects of disclosure processing costs from the effects of variation in the underlying transaction, firms' strategic disclosure choices, and other correlated changes, leaving room for research to re-examine questions using stronger research designs. Fourth, most studies examine earnings announcements and surprises, but these are just a small portion of the disclosures that warrant investigation. Fifth, new technologies are fundamentally changing both investors' processing costs and researchers' abilities to examine processing costs, providing opportunities for new predictions and tests, and for re-examining prior findings in the current institutional environment.

A final takeaway from Section 4 is that many seemingly disparate literatures have common

[2] The objective of the descriptive analysis is threefold. First, it introduces and critiques empirical proxies before discussing their use in specific papers. Second, it provides an intuitive example of how processing costs can affect market outcomes. Third, the related Data Appendix provides details to guide future empirical research.

economic grounding in a disclosure processing cost framework. For example, findings related to recognition versus disclosure, information overload, disclosure readability, reporting standard comparability, and investor inattention are all potentially driven by disclosure processing costs. Further, some findings originally characterized as anomalies or attributed to behavioral biases are plausibly the rational effects of processing costs. Existing research often neglects to consider rational theory when developing hypotheses or is too quick to attribute results to behavioral theory when rational theory fits equally well. We encourage future researchers to more intentionally consider costly disclosure processing as an explanation for market phenomena, and to disentangle rational responses from behavioral biases where possible.[3]

Section 5 reviews the literature on the role of data providers, journalists, and social media in mitigating investor disclosure processing costs.[4] These intermediaries have emerged to: (i) reduce awareness and acquisition costs by monitoring, curating, and rebroadcasting disclosures; and (ii) reduce integration costs by synthesizing and interpreting disclosures. The literature finds compelling evidence that data providers and journalists can mitigate processing costs and affect market outcomes. Research on social media as an intermediary is nascent.

Section 6 reviews the literature on managers' strategic considerations of investor processing costs when making decisions about disclosures and corporate actions. Managers can adjust disclosure content, quantity, and timing to either mitigate or exploit investor processing costs, and evidence suggests that both occur. Disclosure processing costs also affect investors' monitoring abilities and corporate governance, and studies find that managers strategically

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[3] To be clear, we are comfortable with the possibility that behavioral biases affect the market, and some papers we review have findings that are more consistent with behavioral theory than with existing rational theory. Still, we share Veldkamp's (2011) view that rational theory is a useful default starting point for empirical research because its structure can impose greater discipline on researchers and can be less vulnerable to ad hoc assumptions.
[4] We refer readers to Bradshaw et al. (2017) for a review of equity analyst research, including their roles in mitigating disclosure processing costs.

exploit processing costs when taking corporate actions such as value-destroying acquisitions. Examining the feedback effects of investors' disclosure processing costs on managers' decision-making and real outcomes is an interesting and broad avenue for research.

Finally, while the focus of this review is disclosure processing costs and equity investing, we conclude by noting that processing frictions and capacity constraints are likely relevant to many information sources, stakeholders, and decision contexts. The studies we review provide compelling evidence that even the most sophisticated equity market participants can struggle to monitor, acquire, and analyze information. For investors, information frictions impair not only their abilities to process disclosures, but also their abilities to identify investment opportunity sets, optimize portfolio allocations, monitor their holdings, and make other investment-related decisions. Disclosure processing costs likely also affect investors' required expected return (i.e., cost of equity capital). Beyond investors, information processing frictions and the related theory likely also extend to lenders, suppliers, labor markets, boards of directors, auditors, intermediaries, regulators, tax authorities, and other parties with which the firm transacts. Finally, information processing frictions likely also affect managers and, thus, an array of managerial decisions and corporate outcomes (e.g., project selection, budgeting, compensation, etc.). The ideas of costly processing and active information choice are relevant to much of the accounting literature and raise many questions for future research.

2. Conceptual Underpinnings

Hayek (1945) argues that asset prices aggregate disperse information and coordinate resource allocation. Fama (1970) formalizes the theoretical ideal of strong market efficiency, in which prices are sufficient statistics for all public and private information available to investors.

Strong market efficiency is not possible when private information is costly because, if private information were immediately revealed in prices, nobody would have an incentive to acquire it (Grossman & Stiglitz 1980). To incorporate the cost of acquiring information, Fama (1970) defines semi-strong efficiency as a situation where prices fully reflect "information that is obviously publicly available" (p383). Here, "public information" is defined as information that is costless to process (Fama 1970; Marshall 1974).

Are firms' disclosures "public information" in the context of semi-strong market efficiency? If firms' disclosures are "public" and so costlessly reflected in price, then there is no incentive to monitor and acquire disclosures, and there are no profits to be made from fundamental analysis. This characterization is at odds with the thousands of hours we spend each year teaching students how to prepare and analyze financial statements. It is at odds with the investment strategies of leaders such as Warren Buffett, and at odds with large industries that specialize in monitoring and analyzing disclosures (e.g., journalists and data providers).[5] In practice, it takes time, effort, and money to process firms' disclosures, and there are physical limits to the amount of information that even the most sophisticated investors (human or computer) can process in real time. Firms' disclosures are therefore not truly "public," at least in the sense required for semi-strong efficient pricing.

Once we accept the notion that disclosures are costly to process, it becomes evident that disclosure pricing must be imperfectly efficient. Disclosure pricing is at best efficiently inefficient, with the inefficiency depending on the nature and magnitude of specific disclosure processing frictions. Thus, studying processing costs is essential for understanding the effects of disclosure on capital markets.

It also becomes evident that, when investors face processing costs, learning from a disclosure

[5] Section 5 discusses compelling evidence that journalists and data providers improve disclosure pricing efficiency by mitigating disclosure processing costs.

is an economic choice like that of acquiring any other private information. Investors consider expected costs and benefits in choosing their alertness to the existence of new disclosures, whether to acquire a disclosure, and the extent to analyze and integrate a disclosure into trading decisions. Investors allocate scarce processing capacity to disclosures for which they expect processing to maximize their risk-adjusted profits, and reap competitive rewards from doing so.

This "Conceptual Underpinnings" section introduces types of processing costs (Section 2.1), market outcomes (Section 2.2), and classes of analytical models (Section 2.3). Section 2.4 provides intuition for how processing costs affect market outcomes. Section 2.5 briefly critiques the literature and provides recommendations for future research. For brevity, this Section is not intended to be a comprehensive review of theory on processing costs (much of which is from outside accounting and developed in contexts other than firms' disclosures), but is instead a primer to understanding the empirical research in Sections 3 onwards.

2.1 Disclosure Processing Costs

Section 1 described three steps to processing a disclosure – awareness, acquisition, and integration – each of which involves explicit costs and opportunity costs. These processing costs appear with different combinations, labels, and forms in theory developed across papers with a broad variety of research questions and methods. Following Blankespoor et al. (2019), we use the labels awareness, acquisition, and integration because they lie most closely at the intersection of the literatures relevant to this review. We note, though, that this trichotomy of processing actions and costs is a theoretical simplification, and the lines between costs can be blurry. Further, this framework represents a compromise across diverse literatures (analytical, empirical, etc), so likely does not perfectly fit the framework used in any particular paradigm.

Separately considering processing costs is useful for at least four reasons. First, the three steps to processing a disclosure are descriptive of practice, and thus useful for describing and understanding the markets we study. Second, there is no reason to believe the three actions are equally costly, so they could have different effects on disclosure processing and market outcomes. Third, the three costs likely have interactive effects on processing and market outcomes. For example (and as described below), models predict that acquisition and integration costs individually decrease price informativeness, but combining both costs can generate non-monotonic effects. Fourth, strategies to mitigate market frictions vary depending on the specific processing cost. For example, improving disclosure availability reduces awareness and acquisition costs, but does little to alleviate integration costs. The remainder of this section further describes the three costs, as well as their related opportunity costs.

Awareness costs

Awareness costs are the costs necessary to improve one's probability of knowing that a particular disclosure exists; e.g., monitoring EDGAR or Twitter, or skimming a 10-K for a specific footnote. Monitoring for a disclosure's existence is costly, so monitoring is often outsourced to data providers and other intermediaries such as IBES or Dow Jones (in which case subscription fees are an awareness cost, as further discussed in Section 5.1).

In the analytical literature, a version of an awareness cost has existed since at least Merton (1987), in which investors pay to become aware of a firm (or more precisely the security's return generating process). Subsequent literature introduces the idea that investors may be aware of a firm but unaware of a specific disclosure, either in general or at a specific point in time (e.g., Hirshleifer & Teoh 2003). For example, an investor may be unaware that 10-K filings ever contain disclosure on subsequent events (i.e., material transactions that occur after the fiscal period end), or may be unaware that a 10-K containing a subsequent event disclosure was filed at a certain date and time.

Acquisition costs

Acquisition costs include the costs necessary to extract and quantify a disclosure signal so it is ready for use in a valuation model (Bloomfield 2002). Acquiring a disclosure signal does not mean that an investor knows its full implications for firm value; processing an acquired disclosure into a valuation estimate requires integration, as discussed below. Acquisition costs may be low for simple disclosures such as insider trade filings on EDGAR, higher for footnote details buried in a report, and higher still for qualitative information such as the tone of MD&A or inflections in managers' voices on a conference call. The fact that investors pay providers such as Compustat for disclosure data indicates that acquisition costs are material. Acquisition costs have appeared in models since at least Grossman & Stiglitz (1980), in which investors pay a one-time cost to acquire a signal. Some models acknowledge that investors may not know the particular characteristics of a signal before it is acquired (e.g., its precision or quality), which complicates the investor's acquisition decision (e.g., Fischer & Heinle 2018).

Integration costs

Integration costs include the costs necessary to combine and refine acquired signals into a valuation estimate or investment decision. For example, downloading Compustat data does not immediately reveal their implications for firm value. Rather, investors must incur integration costs to analyze those disclosure data. The field of financial statement analysis rests on the assumption that it takes time and effort to integrate accounting signals into valuation models. Integration is a largely continuous choice in that investors can increase their integration efforts to arrive at increasingly accurate estimates of firm value.

In the analytical literature an integration cost most closely resembles a "variable acquisition cost" like in Verrecchia (1982a), in which investors can acquire increasingly precise versions of signals by paying a continuous cost. Indjejikian (1991) refers to integration costs as the "cost of information interpretation" (p278), and Myatt & Wallace (2012) study how integration costs affect which signal users choose to process. While many other models so far focus on a single processing cost and are agnostic about whether the cost relates to integrating versus acquiring a disclosure, conceptualizing integration as a distinct friction can be important in models of multiple costs (see below) and is essential in many empirical studies (see Section 4).

Opportunity costs of awareness, acquisition, and integration

Awareness, acquisition, and integration are economic costs and thus involve both explicit and opportunity costs. Opportunity costs arise because processing a disclosure consumes resources that could otherwise be allocated to other activities or processing other disclosures. All investors – individuals, institutions, and computers – have capacity or budget constraints. If a disclosure occurs in a period of a capacity shortfall, rational investors consider the explicit costs as well as opportunity cost of processing the disclosure.[6] Thus, disclosure processing is an optimization problem in which investors allocate scarce processing resources across multiple disclosures. The presence of processing capacity constraints has been particularly emphasized by the rational inattention literature (Sims 2010).

2.2 Introducing five market outcomes

Disclosure processing costs affect the way the market operates. Here we introduce five market outcomes that commonly appear in the literature: price informativeness, price responsiveness, liquidity, volatility, and volume. Sections 2.3 and 2.4 then discuss how models incorporate these outcomes.

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[6] We characterize optimization across disclosures as an opportunity cost problem. An equivalent characterization is that investors have convex marginal capacity costs; e.g., due to diminishing returns to scale or increasing input costs.

We define price informativeness with respect to a disclosure as the extent to which prices reflect the information available in the disclosure (Brunnermeier 2005). If prices are perfectly informative, the price will fully reveal all information and there is no need to process disclosures to make investment decisions. In the analytical literature, price informativeness is often referred to as price precision or price efficiency.

Most models assume that all disclosed information is eventually priced (i.e., prices eventually become fully informative), but pricing takes longer when processing costs are higher. Price responsiveness is the speed with which disclosed information enters price; e.g., of the total disclosed information priced over two periods, how much is priced in the first period. In the empirical literature efficient price responsiveness is often characterized by large earnings response coefficients (ERCs) and small post-earnings announcement drift (PEAD), holding constant other ERC determinants such as earnings persistence. In some models, prices can be overly responsive followed by a reversal.

Liquidity is loosely described as the ability to trade without moving price. A market is perfectly liquid (or deep) if an investor's trades do not impact price. In illiquid markets, traders' individual orders affect prices, and the price movement is a form of transaction cost. Bid-ask spread is a common measure of liquidity because the difference between the midpoint price and the bid/ask price is the amount by which price must "move" in order to sell/buy. Liquidity is generally decreasing with adverse selection (Glosten & Milgrom 1985; Goldstein & Yang 2017).

Price volatility around a disclosure event measures the average (absolute) price change during the disclosure event, and trading volume is the dollar amount of trades occurring around a disclosure event.

2.3 Models of disclosure processing costs

This section briefly introduces three classes of models used in the literature: classic rational models; behavioral models; and rational inattention models. Our goal is to discuss key assumptions and areas of focus for each class of models, as well as define important terms. Section 2.4 more fully discusses the models' predictions for market outcomes. See Figure 2 for a framework of representative papers for each class of models, and their focus on specific processing costs and market outcomes. While many models below focus on costly acquisition of private information, we apply their results to costly processing of firm disclosures. Also, to unify our discussion of the literature, we use a set of consistent terms, some of which are different from those used in the original papers. Finally, we discuss predictions that are not explicitly considered in studies but are implicit in their analyses.

2.3.1 Classic rational models

Classic rational models have several common features. First, they typically make three key assumptions: (i) investor expectations are consistent with Bayes' rule; (ii) investors hold common prior beliefs about the joint distribution of fundamentals and disclosures; and (iii) investors maximize expected utility considering their risk preferences.[7] Second, they often include several of three investor types: informed, uninformed, and noise. Informed investors use private information and price, while uninformed investors choose not to process private information and only learn from price. In our interpretation, firm disclosures are costly to process and thus are a form of private information. Noise trades are not driven by disclosures or prices. Third, rational models typically include additional frictions such as liquidity constraints, market

[7] Bayes rule is a logical consistency rule for probability statements that describes how rational investors form and update expectations. Investor rationality is not meant to be an exact description of how investors form their expectations, but an approximation that helps describe the behavior of the average investor. Investor rationality does not imply that markets will be informationally efficient. Rather, phenomena such as bubbles, price drifts, crashes, and crises can exist in rational models (Vives 2010).

power, or trading costs that prevent informed investors from trading until price fully reflects all their private information. Instead, price is a weighted-average of both the uninformed and informed investors' beliefs. Fourth, rational models tend to incorporate either acquisition or integration costs. To our knowledge, no existing classic rational models of disclosure processing formally model awareness costs.

Some rational models feature perfect competition with a large number of price-taking traders (e.g., Grossman & Stiglitz 1980; Hellwig 1980), while others feature imperfect competition in which traders can individually affect prices (e.g., Kyle 1989; Banerjee & Breon-Drish 2018). Both types of models can be used to analyze a variety of market outcomes, but only models of imperfect competition can examine liquidity because, by assumption, a single investor cannot impact prices in models of perfect competition.[8]

Initially, classic rational models considered static settings with a single risky asset. The literature has further developed to settings featuring multiple assets (Admati 1985; Van Nieuwerburgh & Veldkamp 2010) and multiple trading periods (He & Wang 1995; Banerjee & Breon-Drish 2018).

2.3.2 Behavioral models

Behavioral models use insights from psychology to relax the rationality assumptions discussed in the prior section. There are several common threads in the literature.[9] First, as shown in Table 1, behavioral models tend to focus on awareness of disclosure rather than acquiring or integrating disclosure, and often assume that some investors are unaware of a

[8] Competitive models that examine liquidity typically define it as the sensitivity of prices to aggregate noise trading (e.g., Vives 2010; Goldstein & Yang 2017).

[9] Our discussions of behavioral models (this subsection) and rational inattention models (following subsection) are focused narrowly on their relevance for disclosure pricing. Broader reviews of the behavioral and rational inattention literatures can be found in Sims (2010), Veldkamp (2011), Gabaix (2018), and DellaVigna (2009).

disclosure.[10] Second, irrationality often manifests as either investors disregarding information in prices or persistently disagreeing about the implications of disclosures (i.e., agreeing to disagree).[11] For example, in Peng & Xiong (2006), processing-constrained investors have poor information but trade aggressively because they are overconfident in their valuations. Or, in DellaVigna & Pollet (2009), unaware investors irrationally disregard price movements and continue to trade on stale information (see also Eyster et al. 2019; Corona & Wu 2019). Third, most behavioral models focus on price responsiveness or volume.

The distinction between behavioral and rational models is not clear-cut. Classic rational models such as Grossman & Stiglitz (1980) and Kyle (1985) require at least some noise trading that could be irrational, and behavioral models typically impose at least some restrictions on investors' beliefs and require some form of optimizing behavior. One distinguishing factor is that behavioral actions in rational models "are convenient shortcuts for getting trading into the model… They are not deeply micro-founded in the psychology literature as in true behavioral finance" (Cochrane 2013, p43).

2.3.3 Models of rational inattention

Rational inattention models adhere to the three rationality requirements, but also incorporate the assumption that investors have limited processing capacity (Sims 2003; Sims 2010). Limited processing capacity means that investors must rationally allocate scarce resources to process disclosures. While rational inattention models are often based on human decision-making,

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[10] An interesting exception is Hirshleifer et al. (2011), which incorporates both investor unawareness and incomplete disclosure processing, the latter of which can be characterized as due to integration costs.

[11] We classify difference of opinions and disagreement models as behavioral because they include investors that have incorrect priors about the data generating process, yet assign zero probability to the possibility that the other investors' priors are correct and are unwilling to learn from them (e.g., Morris 1994, Banerjee & Green 2015, Banerjee 2011). Some researchers characterize differences of opinions models as standard rational models in which investors have heterogenous priors.

limited processing capacity also applies to organizations and computers.[12] For example, organizations and computers have finite capacity limits in the short-term, and scaling-up long-term capacities for peak loads can require inefficient off-peak idleness. Rational inattention models represent processing costs as an opportunity cost arising from investors' finite processing capacity where, if an investor processes a disclosure, she forgoes the benefit of processing another disclosure.

Veldkamp (2011) argues that rational inattention models provide non-behavioral explanations for investors' partial use of information, bridging the gap between classic rational models and behavioral models. For example, in behavioral models an investor not learning from prices is usually attributed to psychological biases, while rational inattention models show that not learning from prices can be a rational choice stemming from processing costs (e.g., Kacperczyk et al. 2016). Essentially, rational inattention models describe how investors' mistakes can be the outcome of a cost-benefit analysis. As summarized by Mackowiak et al. (2018), "people often cannot avoid mistakes, but they can choose what to think about and to what level of detail, i.e., what type of mistakes to minimize."

Rational inattention models thus far focus mostly on price responsiveness, in part because they enable information choice-related explanations for slow reactions to disclosures, excess volatility, and price stickiness or drifts (Veldkamp 2011). In addition, rational inattention models can explain gains to (learning) specialization or home biases (Van Nieuwerburgh & Veldkamp 2009). Most rational inattention theory comes from economics but is starting to emerge in the accounting literature (e.g., Fischer & Heinle 2018; Chen et al. 2018b; Jiang & Yang 2017).

2.4 Effects of processing costs on market outcomes

[12] Consistent with broad applicability, the roots of the rational inattention literature are in information theory applications to physical capacity constraints in engineering and communication settings (Shannon 1948).

Disclosure processing costs are important because they affect the market's informational efficiency and hence its ability to effectively allocate capital. Disclosure processing costs also affect information asymmetries between investors, and hence the willingness of investors concerned with adverse selection to participate in the stock market. Below we discuss the effects of disclosure processing costs on five market outcomes: price informativeness, price responsiveness, liquidity, volatility, and volume.

2.4.1 Price informativeness

The earliest classic rational models focus on price informativeness, perhaps because it is at the core of the efficient market hypothesis. Price informativeness depends on both the fraction of investors who process a disclosure and become at least partially informed (the "extensive margin" of investor informedness), and the extent to which those investors choose to integrate information (the "intensive margin"). Grossman & Stiglitz (1980) show that acquisition costs reduce the extensive margin of informedness. Verrecchia (1982a,b) show that integration costs reduce the intensive margin, and cause heterogenous estimates of firm value. Lower extensive or intensive margins, in turn, reduce price informativeness. Extensions to these models find similar results: individually, higher acquisition or integration costs reduce price informativeness (e.g., Kyle 1989; Vives 2010; Fishman & Hagerty 1989, 1992).

Goldstein & Yang (2017) point out that acquisition and integration costs likely have interactive effects, so the negative relation between processing costs and price informativeness could reverse if models consider both costs together. For example, as integration costs rise, investors reduce their integration and price becomes less informative. However, as price becomes less informative, more investors are motivated to acquire the disclosure. This substitution between acquisition and integration can generate non-monotonic predictions for the effect of processing costs on price informativeness.[13] Predictions are further complicated by introducing awareness costs, which are not considered in existing classic rational models.

Behavioral and rational inattention models do not explicitly examine price informativeness, but simple predictions similar to the classic rational model findings can be inferred from the models. For example, unaware or uninformed investors that cause delayed price responsiveness in behavioral and rational inattention models can likely also be shown to reduce price informativeness (e.g., Sims 1998, 2003; Kacperczyk et al. 2016; DellaVigna & Pollet 2009).

2.4.2 Price responsiveness

Price responsiveness encompasses both the strength and speed of the change in price given a disclosure. In a market without processing costs, the strength of the response is given by a disclosure's "signal-to-noise ratio" (Kothari 2001; Holthausen & Verrecchia 1988) and the price immediately reflects the disclosure. In practice, the strength and speed are determined by processing costs (as well as risk aversion and other frictions), with low strength and speed equating to a weak initial price response followed by drift. Like many accounting studies, we define "drift" as a positive correlation between a disclosure signal and post-disclosure returns (e.g., PEAD). Our definition differs from models that define "drift" as positively autocorrelated returns (e.g., Allen et al. 2006; Banerjee et al. 2009).

While few classic rational models explicitly model price responsiveness and drift, their findings imply that processing costs reduce price responsiveness through their effect on investor informedness, similar to price informativeness. For example, in Grossman & Stiglitz (1980), only a subset of investors choose to acquire costly information before trading. Risk aversion

[13] This substitution effect is reminiscent of the crowding-out effect of public information, i.e., that more public information may crowd-out private information acquisition and lead to lower price informativeness (Verrecchia 1982b; Diamond 1985; Kim & Verrecchia 1994; Gao & Liang 2013; Goldstein & Yang 2017).

prevents informed investors from trading so much that price reflects all their information; instead, price becomes the weighted average of informed and uninformed investors' beliefs plus a risk bearing term. When the costly information is revealed in a subsequent period, the price continues adjusting, or "drifts" to the final correct price. All else equal, the greater the cost the greater the drift. Importantly, the presence of drift, or the ability of the costly information to predict future returns, is rational: even though costly information in the interim period predicts returns in the final period, acquisition costs and risk aversion mean that it is not profitable for investors to arbitrage the disclosure under-pricing. Along these lines, a working paper by Andrei et al. (2019) extends Grossman & Siglitz (1980) to explicitly model price responsiveness, showing that macroeconomic uncertainty motivates investors to increase their disclosure processing, which in turn improves price responsiveness. Integration costs also affect price responsiveness and drift (Verrecchia 1982a). Similar results would hold in models of imperfect competition with acquisition or integration costs, although the mechanism would be more aggressive trading by more informed investors when processing costs decrease (Kyle 1989; Fishman & Hagerty 1992; Avdis & Banerjee 2018).

Behavioral models explain weak price responsiveness and drift based on psychological biases. For example, investors that are unaware of a disclosure yet continue to trade can cause initial price underreactions followed by drift (DellaVigna & Pollet 2009; Hirshleifer et al. 2011), as can investors that have poor information but continue trading due to overconfidence or biases that cause persistent disagreement with other investors (e.g., Peng & Xiong 2006; Banerjee et al. 2009; Barber & Odean 2013). Trading due to behavioral biases can even lead to price overreactions and reversals (Hong & Stein 1999; Peng & Xiong 2006; Hirshleifer et al. 2011).

Rational inattention models also predict underreaction to information, with the innovation that the underreaction is based on users' rational allocation of scarce resources to process the most advantageous signals, rather than due to psychological biases. Initial models mostly focus on macroeconomic signals and labor outcomes (e.g., Sims 1998, 2003, 2010; Reis 2006; Mackowiak & Wiederholt 2009), finding delayed responses of prices and wages to economic signals. These models could be used to test delayed disclosure price responses. For example, Peng (2005) studies a dynamic model of rational inattention and shows processing costs reduce the speed of price adjustments to fundamental shocks and firm disclosures (see also Jiang & Yang 2017).

2.4.3 Liquidity

Analytical work on liquidity is concentrated in classic rational models with imperfect competition, where processing costs can affect liquidity due to their effect on investor informedness. A decrease in processing costs motivates more investor processing, leading to more informed investors (Kyle 1989). Avdis & Banerjee (2018) show that greater investor informedness increases competition among informed investors and motivates more aggressive trading, which improves liquidity (see also Fishman & Hagerty 1989, 1992).

However, rational models also show a countervailing force that makes the effect of processing costs on liquidity ambiguous. As more investors process the disclosure and become informed, any price change is more likely to reflect information that the uninformed investor has not processed. This increase in adverse selection can lead to reduced liquidity (Glosten & Milgrom 1985; Vives 2010; Avdis & Banerjee 2018, Fishman & Hagerty 1992). The net result is a non-monotonic (U-shaped) effect of processing costs on liquidity, with low and high processing costs leading to greater liquidity, and mid-range processing costs having lower liquidity. The shape of the curve and where the positive or negative relation dominates depends on model parameters such as risk aversion, noise trading, and intensity of competition.[14] Future analytical work could examine specifics of this relation.

The behavioral and rational inattention literatures have not focused on liquidity. However, in behavioral models with unaware investors who do not learn from orders or prices, an increase in the fraction of unaware investors should cause higher liquidity because unaware investors do not perceive adverse selection and are thus willing to trade (see Eyster et al 2019; Biais et al. 2010). An open question is whether such liquidity effects change if behavioral models are modified to allow unaware investors to rationally learn about the existence of disclosures from price. Also, in rational inattention models, investors' infrequent information processing and trading (Duffie 2010; Reis 2006; Mackowiak & Wiederholt 2009) could also affect liquidity.

2.4.4 Volatility

Several models of information processing examine price volatility directly (Peng & Xiong 2006; Banerjee & Kremer 2010; Fischer & Heinle 2018; Veldkamp 2006, Scheinkman & Xiong 2003). Two factors contribute to price volatility around a disclosure: investors using the disclosure to revise their beliefs about firm value (i.e., price responsiveness), and noise traders impacting price in illiquid markets. Thus, predictions for the effect of processing costs on volatility rely on the same arguments discussed for price responsiveness and liquidity. In classic rational models, greater processing costs reduce price responsiveness and thus reduce disclosure-related volatility. However, they have an ambiguous effect on liquidity, and thus an ambiguous effect on liquidity-related volatility. The end result is a likely non-monotonic relation between processing costs and volatility.

2.4.5 Trading volume

[14] In addition, differences across investors in their risk aversion or their processing ability can combine with processing costs to affect liquidity (e.g., Verrecchia 1982a; Bushman et al. 1996; Kim & Verrecchia 1991a,b).

Bamber et al. (2011) comprehensively review the literature on trading volume, and we agree with their conclusion that the field lacks consensus on how disclosures affect trading volume. Still, volume has been tied to disclosure processing since at least Beaver (1968), and understanding volume is essential for understanding disclosure pricing efficiency. Here we briefly describe a few models in which processing costs affect trading volume but, from the outset, we note that there is ample room for growth in the literature.

Milgrom & Stokey's (1982) results imply that, under certain conditions, information arrivals do not generate trading volume because investors agree on the change in price. In a "no-trade" environment such as this, volume only comes from noise traders. As noted by Cochrane (2013), though, "the theory that prices reflect information with zero trading volume is of course dramatically at odds with the facts … The fact staring us in the face is that 'price discovery,' the process by which information becomes embedded in market prices, uses a lot of trading volume, and a lot of time, effort, and resources." The analytical literature has long struggled to understand why this is the case.

In competitive rational models, the main reason for trading around events (besides noise trading) is that trading benefits both parties because they have different preferences or endowments. For example, better-informed investors are more willing to hold risky shares than worse-informed investors, which creates mutually-beneficial reasons to trade. Thus, one way for processing costs to cause trading volume is by causing investors to have different levels of informedness. Kim & Verrecchia (1991a,b) provide such a model in which investors have different processing abilities, and they prove that an integration cost has an inverse U-shaped effect on trading volume and information asymmetry. However, unlike Milgrom & Stokey (1982) they assume incomplete markets (also see Kim & Verrecchia 1997).

In imperfect-competition rational models, processing costs generally reduce volume because processing costs reduce the number of informed traders. Facing fewer competitors, informed traders are more reluctant to trade aggressively for fear of inducing large price revisions. Kim & Verrecchia (1994), Fishman & Hagerty (1992), and Kyle (1989) consider an acquisition cost, while Avdis & Banerjee (2018) consider an integration cost with similar implications.

Behavioral models have an easier time generating trading around disclosures because they allow for persistent differences in opinions; i.e., for investors to agree to disagree about value (Hong & Stein 1999, 2007). When processing costs create differences in opinions, these investors continue to trade and drive up volume. For example, in Harris & Raviv (1993), investors disagree about the value implications of disclosures, perhaps due to differences in processing costs. They are overconfident in their disclosure assessments (a behavioral bias), and therefore continue to trade (also see Harrison & Kreps 1978; Scheinkman & Xiong 2003; Peng & Xiong 2006). In DellaVigna & Pollet (2009) and Hirshleifer et al. (2011), processing-constrained investors do not realize they are unaware of a disclosure and do not learn from prices, which allows them to have persistently different beliefs and continue trading against aware investors. While neither model considers volume, it seems both would increase volume. In general, behavioral models indicate that higher processing costs lead to greater differences in opinions, and therefore greater volume.

In sum, the effects of disclosure processing costs on trading volume are largely unmodeled, and different classes of models seem to generate different predictions.

2.5 Conclusions and directions

This section discusses theory on how disclosure awareness, acquisition, and integration costs can cause markets to be efficiently inefficient with respect to firm disclosures, or efficient subject to information processing costs. Investors who incur processing costs must be compensated for their efforts, prices reveal disclosure information with a delay, and liquidity, volatility, and volume can all be affected.

A robust analytical literature on disclosure processing costs could help the empirical literature in at least two ways. First, it can help researchers develop more well-grounded and complete empirical predictions, including predictions that incorporate non-monotonic relations and competing influences of multiple processing costs. Second, analytical models can help inform structural analysis to estimate unobservable parameters and quantify their relative importance, or examine counterfactual settings, subject to model assumptions.

We conclude with several insights and suggestions for future analytical research. First, most models discussed above focus on the costly processing of private information, and very few papers focus on processing firm disclosures in particular. We assume that insights from models of private information processing discussed above extend to firm disclosures, but future research can investigate whether disclosure processing entails nuances we have not foreseen. Also, there are many models on private information processing that we do not discuss above because they are not as obviously relevant to disclosures, but there are likely many opportunities to adapt other existing private information models to a disclosure context.

Second, most existing studies model a single type of processing cost, but predictions can differ substantially when more than of one of awareness, acquisition, and integrations costs are considered together. For example, in a multiple cost setting, it is no longer obvious that an increase in integration costs leads to lower price informativeness. Analysis of the model in Goldstein & Yang (2017) indicates that an increase in integration costs causes the average investor to integrate less but can simultaneously incentivize more investors to acquire the disclosure. Under plausible conditions, the effects of the increase in number of informed investors more than offsets the decrease in the average investor's integration, leading to an (initially counter-intuitive) increase in overall price informativeness. Interactive and substitution effects between types of processing costs are an important area for future research.

Third, awareness is primarily modeled as a behavioral phenomenon, where unaware investors assign zero probability to the existence of such disclosure. Understanding unawareness as a rational phenomenon, in which unaware investors assign a positive probability to a disclosure and learn from price about its existence, would contribute to the literature.[15]

Fourth, the accounting literature has only just begun to investigate rational-inattention models, despite their influence in economics (Sims 2010; Veldkamp 2011). By modeling learning as a rational choice, this paradigm accurately describes real world activities and has the potential to explain empirical phenomena that may otherwise be considered behavioral.

Fifth, we need more research modelling the dynamics of disclosure and prices. While much of the empirical literature is concerned with the speed of price discovery, extant analytical theory literature has not spent much time rationalizing the dynamics of price discovery. Importing the methods of the rational inattention literature might help theorists and empiricists better understand the dynamic process of price discovery and how to measure it empirically.

Sixth, Keynes (1936) introduces the possibility of "beauty contest" effects. A short-horizon investor is more concerned with the perceptions of other buyers than his own beliefs about fundamental values. In this context, lack of common knowledge about other investors' disclosure

[15] Dye (1985, 1998) introduces a related concept in a voluntary disclosure setting. He assumes that investors are uncertain about a manager's private information endowment but assign positive probability to the manager having private information. One could extend this idea by assuming that investors are unaware of a disclosure but assign positive probability to a disclosure existing. Under this interpretation, unawareness means investors are uncertain about the existence of firm disclosure rather than the manager's endowment of private information.

processing activities may induce price drifts and other anomalies (e.g., Allen et al. 2006; Banerjee et al. 2009; Myatt & Wallace 2012). Exploring this possibility is an interesting avenue for future research.

Seventh, incorporating increasingly realistic assumptions into accounting models would improve their connections to empirical work. For example, examining multiple-asset settings, multiple periods, and non-normal distributions would better reflect practice and likely improve our understand investors' information choices.

Finally, as discussed in Section 6, the literature has spent little time modeling the effects of disclosure processing costs on managers' disclosure decisions or other corporate actions.

3. Descriptive analyses

This section provides descriptive analysis of how disclosure processing and market outcomes change as the opportunity cost of disclosure processing increases. We replicate and extend Hirshleifer et al. (2009) and deHaan et al. (2015), examining busy days when many firms are announcing earnings; i.e., when capacity constraints are more likely to bind and processing one disclosure takes resources away from another.[16] The data indicate that many market participants – big investors, small investors, and intermediaries – process earnings announcements (EAs) less completely or less quickly when opportunity costs are higher. "Less disclosure processing" means the average investor becomes less informed; i.e., acquires and integrates less information from the disclosure within a given time window.[17]

Our sample includes Compustat/CRSP/IBES EAs from 2006 through 2016. Figure 3A shows

[16] Market participants can allocate resources for predictably busy EA dates but maintaining capacity to process peak loads likely requires inefficient off-peak idle capacity. If so, disclosure processing per EA likely decreases as the number of contemporaneous EAs increases. Section 4.1 discusses other papers examining busy earnings days, including Chakrabarty & Moulton (2012) and Driskill et al. (2019).

[17] The objective of these analyses is to motivate our review of archival literature and introduce the empirical measures used therein. These analyses are purely descriptive and processing costs are likely not the sole cause of the observed associations. Other factors such as capital constraints and EA timing choices should be considered.

the EAs per day for 2015 as a representative year, with EAs per day reaching a high of 666. These EAs are largely concentrated in the few hours before and after normal trading, and 32% of EAs happen from 4:00 pm – 4:05 pm (untabulated). Our analyses sort each day into annual quintiles of the number of contemporaneous EAs. The Appendix provides variable details.

3.1 Measures of disclosure processing activities

Trading volume is an early proxy for disclosure processing (e.g., Beaver 1968; Cready 1988). Empirical papers often assume that more disclosure processing leads to more belief revision and greater trading volume. Volume is a noisy proxy for disclosure processing because it has many drivers, including the disclosure's information content and different investor interpretations (see Section 2). Further, volume would be a poor proxy for processing in non-trade equilibria (e.g., Milgrom & Stokey 1982), although non-trade theorems are generally considered to be useful theoretical ideals rather than descriptive of observed markets (Cochrane 2013).

The dotted line on the right axis of Figure 3B shows that total market volume (in $billions) increases across each quintile of busy EA days, consistent with investors processing and trading on the heightened information flow. At the same time, the dotted line with square markers on the left axis plots average firm-level abnormal trading volume on days [0,1] around EAs, and finds a monotonic decline across each quintile.[18] These data suggest that investors scale-up their total processing on busy EA days, but processing of each individual EA declines because of capacity constraints. Tests in Table 1A find that this decline is highly significant and robust to including firm and year-quarter fixed effects. This phenomenon is not limited to small firms: Figure 3A and Table 1A find similar trends for S&P 500 firms, S&P 100 firms, and the Dow Jones 30.

More direct measures of investor processing

[18] All market variables use event windows of [0,1]. "Abnormal" activity is relative to a pre-event window of days [-41,-11] unless otherwise noted, but there is little consensus in the literature about the appropriate pre-event window.

Given that volume is a noisy proxy for disclosure processing, it is useful to examine more direct measures of processing activities. Doing so can help researchers better understand investors' actions and better identify the mechanisms for how processing affects market outcomes. From here on we tabulate results only for the complete sample of firms. Untabulated analyses find that not all results hold among subsamples of larger firms.

- *EDGAR downloads* – the abnormal quantity of reports downloaded from EDGAR in the EA window (Drake et al. 2015). EDGAR downloads are characterized as a measure of disclosure acquisition by at least moderately sophisticated investors who can understand accounting reports, but many professional investors likely obtain disclosures from a direct EDGAR feed or other subscription service. A weakness of EDGAR is that low overall download counts indicate that it is unlikely to be most investors' primary source of disclosures.
- *Google ticker searches* – the abnormal search volume index ("SVI") for ticker searches on Google during the EA window (Drake et al. 2012). SVI is thought to capture processing by non-professional investors searching for disclosures or related interpretations by intermediaries (Da et al. 2011). SVI has measurement error due to search term ambiguity (e.g., CAT can be Caterpillar Inc or felines) that varies systematically across firms and can bias cross-sectional tests (deHaan et al. 2019a). A recent version of SVI released by Google and specifically capturing investing-related searches ("ISVI") likely has less measurement error and produces unchanged results in our sample.
- *Bloomberg attention* – a binary variable for "abnormal institutional attention" (AIA) to firm-specific news on *Bloomberg* (Ben-Rephael et al. 2017), calculated relative to attention over the trailing 30 days. This measure likely captures processing by professional investors.
- *Retail trading volume* – the abnormal volume of retail trading, as identified in TAQ using the

method in Boehmer et al. (2019). The Boehmer et al. measure is thought to have a low type I error rate but high type II error rate because many retail trades are unidentified. The effects of type II errors should be carefully considered in designing and interpreting tests.

Table 1B shows declines for all measures across quintiles of busy EA days. Ceteris paribus, these results are consistent with less disclosure processing when opportunity costs are higher.

Measures of intermediaries' disclosure processing

Table 1C examines intermediaries' activities. Studies often examine intermediaries because their disclosure processing decisions resemble those of investors (discussed in Section 4), or because intermediaries directly affect investors' processing costs (discussed in Section 5).

- *Dow Jones Media Articles* – the number of earnings-specific articles written by Dow Jones journalists. Counting strictly earnings-related articles reduces measurement error, especially for firms that frequently receive non-earnings news coverage. Fewer articles per EA indicates that either journalists are resource-constrained and less able to process disclosures, or that journalists reduce output due to lower expected demand from investors.
- *Dow Jones Newsflashes* – newsflashes are snippets broadcasting single facts from an EA (Twedt 2016). Newsflashes are primarily intended for professionals who subscribe to news services, and are designed to be low-cost for journalists to produce and investors to process.
- *Equity Analyst Forecasting Likelihood* – the percentage of analysts following the firm that provide a forecast within a timely window of the EA (Zhang 2008). Ceteris paribus, analysts are less likely to release a forecast when experiencing capacity constraints.
- *Equity Analyst Forecasting Delay* – analysts' average delay for releasing their first forecast after the EA (deHaan et al. 2015). Longer average delays are thought to be indicative of reduced disclosure processing.

- *IBES Update Speed* – the number of minutes between the EA and when IBES disseminates the earnings news (Akbas et al. 2018; Bochkay et al. 2019). Longer delays indicate that IBES's system of humans and computers are slower to process firms' EAs.
- *Twitter Activity* – the abnormal volume of tweets about a firm during the EA window. Social media platforms allow users to act as intermediaries for one another by disseminating and interpreting disclosures (see Section 5.3). Research on social media is nascent, but a greater volume of social media activity likely captures greater disclosure processing.[19]

Again, all intermediary measures suggest that processing is slower or reduced on busy EA days.

3.2 Measures of liquidity, price responsiveness, volatility, and price informativeness

Results above are consistent with reduced disclosure processing by a variety of market participants on busy EA days. We next examine whether reduced disclosure processing affects market outcomes other than volume.

Measures of liquidity: bid-ask spread, depth, and price impact

Market makers and other investors use both bid-ask spreads and depth to protect against better-informed traders (Lee et al. 1993). This section also discusses liquidity measures based on price impact (e.g., Amihud 2002).[20]

Higher spreads mean that trading is costlier and so liquidity is reduced. Column (i) of Table 1D presents data for abnormal percent effective spreads measured using transaction-level TAQ data (Holden & Jacobsen 2014). Abnormal spreads increase monotonically across busy EA

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[19] Unlike the other variables in this section, *Twitter Activity* has not been vetted as a measure of disclosure processing around EAs. Bartov et al. (2018) examine tweets in advance of EAs and Curtis et al. (2016) examine a proprietary measure of social media activity around EAs, but to our knowledge research has not examined twitter activity around EAs. A potential concern is that *Twitter Activity* can be directly affected by tweets from managers or employees. We leave this for future research to investigate.

[20] While the disclosure processing cost literature tends to examine liquidity using measures of spread, depth, and price impact, other literatures examine other dimensions of transaction costs and constraints. For example, So & Wang (2014) examine return reversals as a measure of market makers' premia for supplying liquidity around EAs.

deciles, consistent with a decline in liquidity as processing opportunity costs increase.

Several studies find that spreads measured using daily closing values (e.g., from CRSP) can reasonably approximate intraday data measures (e.g., Hasbrouck 2009; Goyenko et al. 2009; Chung & Zhang 2014; Fong et al. 2017).[21] However, these papers tend to examine correlations between daily and intraday measures over long windows such as months or years, and do not compare daily versus intraday measures in the context of short-window responses around information events (e.g., over hours or days). CRSP-based measures tend to use closing spreads so do not capture spreads during the first few minutes of trading after the EA, when much of the trading and price response occur. Thus, using intraday data is likely preferable when examining event-related, short-window market activity.

TAQ- and CRSP-based abnormal spreads are correlated at 32% in our sample, and results in column (ii) of Table 1D find that CRSP-based spreads also increase across busy EA days. However, inferences from examining the levels of TAQ-based and CRSP-based spreads are different: TAQ-based abnormal spreads are positive while the CRSP-based versions are negative, providing opposite inferences about the levels of abnormal liquidity around EAs.[22]

Depth is the amount one can trade at the current ask and bid quotes. Greater depth allows more trading without moving price, so greater depth contributes to greater liquidity (all else equal). Column (iii) of Table 1D presents quoted depth measured using TAQ data. Depth

[21] WRDS's Intraday Indicators data provides TAQ-based summary measures at the daily level, which reduces researchers' cost of using intraday measures. Still, intraday data is not available for early years or for many international markets. Also see Corwin & Shultz (2012) for an estimate of bid-ask spread based on daily high and low prices.

[22] Differences in timing possibly contribute to the opposite signs of TAQ- and CRSP-based spreads. Prior literature finds that EAs cause temporary increases in spreads as investors race to process the disclosure, followed by declines in spreads as information asymmetry dissipates (e.g., Lee et al. 1993; Kim & Verrecchia 1994; Krinsky & Lee 1996; Amiram et al. 2016). Intraday spreads capture this full process and indicate that spreads are overall higher in the EA window. The CRSP-based proxy measures spread only at closing, after a full day of trading when spreads may have dropped to below control-period levels. We leave this for future research to investigate.

declines across the busy day quintiles, again consistent with reduced liquidity. We are not aware of a depth measure based on daily CRSP data.

Price impact is a measure of illiquidity that gauges the extent to which prices move in response to order flow, akin to lambda in Kyle (1985). Larger price impact indicates lower liquidity. Column (iv) of Table 1B presents abnormal percent price impact using five-minute intervals in TAQ data (Holden & Jacobsen 2014). Abnormal price impact increases across the busy day quintiles, consistent with decreased liquidity.

Fong et al. (2017) find that a price-impact measure based on daily absolute returns divided by daily volume (Amihud 2002) is a reasonable approximation of TAQ-based price impact. TAQ- and CRSP-based abnormal price impacts are correlated at 16% in our sample, and results in column (v) find that CRSP-based price impact again increases on busy EA days. Similar to the spread results, though, the levels of price impact differ between the TAQ- and CRSP-based proxies: the TAQ-based measure indicates that abnormal impact is generally positive around EAs while the CRSP-based measure indicates the opposite. Given these differences and that Fong et al. (2017) do not examine short-window changes in price impact around events, a TAQ-based depth measure is likely a safer choice for short-window studies.

Measures of price responsiveness: ERC/PEAD and intraperiod efficiency (IPE)

ERCs and PEAD are used together to examine price responsiveness to EAs. ERC measures the short-term elasticity of prices with respect to earnings news, and is calculated as the coefficient from regressing EA-window returns on earnings surprises. PEAD is longer-term price response to earnings surprises, calculated analogously to ERCs but using post-EA returns (e.g., days [2,75]). All else equal, slower price responsiveness should manifest as smaller ERCs combined with higher PEAD. Importantly, slow price responsiveness does not necessarily equate to a profitable trading strategy. In addition to implementation and transaction costs (Richardson et al. 2010; Lee & So 2015), disclosure processing costs must be taken into account.

Earnings surprises are based on analyst forecasts errors, sorted into annual decile ranks. We calculate abnormal returns net of a portfolio matched on size, book-to-market, and momentum (Daniel et al. 1997). Our ERC window is days [0,1], and our PEAD window is days [2, 75] to capture price adjustments that occur around the next quarter's EA (Bernard & Thomas 1990).[23] Consistent with Hirshleifer et al. (2009), results in Table 1D find that ERCs decline and PEAD increases across the busy EA quintiles.

Another measure of price responsiveness is Intra-Period Efficiency (IPE). IPE is an area-under-the-curve measure of the speed of price adjustment within a fixed window [t,T], set here to days [0, 5], where faster adjustments indicate higher price responsiveness. IPE is calculated as the average of: $[1 - (|AR_T - AR_t|)/|AR_T|]$, where AR is the abnormal return over [0,t]. A perfectly efficient price response that immediately jumps to its day T value has IPE = 1. IPE is an improvement over earlier measures of Intra-Period Timeliness (IPT) (Freeman 1987; Beekes & Brown 2006) because IPE penalizes over-reactions and reversals (in IPT, overreactions incorrectly appear as exceptionally efficient price responsiveness) (Blankespoor et al. 2018).

An advantage of IPE over ERC/PEAD is that it does not require a quantitative measure of the information contained in the disclosure (e.g., calculating ERC requires a quantitative earnings surprise). Thus, IPE can be used to examine price responses to disclosures such as 8-K filings that do not have an easily quantifiable summary statistic. A drawback of IPE is that it can be highly noisy for small price responses, so researchers often set IPE to missing for disclosures

[23] Using a 75-day PEAD window captures 89% of the *q+1* EAs, and 19% of the PEAD-window return is earned in the two-day *q+1* EA window. Using a 100-day window captures nearly 100% of *q+1* EAs and produces similar results. Using a 60-day window captures 24% *q+1* EAs and produces slightly weaker results, although still significant at 5%.

with small absolute IPE-window returns (here, we use a one percent cutoff). Further, IPE is sensitive to the return accumulation window. Still, results in Table 1D find declines in IPE across the EA quintiles, consistent with reduced price responsiveness.

Measures of volatility

Realized volatility is typically described as the sum of squared intraday returns. Due to microstructure noise, intraday returns measured over five-minute intervals tend to be better specified than measures using narrower intervals (Hansen & Lunde 2006; Liu et al. 2015). The theory discussed in Section 2 generally predicts that information-related volatility decreases when disclosure processing decreases but the effect on liquidity-related volatility is ambiguous, so the overall effect on volatility is unclear. We find in column (v) of Table 1D that abnormal volatility declines across EA quintiles. Liu et al. (2015) find that measuring volatility using daily open-to-close returns is inferior to using intraday returns, but in our sample TAQ- and CRSP-based abnormal volatility are correlated at 61% and produce similar results (column vi).

Measures of price informativeness

To our knowledge, price informativeness has not been empirically investigated in the context of disclosure processing immediately around EAs. Two measures have been used to capture aspects of price informativeness over long windows. The first is stock price "synchronicity," or the comovement of a firm's stock price with a benchmark group of firms (Morck et al. 2000; Durnev et al. 2003). Prices that incorporate more firm-specific information are predicted to be less synchronous with the benchmark group, all else equal. Synchronicity is typically measured over quarters or longer, but could potentially be adapted for short-window tests using intraday data (e.g., Patton & Verardo 2012). The second proxy is the future ERC (FERC), or the empirical association between current stock returns and future earnings innovations (e.g, Kothari

& Sloan 1992; Lundholm & Myers 2002; Israeli et al. 2017). Prices that incorporate more firm-specific information should incorporate future earnings more quickly and accurately, and therefore have higher FERCs. FERC is typically measured using returns over a fiscal period, but again could potentially be adapted to short-window returns around the EAs. We leave it for future research to assess the construct validity and empirical viability of such approaches.

Concluding remarks

The results in Table 1 are purely descriptive and potential confounds abound. Still, the results provide descriptive evidence that processing public disclosures is costly, and that capacity constraints force investors to allocate limited resources across disclosures.

4. Empirical literature on variation in processing costs

Subsections 1 through 3 are organized based on the source of variation in disclosure processing costs: **intra-investor variation** in costs and resources, abstracting from the characteristics of the disclosure or investor type; **inter-investor variation**, such as retail traders versus professionals; and variation **across types of firms and disclosures**, abstracting from investor characteristics. Section 4.4 discusses **market technologies** that affect disclosure processing.

4.1 Intra-investor variation in processing costs

We start with intra-investor variation: variation for a given investor over time, abstracting from the characteristics of the disclosure and fixed investor characteristics. We start with intra-investor variation because it builds on the analyses in Section 3. Also, studies in this area provide evidence that both large and small investors can be affected by disclosure processing costs, thus motivating why processing costs are relevant beyond just studies of retail investors.

4.1.1 Variation in opportunity costs

Most research on disclosure processing opportunity costs focuses on two sources of variation: (i) contemporaneous information events; and (ii) investors' preferences for work versus leisure.

Contemporaneous events: earnings announcements

As discussed in Section 3, while aggregate trading volume increases on busy earnings days, Hirshleifer et al. (2009) find that each individual EA firm has lower trading volume. These results indicate that capacity constraints and opportunity costs prevent investors from scaling-up their disclosure processing proportionally to the heightened EA information flow. DeHaan et al. (2015) find corroborating evidence in the form of fewer EDGAR downloads, Google ticker searches, and media articles, and delayed analyst responses. Driskill et al. (2019) use a strong within-EA research design to show that equity analysts are slower and less thorough in responding to EAs when firms within their portfolios have contemporaneous EAs. In a closely-related setting, Akbas et al. (2018) find that IBES dissemination of analyst forecasts takes longer when there are more contemporaneous forecasts. And, Kempf et al. (2017) find that institutional investors are less likely to participate in firms' conference calls when other firms in their portfolios demand attention. These papers, along with the data in Section 3, provide compelling evidence of reduced or delayed disclosure processing when opportunity costs are high.

Busy EA days are also associated with systematic differences in market outcomes other than volume. Hirshleifer et al. (2009) find lower ERCs and higher PEAD on busy days. Our descriptive analyses in Section 3 find reduced price responsiveness, reduced volatility, and reduced liquidity. In a related setting, Frank & Sanati (2018) find that professional arbitrageurs are capital constrained on busy days, which exacerbates mispricing for firms with news events. Busy EA days also affect market outcomes for non-announcing firms; e.g., when one of a market maker's or institutional investor's firms announces earnings, they reduce information monitoring and decrease liquidity for non-announcing firms (Chakrabarty & Moulton 2012; Schmidt 2018).

The consistent associations between busy EA days and market outcomes strongly suggest that opportunity costs impair liquidity and price discovery, but the mechanism causing these results is not well identified. Hirshleifer et al. (2009) explain delayed price responses using behavioral theory in which unaware investors disregard information in prices and continue trading on stale valuations. However, it seems that trading between unaware and aware investors in such a model would generate disagreement and higher trading volume relative to a world without awareness frictions, which is inconsistent with findings of lower trading volume on busy EA days. Given that reduced price responsiveness can also be generated by processing costs in classic rational models and rational inattention models, future research can endeavor to identify the best match between theory and empirical results. Also, beyond the PEAD tests that indicate disclosures on busy days are eventually priced, we know little about whether and when investors return their focus to disclosures that were incompletely processed on busy days. Finally, future research can develop stronger research designs to control for transaction costs and capital constraints that affect pricing and likely also covary with busy days, and can do more to address endogeneity from managers selecting EA timing (see Section 6).

Contemporaneous events: non-business news

Non-business news events appear to affect retail investors' disclosure processing but not professionals'. Israeli et al. (2019) find that major mainstream news events such as a bridge collapse or police chase are associated with reduced Google ticker search and retail trading volume around EAs, but do not find reduced institutional investor attention based on Bloomberg searches. They also find no evidence of differences in price responsiveness for EAs that coincide with major non-business news. Finding that non-business (and likely low-value-relevant) news reduces disclosure processing by retail investors but not professionals has two implications. First, finding that institutional investors are not distracted by non-business news indicates that they are not susceptible to random distraction, suggesting that their distraction by competing EAs is likely intentional. Second, finding that pricing is not affected by distracted retail investors indicates that retail investors are not the primary driver of delayed price responses on busy EA days.

Labor-Leisure Preferences

Humans allocate their finite time between work and leisure, and at some points the opportunity cost of working becomes prohibitive. Evidence is mixed on whether intra-investor tradeoffs between work versus leisure cause systematic variation in market outcomes. Research dating to at least Patell & Wolfson (1982) and Damodaran (1989) speculate that investors' preferences for leisure are stronger in the evenings and on Fridays, causing them to devote fewer resources to processing firms' disclosures. DellaVigna & Pollet (2009) and Louis & Sun (2010) interpret evidence of delayed price responses to Friday disclosures as being consistent with reduced processing, but Michaely et al. (2016a) and deHaan et al. (2015) show that what appear as slower price responses on Fridays are a function of sample selection biases. Specifically, the firms that choose to release earnings on Fridays have slower price responses even when they report on other days, so Fridays are not the causal mechanism. Evidence on systematic variation in processing of before- and after-hours EAs is also mixed (deHaan et al. 2015; Michaely et al. 2016b; Lyle et al. 2018). Drake et al. (2016a) do find delayed EA price responses during major sporting events, consistent with investors substituting leisure for work. While there is some evidence that labor-leisure preferences affect market outcomes, mixed results potentially indicate that professionals and institutions can allocate resources to accommodate normal variation in the opportunity cost of working, at least in some settings.[24]

4.1.2 Intra-investor variation in capacity and explicit costs

Explicit costs (as opposed to opportunity costs) and processing capacities both affect processing choices and often change simultaneously. For example, computers both lower marginal processing costs and increase capacity per hour. Research on intra-investor variation in capacities and explicit costs is limited, likely due to difficulties in measuring either construct.

Much of the evidence on intra-investor variation in explicit processing costs and capacity costs comes from the intermediaries literature (Section 5). Investors outsource disclosure processing to intermediaries, presumably because investors find it more cost-effective than processing the disclosures themselves (Taylor & Verrecchia 2015). When an intermediary unexpectedly reduces its disclosure coverage, investors' explicit processing costs increase and their responses to disclosures are impaired (Kelly & Ljungqvist 2012). Likewise, increases in intermediary coverage reduce investors' processing costs and improve disclosure responsiveness.

Other papers attempt to more directly measure intra-investor variation in investors' cognitive capacities using analysts as a proxy for investors. DeHaan et al. (2017) test a hypothesis from psychology and economics that weather-induced negative moods impair workers' productivity, and find that analysts experiencing unpleasant weather are less responsive to EAs. Hirshleifer et al. (2019) find that the quality of analysts' earnings forecasts declines in the afternoon, consistent with decision fatigue limiting analysts' cognitive capacities. While both papers provide fairly compelling evidence regarding the processing and output of individual analysts, their tests of associated market outcomes are not as well-specified.

[24] Still, there is extensive evidence that predictable variation in labor-leisure preferences can affect the performance of organizations with salient economic incentives. For example, it is frequently documented that medical outcomes are worse for hospital admissions on nights and weekends (e.g., Bell et al. 2001; Bendavid et al. 2007; Snowden et al. 2017; Bhanji et al. 2017).

4.1.3 Allocation of scarce processing resources

Rational investors should allocate scarce processing capacity to disclosures for which processing is expected to maximize their risk-adjusted profits (Peng 2005; Veldkamp 2011) or, largely equivalently, to disclosures with the lowest opportunity costs. Unskilled or irrational investors may allocate scarce capacity in biased or random ways. A challenge in studying resource allocation is that it is difficult to estimate the costs and benefits of allocation decisions, so it is difficult to assess whether allocation decisions are rational. For example, Frederickson & Zolotoy (2016) find that contemporaneous EAs have more negative effects on price responsiveness when the competing firms are more visible, as proxied by size, media coverage, and analyst coverage. While Frederickson & Zolotoy note that prioritizing firms based on visibility seems irrelevant and unsophisticated, this prioritization could be rational if the expected return is higher or marginal processing costs are lower.

Net benefits are easier to identify when examining market participants with more observable objectives and activities. Analysts rationally prioritize firms that are more important to their brokerages and firms with disclosures that are cheaper to process, and analysts who do so experience better career outcomes (Driskill et al. 2019; Harford et al. 2019). Corwin & Coughenour (2008) and Chakrabarty & Moulton (2012) find that market specialists temporally allocate resources to the most active firms within their portfolios, at the expense of reduced liquidity for other firms. Several papers find that data providers such as Compustat and IBES prioritize processing information about firms that are of greatest interest to subscribers (D'Souza et al. 2010; Akbas et al. 2018; Schaub 2018). Thus, there is some evidence that sophisticated market participants allocate scarce processing resources in a rational manner.

Deciding how to allocate processing capacity across disclosures is itself costly. Fischer &

Heinle (2018) develop a rational inattention model in which investors use low-cost data on stock returns and earnings surprises as screening devices, and only process disclosures for events that exceed screening thresholds. Koester et al. (2016) find empirical evidence of such behavior in that firms with extreme positive earnings surprises attract greater visibility, institutional ownership, and trading volume for up to three years. Similarly, Brown et al. (2009) find that firms that beat the earnings consensus have lower future information asymmetry, possibly consistent with investors using positive earnings surprise (or the related media coverage) as a screening mechanism.

4.1.4 Conclusions and directions

The literature provides compelling evidence that all types of investors and market participants – from individuals to institutions to data providers – are affected by processing costs and capacity constraints, and process disclosure less thoroughly when opportunity costs are high. While the capacity constraints affecting individuals are obvious, we have little understanding of the frictions that prevent institutions from creating enough capacity to process all disclosures for which trading gains exceed the direct costs. One explanation is that disclosures (and news more broadly) are lumpy, and maintaining capacity to process peak-load capacity is unprofitable. This is an area for future research.

Another avenue for research is to better understand the specific mechanism causing delayed price responses. Many empirical papers so far attribute delayed price responses to behavioral theory, but the predictability and pervasiveness of some results such as those for busy EA days indicates that more rational economic frictions are potentially at play. As discussed in Section 2, classic rational models and rational inattention models can produce many of the same results as behavioral models. Empirical researchers can do more to test existing and new theory, and devise tests to differentiate between competing theories.

Third, we know little about how time-varying industry or macroeconomic factors affect disclosure processing decisions. Prior research finds that firms' disclosures elicit smaller or larger market reactions depending on macroeconomic conditions (e.g., Lang 1991; Johnson 1999), and attributes these findings to fully-informed investors responding to temporal variation in earnings properties (e.g., persistence). An additional explanation is that costs and benefits of disclosure processing vary with economic conditions, so variation in market reactions is due to variation in investors' information choices. As an early example, Andrei et al. (2019) analytically show that the benefits of disclosure processing increase during periods of economic uncertainty (or, equivalently, that the opportunity costs are lower), so investors choose to process more information. They find empirical evidence of greater processing in the form of higher EDGAR downloads, and find some evidence of improved price responsiveness. Nagar et al. (2019) use different theory to motivate a similar empirical prediction, but do not find evidence of greater EA price responsiveness when economic uncertainty is higher.

Other promising areas for future research include how and why investors allocate constrained resources, the effects of new technologies on capacity constraints, managers' considerations of capacity constraints in strategic disclosure decisions (Section 6), and the potential effects of capacity constraints on governance and monitoring (Section 6). Broadly, intra-investor variation in disclosure processing is a nascent area of research with many growth opportunities.

4.2 Inter-investor variation in processing costs

Section 4.1 examines intra-investor variation in processing costs and finds that many types of small and large investors occasionally under-process disclosures. This section focuses on persistent differences between how different types of investors process disclosures.

There are two main sources of inter-investor variation in processing costs. The first is economies of scale, such that large investors can spread processing costs over more investment dollars (i.e., reduce average processing cost per investment dollar), or can capitalize on increasing returns to processing effort (e.g., Cready 1988; Lev 1988; Veldkamp 2011). Second, differences in sophistication can affect marginal processing costs (e.g., Lee 1992; Bushman et al. 1996). Investor size and sophistication are difficult to distinguish empirically, so most studies assume they act in concert. We use the term "small investors" to refer to retail and individual investors, and "large investors" to refer to large, institutional, and professional investors.[25]

One motivation for researching inter-investor variation in processing costs is to understand the extent to which such variation affects market outcomes. Given that most disclosure pricing models require a group of uninformed or partially-informed investors, empirical studies investigate: 1) whether processing costs cause systematic differences in informedness between investor groups, and 2) whether and how their trades affect market outcomes. We organize our discussion below around these two objectives: Section 4.2.1 discusses studies of disclosure usage and trading, and Section 4.2.2. discusses studies of market effects.

4.2.1 Inter-investor variation in processing costs: disclosure usage and trading volume

An empirical challenge in researching inter-investor behaviors is identifying the trading activities of types of investors. Some papers examine trading or portfolio data in which the trader type and buys versus sells are known (e.g., retail brokerage account data). These data have high internal validity but are scarce and have potentially low external validity. Many other papers use anonymous trade-level data (e.g., TAQ), and assume that large/small trades are done by large/small investors and that buys versus sells can be inferred using a tick test (Lee & Ready

[25] Algorithmic and high-frequency traders that do not use accounting information are discussed in Section 4.4.

1991). Advantages of a TAQ-based approach are that researchers can examine large samples and trades by small and large investors in the same data. A disadvantage is that classifying investor types based on trade size is noisy and can lead to erroneous inferences. Beginning in the late-1990s and increasing in the mid-2000s, microstructure and technology changes rendered traditional TAQ-based methods of identifying trader size and direction unreliable, due both to larger investors breaking up trades into small batches and to errors in the tick test (Campbell et al. 2009; Easley et al. 2012; Cready et al. 2014).

4.2.1.1 Small investors

An early finding from TAQ-based studies is that large investors trade quickly after EAs while smaller traders are slower (Cready 1988; Lee 1992). These findings are consistent with economies of scale or lower marginal costs allowing large investors to process disclosures quickly. Small investors take longer or wait for processing through intermediaries. In modern markets, trading occurs within milliseconds of disclosure filings, at speeds requiring technology far beyond the reach of most small traders (Stiglitz 2014).

Several papers find that small investors actively trade around EAs but appear to disregard the contents of the earnings report itself, consistent with the behavior of noise traders. Lee (1992) finds that large traders predictably buy (sell) on positive (negative) analyst-based earnings surprises but that small traders tend to buy regardless of the earnings news. Using brokerage account data, Hirshleifer et al. (2008) and Engelberg & Parsons (2011) find that small investors buy and sell in equal amounts to good and bad earnings news. Blankespoor et al. (2019) use a quasi-experimental approach and market data, and find that many small investors disregard analyst-based earnings surprises even when provided with the information, choosing instead to trade on technical trends. A broader literature in finance finds that small investors systematically lose money relative to the market (Barber & Odean 2013), but most studies do not examine disclosure processing as an explanation for underperformance.[26] Together, these results indicate that many small investors find disclosure processing to be too costly and, instead, underperform by investing in ways that resemble noise trading. In particular, disregarding accounting information even when readily available indicates that integration costs are a major friction.

Other studies find that small investors use earnings information when trading around EAs, but do so in a more simplistic manner than large investors. Using trade data similar to TAQ, Bhattacharya (2001) find that small traders respond to seasonal random walk earnings surprises while large traders respond primarily to analyst-based surprises. Battalio & Mendenhall (2005) find that small investors respond even to the predictable component of random walk surprises, and trade against analyst-based surprises that contradict random walk surprises (also see Campbell et al. 2009; Ayers et al. 2011). Bhattacharya et al. (2007) find that only small traders respond to managers' pro forma earnings. Battalio et al. (2012) find that small and medium-sized traders disregard accruals versus cash flow information, but the largest traders do take accruals into account. Miller (2010) finds that 10Q/K complexity deters small traders more than large traders, and that complexity drives greater heterogeneity in small traders' interpretations of the disclosure. Papers examining investor-level trading data or portfolio data generally find similar results: small investors actively trade around disclosures but process disclosures more simplistically than large investors (e.g., Welker & Sparks 2001; Vieru et al. 2006; Lawrence 2013). These findings indicate that small investors are aware of and have acquired at least some information from the earnings report, again suggesting that integration costs are a primary friction to disclosure processing. One exception is Kaniel et al. (2012), who find small investors'

[26] We discuss large investors below in Section 4.2.2.2, many of which also tend to underperform the market.

trading against earnings news is partially due to unwinding privately-informed trades made before the EA.

New data are permitting another wave of research on how small and large investors process disclosures. Ben-Rephael et al. (2017, 2019) analyze Bloomberg searches, Google searches, and media articles to examine differences in how professional and individual investors research EAs and 8K filings, and find that small investors are slower to research information events than large investors. Israeli et al. (2019) also compare Google and Bloomberg activity, and find that individual investors pay less attention to EAs when major news events take place, but there is no effect on professional investors. Liu et al. (2019) find similar results when EAs coincide with macroeconomic news. A working paper by Boehmer et al. (2019) develops a new TAQ-based method for identifying individual investors' trades, which may be useful for future research.

In sum, many studies find that disclosure processing costs, and especially integration costs, impair small investors' use of disclosure information. Difficulties in observing investor portfolios mean that few studies can quantify the losses these investors incur, but their trades appear to underperform as compared to the observed trades of professional investors and to hypothetical trades that perfectly incorporate accounting information.

While high processing costs are one explanation for why small investors under-use accounting information (i.e., relative to the full amount of information available in the disclosure), they do not explain why small investors who underperform the market continue to trade in single-name stocks. The recent increase in passive investing indicates that investors are adopting low-cost, diversified strategies (see Section 4.4), but research finds that high costs of processing fund disclosures still prevent small investors from choosing the lowest-fee versions of identical index funds (Carlin 2009; deHaan et al. 2019b). One explanation is that the same lack of sophistication that prevents small investors from processing disclosures also prevents them from understanding their underperformance (Fama 2008). Another explanation is that small investors recognize their underperformance but invest for entertainment. Barber & Odean (2013) discuss how nonstandard utility functions (e.g., risk-seeking) and psychological biases (e.g., over-confidence) can also prevent small investors from using disclosures or investing in index funds.

4.2.1.2 Large investors

Large investors such as mutual funds and pensions generally appear to use disclosure information in a more sophisticated manner than small investors (e.g., Campbell et al. 2009; Battalio et al. 2012; Lee & Zhu 2019), but they often still fail to fully exploit value-relevant disclosure information. For example, Cready et al. (2014) find that mutual funds and pensions trade in the opposite direction of earnings surprises, despite the presence of PEAD in their sample. Edelen et al. (2016) find that institutions fail to exploit accounting-based sources of return predictability and under-perform over long horizons (also see Lewellen 2011; Burch & Swaminathan 2002). Bhattacharya et al. (2018b) find that small institutions trade more, faster, and more intelligently after the eXtensible Business Reporting Language (XBRL) introduction, indicating that they under-use disclosures in the pre-XBRL period.[27]

A different approach to examine disclosure processing by professional investors is to study the behaviors of sell-side analysts, under the assumptions that: i) the decision-making of analysts resembles professional investors; and/or ii) analysts directly influence the trades of professional investors. The strength of this approach is the ability to observe forecasts and recommendations for large samples. Drawbacks are that accurate forecasting is not analysts' highest priority

[27] Finding that large investors under-use information in accounting reports is consistent with findings that institutional investors such as mutual funds typically underperform the market (Fama & French 2010; French 2008).

(Groysberg et al. 2011), they may have incentives to intentionally under-use disclosures or bias their forecasts (e.g., Das et al. 1998; Matsumoto 2002; Jackson 2005; Ke & Yu 2006), and they may not represent the most sophisticated opinions. Still, studies find that analysts fail to fully incorporate disclosures into their forecasts (Abarbanell & Bernard 1992; Bradshaw et al. 2001).

Given evidence that some groups of large investors systematically and persistently under-use disclosure information even relative to other groups of large investors, a natural question is which frictions prevent them from doing so. One likely explanation is that some large investors rationally under-use disclosures because processing costs exceed expected benefits. For example, many high-frequency traders solely arbitrage inter-market price discrepancies without performing fundamental analysis, likely because the cost of also incorporating an accounting-based strategy exceeds the expected trading gains (Section 4.4). Or, the finding that small institutions make better use of disclosures after XBRL introduction indicates that small institutions aim to maximize trading profits but rationally neglect some disclosure information in the pre-XBRL period due to high processing costs (Bhattacharya et al 2018b). Still, there is little direct evidence in support of a processing cost explanation for why large investors persistently under-use accounting information.

Alternative or complementary explanations for why large investors persistently under-use disclosures are because of agency conflicts or that they are not incentivized to maximize long-term profits. For example, Edelen et al. (2016) find that fund managers buy over-valued stocks because horizon conflicts cause them to maximize short-term momentum profits rather than follow long-term fundamental strategies. A final explanation is that large investors suffer from persistent behavioral biases such as over-confidence or non-standard risk preferences (French 2008; Weisbrod 2019), although this is perhaps a less significant factor for large investors than for individuals.

4.2.1.3 Conclusions and directions

The literature finds that some small investors actively trade around disclosures in ways that appear to disregard information in the disclosure itself, while other small investors do use disclosures but in a less sophisticated manner than large investors. This latter result is important because it indicates that the trades of small investors are not random noise as conceptualized in many disclosure pricing models. Rather, small investors attempt to process disclosures but do so less effectively than large investors. Thus, small investors often behave like the noise traders envisioned in Black (1986): they think they are trading on information but their trades are actually orthogonal or even contrary to disclosure signals.

The literature also finds that large investors fail to fully exploit disclosure information. Processing costs are a likely contributing factor, in conjunction with agency frictions and non-standard incentives. This result indicates that large investors do not perfectly update like the sophisticated traders in many disclosure models. Rather, large investors occasionally act in ways that resemble noise trading.

Together, findings that both small and large investors under-use financial disclosures indicate that binary classifications of sophisticated versus noise traders are overly simplistic. There is instead a spectrum of sophistication. Further, while small and large investors have average differences in processing costs and trading decision quality, their distributions appear to overlap.

We see several avenues for future research. First, most of the literature uses older data, and it is unclear how modern technologies affect inter-investor differences in processing costs. Small investors now have cheaper data and resources that may reduce processing costs, but easier market access and decreased use of financial advisors may have driven up the number of small investors making poor decisions (Aroomoogan 2016).[28] Thus, it is unclear whether the trading of small investors makes better or worse use of disclosures in recent years. Also, improvements in professional investors' disclosure processing and trading speeds plausibly surpass improvements for individuals, widening the gap between groups of investors (see Section 4.4). It would be useful to reexamine the extent to which prior findings hold or differ in modern markets.

A second question is the extent to which trades that under-use disclosed information are rational outcomes of weighing processing costs and risk-adjusted profits. Alternative explanations are that under-using disclosures is driven by behavioral biases, non-standard incentives (e.g., investing for entertainment), or simply lack of sophistication. For professional investors, another alternative explanation is that agency conflicts may prevent them from maximizing profits for their clients.[29] Relatedly, we know very little about what information investors use in place of financial disclosures. A better understanding of information used in investing decisions would help us further understand why investors do not use disclosures, and provide broader insights for the types of information flowing into security prices.

A final avenue for research is to continue to inform discussions by private organizations and regulators of how to exploit or mitigate inter-investor differences in disclosure processing costs. Research can inform large investors about how to exploit mispricing caused by processing costs, and can help regulators design policies to mitigate processing inequalities that deter stock market participation and impede economic growth (Lev 1988). In doing so, we encourage studies to go beyond simply documenting poor investing decisions by classes of investors, and instead aim to

[28] In 2015, 47% of individual investors were self-directed, including 30% of high-net-wealth individuals with assets exceeding $5 million. https://www.forbes.com/sites/kumesharoomoogan/2016/06/02/more-investors-striking-out-on-their-own-what-does-all-this-self-directed-trading-mean/

[29] Another possibility is that large investors do fully use disclosure information but academic studies are mis-specified. As always, future research with stronger research designs would help reduce this concern.

identify the specific frictions that impair disclosure processing. Without knowing the friction, it is hard to know what strategies and policies may be effective. For example, several SEC regulations aim to aid small investors by reducing disclosure acquisition costs, but recent research finds that high integration costs or behavioral biases are significant barriers to small investors' disclosure processing (indicating that policies targeting acquisition costs alone are unlikely to help). Research can also help inform regulators about potential alternative assumptions, objectives, and scope of regulation, such as targeting only investors with a minimum reasonable processing ability (as does the FASB), or directing small investors towards low-cost, passive investments.

4.2.2 Inter-investor variation in effects of processing costs: market effects other than volume

Uninformed or partially-informed investors play an important role in many information pricing models. Given evidence that disclosure processing costs systematically differ between investor groups, it is plausible that inter-investor differences in processing costs affect liquidity, volatility, price responsiveness, and price informativeness. Richardson et al. (2010) survey papers in this area, so our discussion is brief. We organize our discussion around two common empirical approaches.

4.2.2.1 Cross-sectional tests based on shareholder composition

Studies in this category examine imperfect price responses to disclosures, and then perform cross-sectional tests to see whether the mispricing is strongest for firms with greater concentrations of small investors. An assumption is that small investors have higher processing costs and therefore make less sophisticated trades. For example, Bartov et al. (2000) and Collins et al. (2003) find that PEAD and accruals mispricing, respectively, are weaker for firms with more institutional ownership. While these results are consistent with disclosure mispricing being driven by small investors, Richardson et al. (2010) warn that causal attributions are tenuous for several reasons, including that shareholder composition is difficult to measure and endogenously associated with other factors that can also affect mispricing, such as transaction costs.

In addition to Richardson et al.'s (2010) concerns, it is not clear whether having more or fewer sophisticated investors should cause more or less efficient price responsiveness and informativeness. The paradox is that noise trading simultaneously generates mispricing, and profit opportunities for sophisticated investors to exploit mispricing (Black 1986). The composition of sophisticated and unsophisticated investors is endogenously determined, and models do not have uniform predictions for market outcomes.

In sum, researchers should exercise caution in using cross-sectional tests based on firms' shareholder composition to draw strong causal inferences about the effects of inter-investor differences in processing costs.

4.2.2.2 Analysis of investor group activity

Other papers examine the trading and disclosure processing of investor groups, and attempt to link unexpected temporal variation in groups' activities to market outcomes. The assumption is that if poor disclosure processing by a particular group of investors impedes price responsiveness, then we should observe more efficient responses when those investors are less active. Few studies examine market outcomes other than price responsiveness.

An example is Battalio & Mendenhall (2005), who investigate whether under-informed trading by small investors drives PEAD. They find that small investors buy and sell based on the predictable portion of random walk earnings surprises, and that small investors actively trade against analyst-based surprises that conflict with the random walk surprises. This latter result is important because most models of delayed price responses require that the noise trading is contrary to disclosure signals; i.e., purely random noise trading can affect liquidity and volatility, but usually not price responsiveness. Battalio & Mendenhall then find weak, mixed evidence that PEAD is greater when small investors are more active, controlling for normal PEAD associated with the shareholder base and information environment.

Studies following the same general approach also find mixed results, and the literature collectively fails to support the hypothesis that small investors cause delayed disclosure price responses (e.g., Hirshleifer et al. 2008; Shantikumar 2012; Ayers et al. 2011; Battalio et al. 2012; Kaniel et al. 2012; Blankespoor et al. 2018; Drake et al. 2012; Ben-Rephael et al. 2017). This lack of support conflicts with evidence that systematic trading of individual investors can push prices away from fundamentals (e.g., Kumar & Lee 2006; Barber et al. 2009). A potential explanation is that the inflow of sophisticated trading and increase in liquidity around disclosures subsume the activities of individual investors. Or, measurement error in identifying small investors could be at fault.

Studies examining larger and professional investors also find mixed results for whether large trader activity affects price responsiveness. For example, Cready et al. (2014) use trading data from Ancerno and find that institutions often trade contrary to earnings surprises but find little evidence that their trades drive PEAD, but Lee & Zhu (2019) find that institutions trade with earnings news, de-bias management forecasts, and reduce post-forecast drift (also see Ke & Ramalingegowda 2005). Battalio et al. (2012) find that large traders do not mitigate accruals mispricing on average, but do have an effect when especially active. Ben-Rephael et al. (2017) find that heightened Bloomberg search by institutional investors is associated with reduced PEAD but find mixed evidence about whether ERCs are larger.

Inferences from these studies are subject to several concerns. First, the studies rely on noisy proxies for investor group activity, or small samples when using trading data. Second, within-group variations in disclosure processing and trading activity are correlated across groups, making it difficult to conclude that any one group is responsible for market effects (e.g., see Section 3). Third, even if uninformed or partially-informed trading by a particular group of investors does appear to affect market outcomes, it is hard to demonstrate that the trades are uninformed or partially-informed due to processing costs. As discussed in Section 4.2.1, neglect of disclosure information could also be due to nonstandard incentives or behavioral biases.

A few studies attempt to address these second and third concerns by examining changes in processing cost that are specific to a particular group of traders. Blankespoor et al. (2018, 2019) examine the Associated Press' introduction of algorithmic earnings news articles, which reduce individual investors' processing costs but are unlikely to benefit large investors. They find that the articles are associated with increases in uninformed retail trading and market liquidity, but find no evidence of improved price responsiveness. Together, Bhattacharya et al. (2018b) and Blankespoor et al. (2014a) suggest that the initial implementation of XBRL reduces processing costs primarily for small institutions, presumably because large institutions already had private technologies and individual investors lacked the expertise to use XBRL initially. While XBRL puts small institutions on a more level playing field with large institutions, liquidity decreases, consistent with increased information asymmetry between individuals and institutions. Amiram et al. (2016) argue that analyst reports reduce small investors' processing costs more than large investors', and find that analyst reports at EAs are associated with greater liquidity. Similarly, Gomez et al. (2018) argue that crowdsourced financial analyses on Seeking Alpha primarily reduce small investors' processing costs, and find that firms with more pre-EA analyses have greater liquidity around the EA.

4.2.2.3 Conclusions and directions

Research is generally unable to provide compelling evidence that systematic uninformed or partially-informed trading by groups of investors causes delayed price responses to disclosure. Few studies examine how inter-investor differences in processing costs affect liquidity, volatility, and price informativeness, but evidence so far is generally consistent with liquidity improving as inter-investor disparities decline. In addition to the empirical challenges discussed above, another likely confound is that disclosure processing within investor groups is not temporally consistent: small investors sometimes make smart trades, and large investors often make unsophisticated trades. Intra-investor variation in processing not only confounds tests, but also indicates that it is overly-simplistic to argue that one particular group drives market outcomes. Finally, given that a goal of disclosure is to reduce information asymmetry between investors and encourage market participation, it is surprising that we have so little evidence on how inter-investor differences in processing costs affect market participation.

4.3 Processing cost variation across disclosures and firms

This section discusses studies on differences in processing costs due to disclosure characteristics, abstracting from investor characteristics. An econometric challenge in this literature is isolating variation in processing costs caused by differences in the underlying economic transaction versus differences in its disclosure. Also, a selection concern is that managers strategically consider investors' processing costs when making disclosure choices (see Section 6). We further comment on these issues where especially relevant or unique below. Despite these concerns, the literature has made promising inroads. Future research can contribute by revisiting hypotheses with more precise theory and stronger research designs.

4.3.1 Inherent complexity and properties of the underlying event/firm

Complex transactions very likely have higher integration costs that affect market outcomes, but direct evidence of this prediction is scarce. Sources of complexity could include the extent of specialized knowledge required, the quantity and detail of information involved, or how idiosyncratic a given transaction is.

Consistent with analytical predictions, prima facie evidence for complex transactions affecting integration costs is that simple transactions like dividend changes generate fast and precise stock price reactions (Boehme & Sorescu 2002; Liu et al. 2008), while complex, idiosyncratic transactions like acquisitions can have less efficient price responses (e.g., Agrawal et al. 1992). You & Zhang (2009) find that 10-K filings with more complex language elicit greater drift than less complex filings, and Huang et al. (2018a) find that investors rely more heavily on analyst interpretations when firms' conference calls have more uncertain language. These findings are consistent with complex and multi-faceted transactions having higher integration costs, but the linguistic-based measures likely also capture the effects of financial reporting standards and manager discretion. Hoitash & Hoitash (2018) introduce a measure of complexity using the number of XBRL-tagged items in a 10-K, but it too can capture multiple forms of complexity: transaction, reporting, or firm. Plumlee (2003) provides more direct evidence on transaction complexity affecting disclosure processing: the quality of analysts' tax rate forecasts declines when contextual tax law information is more complex. Francis et al. (2019) find similar evidence of lower analyst accuracy when firms have more complex tax planning, and Chen et al. (2018a) find that tax-motivated income shifting increases information asymmetry between insiders and investors.

Moving to the firm level, Cohen & Lou (2012) find evidence that firms' organizational structures affect the cost of processing information. They find that share prices of multi-segment firms are slower to incorporate industry-level information than are pseudo-conglomerates constructed from single-segment firms' prices. Similar results plausibly exist for the processing of firms' disclosures; e.g., a conglomerate firm's filing may be costlier to process than a similar filing by a single-segment firm.[30] Consistent with this prediction, Frankel et al. (2006) find that analyst reports are less informative for firms with multiple segments. Huang (2015) finds that earnings announcement price responses are slower when US firms have a larger fraction of foreign sales, consistent with higher integration costs of understanding foreign operations.

4.3.2 Disclosure construction and presentation

Even for two identical transactions, processing costs can differ depending on how the transactions' disclosures are constructed and presented. As a thought exercise, consider two research studies with identical hypotheses and analyses. One's writing is clear and succinct, while the other is obtuse and long-winded. One presents results with intuitive figures and clean tables, and the other with output pasted from statistical software. One is organized into logical subsections, and the other is a single block of text. The former article is easier to understand, will be more widely read, and will likely have a bigger impact on the field. Just as the construction and presentation of an article affect academics' processing costs, the construction and presentation of firms' disclosures likely affect investors' processing costs. This section highlights major sources of variation in the construction and presentation of disclosures.

4.3.2.1 Effects of financial reporting standards – comparability versus complexity

A primary objective of financial reporting standards is to reduce processing costs by improving disclosure comparability across firms. Studies find that across-firm disclosure

[30] Firm complexity arises from factors such as multiple business models, geographic segments, special purpose entities, legal and tax systems, or other organizational differences that create the need for more detailed information or nuanced understanding of complicated relationships (e.g., Bushman et al. 2004; Doyle et al. 2007).

comparability reduces processing costs and leads to improved liquidity, greater investor engagement, and better understanding of the firm. DeFranco et al. (2011) find that firms with more comparable financial reports, defined using similarity of returns-earnings relations, have smaller analyst forecast errors and dispersion. Bradshaw et al. (2009) find similar results when studying idiosyncratic accounting methods. Several studies find that increased comparability due to IFRS adoption leads to greater foreign investment, which they attribute to lower disclosure processing costs (DeFond et al. 2011; Yu & Wahid 2014). Firms whose annual report text is more comparable to other firms' text have greater liquidity, institutional ownership, analyst coverage, and analyst forecast accuracy (Lang & Stice-Lawrence 2015; Peterson et al. 2015).

In contrast, other studies find that complex financial reporting standards can impair investors' ability to understand the economic substance of a transaction or firm. 10-K reports are longer and less readable over time, largely due to new financial reporting regulations (Dyer et al. 2017; Guay et al. 2016). Peterson (2012) finds that complexity in firms' revenue recognition methods undermines the quality of analysts' forecasts, and Filzen & Peterson (2015) find that analysts are more likely to rely on management forecasts when the firm has a longer accounting policies footnote. Analyst forecast quality declines when firms start using derivatives, especially when the financial reporting standards are ambiguous (Chang et al. 2016).

A challenge for all research on the effects of financial reporting standards on disclosure processing is controlling for inherent characteristics of the transaction and firm, and for managers' discretionary reporting choices that are not mandated by the standard.[31] To better control for discretion, Chychyla et al. (2019) develop a measure of firm-specific financial

[31] While financial reporting complexity is likely correlated with inherent transaction complexity, this does not have to be the case. When differences between inherent and financial reporting complexity occur, they present opportunities for research to isolate the two kinds of complexity.

reporting complexity based on the length of the reporting standards used rather than firm disclosure. Future research can do more to empirically isolate the effects of financial reporting standards on comparability, complexity, and associated market outcomes. Such research would further our understanding of disclosure processing costs, and potentially inform policy-makers concerned about financial reporting complexity (e.g., SEC 2008; FASB 2014).

4.3.2.2 Disclosure location and formatting

Disclosure location: Recognition versus disclosure

One formatting difference is whether an item is recognized on the financial statements (e.g., affecting net income or assets) or provided as additional disclosure. Early studies cite reliability differences as a potential explanation for why recognized transactions are priced more completely than similar but disclosed transactions (e.g., Davis-Friday et al. 1999). However, studies continue to find greater investor reliance on recognized information even when reliability differences are minimal (Davis-Friday et al. 2004; Ahmed et al. 2006).

Later studies propose that recognized information receives greater weight because it has lower processing costs than information contained in footnotes.[32] Bratten et al. (2013) find no difference in the pricing of recognized versus disclosed lease liabilities for which processing costs and reliability concerns are minimal, suggesting that either or both are frictions. Yu (2013) finds more complete pricing of off-balance-sheet pension liabilities when firms have more institutional ownership or analyst following, consistent with processing costs having a larger effect for less sophisticated investors and firms with weaker information environments. Muller et al. (2015) find complementary evidence using recognized versus disclosed investment property.

Michels (2017) mitigates concerns about recognition versus disclosure selection biases by

[32] A third non-exclusive alternative is that investors' cognitive biases cause them to focus more on recognized information. See evidence in Hopkins (1996) and Maines & McDaniel (2000), and discussion in Schipper (2007).

examining disclosures of natural disasters that occur during the period (and are therefore recognized) to disasters that occur just after period-end (so are disclosed in footnotes). This setting provides plausibly exogenous variation in accounting treatment, but still assumes that managers do not otherwise change their behaviors because of the timing and reporting of the disaster. Michels (2017) finds evidence of delayed price responsiveness to disclosed versus recognized disasters, suggesting processing costs play a role. Still, further efforts to isolate the causal effect of processing costs would contribute to the literature.

Disclosure formatting

Reporting rules permit considerable discretion over disclosure formatting, providing opportunities to research the effects of formatting on processing. However, it is especially challenging to control for differences in underlying transactions and managers' strategic disclosure choices when studying disclosure formats.[33] In addition, examining market outcomes requires knowledge (or assumptions) of the disclosure formatting actually seen by investors.

Four studies provide early archival evidence that disclosure formatting is associated with investor processing. Bartov & Mohanram (2014) examine a regulation change and find that the market immediately responds to a gain/loss only when it is presented above net income rather than below. One potential explanation is that investors focus more on gains/losses within net income because of lower processing costs; for example, EPS is widely disseminated by the media and, therefore, has low awareness and acquisition costs. Luo et al. (2018) also find evidence of differential processing depending on income statement formatting. Miao et al. (2016) find that accruals are priced more efficiently when firms provide a statement of cash flows in their EA, even though accruals can be estimated from the balance sheet and income statement

[33] Experimental research has made more progress on examining disclosure formatting while holding constant other cofounds (e.g., Hirst & Hopkins 1998, Maines & McDaniel 2000, Hodge et al. 2010, Bloomfield et al. 2015).

alone. This finding suggests that the statement of cash flows is easier for investors to process, but it is extremely challenging to control for firms' choice to provide the statement of cash flows and for incremental information in the cash flows. Huang et al. (2018b) find that EA press releases with more quantitative information in the headline have larger earnings price responses followed by reversals, and attribute these over-reactions to investors' overweighting the lower-cost quantitative information. Future research can continue to develop stronger research designs to examine the effects of disclosure formatting on processing.

Another avenue for future research is to examine whether processing costs help explain phenomena previously attributed to other mechanisms. For example, different market responses to losses classified as operating income versus special items could be due to investors using classification choices to evaluate loss persistence (e.g., McVay 2006; Riedl & Srinivasan 2010), or could be due to classification affecting processing costs.[34] Or, Schrand & Walther (2000) attribute investors' lack of adjustment for prior transitory losses to processing bias (p152), but the effect could be a rational outcome of disclosure processing costs.[35] Future research can also examine the effects of disclosure formatting on market outcomes other than price responsiveness, which is the focus of most existing research. Finally, the effects of figures, images, and other non-text formatting choices available in modern disclosure channels like social media is relatively unexplored in archival research.

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[34] The non-GAAP literature potentially provides evidence of disclosure formatting influencing investor response, assuming GAAP disclosure by itself is otherwise sufficient to infer non-GAAP estimates. Bhattacharya et al. (2007) find that less sophisticated investors are more likely to use non-GAAP estimates, suggesting that processing costs play a role in budget-constrained investors' information choices. Curtis et al. (2013) find that investors ignore transitory gains when firms exclude them from non-GAAP estimates, but respond and later reverse their reaction when the gains are included in non-GAAP estimates.

[35] In some settings, processing costs would likely not be a primary driver but could still play a role. For example, the greater investor response to conference call discussion sections over presentation sections is primarily due to differences in information content, but could also be due in part to lower costs of processing the spontaneous, interactive discussion (e.g., Matsumoto et al. 2011; Lee 2016).

<u>*4.3.2.3 Qualitative disclosure and linguistic properties*</u>

Qualitative disclosure

While much of the literature focuses on quantitative disclosure, most disclosures come in the form of qualitative (i.e., textual) descriptions. It is not obvious whether qualitative information has higher or lower processing costs than quantitative information. Liberti & Petersen (2018) argue that quantitative disclosures have lower processing costs because: (i) it is easier to outsource the collection of quantitative information from reports, which reduces acquisition costs; and (ii) it is easier to incorporate standardized quantitative information into a decision model, which reduces integration costs.[36] However, qualitative disclosure can also help investors interpret the information, lowering processing costs.

Studies comparing the processing costs of qualitative versus quantitative information struggle to control for differences in the amount of information provided, the underlying transactions, and other disclosure attributes such as summarization or tabulation that likely covary with qualitative versus quantitative portrayal. For example, there are multiple differences between a qualitative disclosure such as "this quarter we smashed all our forecasts" versus a list of forecasts and realizations: the qualitative versus quantitative nature, as well as the level of summarization and the amount of managerial interpretation. More broadly, quantitative formats tend to be more precise and qualitative formats allow more interpretation. Early studies find evidence of more efficient price responses when headlines include more quantities (Huang et al. 2018b) and more reliance on analyst interpretation when conference calls provide fewer quantitative data (Huang et al. 2018a), but these studies rely heavily on the assumption that information does not differ

[36] Liberti & Petersen (2018) place the quantitative nature of information under the broader umbrella of hard versus information. Characteristics of hard information including being quantitative, observable, verifiable, and easily collected. Soft information loses value when hardened into a quantitative format.

across qualitative and quantitative formats.

A second challenge is that, just as it is costly for investors to convert qualitative information into numbers for valuation models, it is difficult for researchers to measure qualitative information for regression models. New technologies are changing how both investors and researchers access qualitative disclosures, which permits research into previously inaccessible hypotheses as well as new hypotheses relevant to modern markets. Technologies to capture qualitative disclosure properties include word dictionaries (e.g., Henry 2008; Loughran & McDonald 2011; Larcker & Zakolyukina 2012; Brochet et al. 2015), computational linguistics (e.g., Engelberg 2008; Lee 2016), and machine learning classification algorithms (Li 2010b; Frankel et al. 2016, 2018; Li 2018). Much of the research thus far examines linguistic properties, which are the focus of the following subsections.

Linguistic tone

Tone is the intended meaning, sentiment, and/or bias of qualitative disclosure.[37] Linguistic tone could increase or decrease disclosure processing costs.

On the one hand, tone can be a low-cost source of value-relevant information. For example, the tone of EAs is positively associated with future performance and current returns (Davis et al. 2012). Further, optimistic forward-looking statements in MD&A's are associated with less accrual mispricing, suggesting that the manager's interpretation helps investors process disclosures (Li 2010b). Even if the same information in tone can be acquired through quantitative analysis of the disclosure, it is plausible that humans' innate ability to understand tone allows investors to acquire and integrate the information at a lower cost.

[37] We limit our review to studies on the effects of linguistic properties on disclosure processing costs. We refer readers to Li (2010a), Loughran & McDonald (2016), and Henry & Leone (2016) for broader discussions of linguistic analysis in accounting, including technical details on variable measurement.

On the other hand, if tone does not faithfully represent the economics, then de-biasing tone plausibly increases investors' integration costs. For example, abnormal tone in EA press releases negatively predicts future earnings and market returns, suggesting it takes time for investors to de-bias management tone in that setting (Huang et al. 2014). Or, managers from more individualistic cultures have more optimistic tone in their conference calls, but only analysts from similar cultures fully remove this cultural bias from their forecasts (Brochet et al. 2019).[38]

Linguistic Complexity or Readability

Linguistic complexity or readability is the ease of comprehending written text. Some readability proxies such as Fog and Bog scores focus on specific linguistic characteristics that impede comprehension, such as jargon, unnecessary details, and complex words (e.g., Li 2008; Bonsall et al. 2017). Other proxies focus on the overall cost of processing a predominantly qualitative disclosure, such as the number of words (Miller 2010) or file size (Loughran & McDonald 2014). Debate continues about the strengths and weaknesses of different readability proxies, with some confusion caused by differences in the construct researchers aim to capture (e.g., Loughran & McDonald 2016; Bonsall et al. 2017). Some researchers aim to capture narrow linguistic complexity while others intend to capture disclosure complexity more broadly, arising from any source.

Studies generally find that linguistic complexity is associated with slower investor processing, less profitable trading, reduced investor interest in the firm, and slower and less accurate analyst forecasts. Investors underreact to disclosure information when filings are less readable (You & Zhang 2009; Lee 2012). Small investors make fewer and less profitable trades on less readable filings (Miller 2010; Lawrence 2013). Drake et al. (2016b) find that investors

[38] Additional textual attributes such as textual uncertainty or time horizon might increase or decrease processing costs for similar reasons (Loughran & McDonald 2011; Brochet et al. 2015).

are more likely to continue accessing old EDGAR filings when they are longer, suggesting the disclosure processing costs are higher. Louis et al. (2008) predict that EAs are less complex than 10-Ks, and find greater accruals mispricing when accrual information is disclosed only in 10-Ks rather than in both 10-Ks and EAs. Lundholm et al. (2014) find that foreign firms with more readable disclosures have greater US institutional ownership, although it's difficult to know the direction of causality. Analysts spend more time writing reports when filings are less readable, and their forecasts are less accurate and more dispersed (Lehavy et al. 2011; Loughran & McDonald 2014). Findings for volatility are mixed: Brochet et al. (2016) find lower volume and volatility around conference calls that are complex because of foreign language differences (i.e., non-US firms with English language calls with more errors), but other studies find greater stock return volatility when reports are more linguistically complex (Bonsall et al. 2017; Loughran & McDonald 2014).

The fundamental econometric challenge of the literature is in separating discretionary linguistic complexity, and the market effects thereof, from complexity caused by the underlying transaction, firm, and reporting rules (Li 2008; Bloomfield 2008; Bushee et al. 2018). Studies employ a variety of variables and fixed effects to control for underlying complexities, and some findings diminish or disappear when controls are included (e.g., Bonsall et al. 2017). Many relations persist, though, suggesting that discretionary complexity contributes to processing costs. Bushee et al. (2018) includes the novel approach of using analysts' language in conference calls as a proxy for inherent firm complexity, and to isolate management's discretionary linguistic complexity from inherent linguistic complexity. They find that linguistic complexity not driven by inherent firm characteristics reduces liquidity. DeHaan et al. (2019b) isolate discretionary complexity by examining index funds that have largely identical inherent complexity. They find that funds charging higher fees have more complex disclosures, consistent with discretionary complexity preventing investors from understanding that they are buying an inferior investment (also see Carlin 2009).

Other Linguistic Properties

Many linguistic properties beyond tone and readability could affect processing costs. Language that is boilerplate or common across firms, redundant or repeated within a firm's filing, or unchanging for a firm over time could increase processing costs if it increases the difficulty of separating relevant from irrelevant information. However, boilerplate language could also provide a standardized structure that aids in finding relevant information, and repeated information in sections of the 10-K report could be useful to investors performing targeted examination of just one section. Similarly, using consistent language over time could make it easier to identify new information in period-over-period comparisons. Thus, the effects of these linguistic properties on processing costs are unclear.

In addition, new technologies alter the way investors process disclosures and could fundamentally change predictions for how linguistic properties affect processing costs, investment decisions, and market outcomes. For example, the added length created by disclosure redundancy and boilerplate language is unlikely to materially increase costs for computer analysis of qualitative disclosure. Or, redundant, consistent, and boilerplate language is helpful for investors using technology to search disclosures and highlight changes from prior periods. However, computer processing introduces new sources of variation in processing costs, such as the quality of HTML formatting or consistency of table of contents headings (Allee et al. 2018).

Despite unclear predictions, existing studies generally find negative implications of boilerplate/redundancy for market outcomes, and positive implications of disclosure consistency.

Lang & Stice-Lawrence (2015) find lower liquidity, institutional ownership, and analyst coverage for firms with more boilerplate disclosure common across firms. Cazier & Pfeiffer (2017) find some evidence of slower price responses to 10-K filings that have repeated phrases within the document. Peterson et al. (2015) find improved liquidity for firms with greater linguistic consistency over time, and Brown & Tucker (2011) find evidence that investors use changes in MD&A language to signal new information.

Exploring linguistic properties beyond tone and readability is important to understanding processing costs, but the literature is nascent and empirically challenging. Work in this area requires carefully defined constructs, proxies, and predictions that incorporate competing influences. Further, new technologies are potentially altering the effects of these linguistic properties and processing, so it is worth investigating whether prior findings reproduce in more recent data.

4.3.3 Dissemination channels and timing

Reg FD requires firms to provide material financial information to all market participants, but managers still have discretion over how and when disclosures are disseminated. This section discusses the effects of dissemination choices on processing costs and market outcomes, and Section 6 discusses strategic dissemination.

Disclosures that are disseminated via multiple channels appear to reach more investors and receive greater processing, indicating that broad dissemination reduces awareness and acquisition costs. Compelling evidence is found in the media literature discussed in Section 5. In brief, several studies find that the media's republishing of information from firm disclosures improves liquidity and price-responsiveness, even when eliminating the effects of media selection and interpretation. Regarding firms' dissemination choices, disclosures disseminated via Twitter have broader awareness and improved liquidity, especially for less visible firms (Blankespoor et al. 2014b; Jung et al. 2018). Lee et al. (2015) find that firms facing a product recall can use social media in addition to standard channels to alert a broader set of consumers more quickly, potentially reducing future damage and negative publicity.

The timing of dissemination can also affect awareness and acquisition costs. Disclosures that coincide with competing information events tend to have slower processing and pricing (Section 4.1). Several studies examine the effects of earnings notifications, which alert investors to the timing of an upcoming EA but provide no explicit information on the earnings news. When firms notify investors of upcoming EAs with more lead-time, the EA has more EDGAR downloads, faster analyst processing, more participants on the earnings call, greater news coverage, more Google searches, and higher abnormal trading volume (deHaan et al. 2015; Boulland & Dessaint 2017). These results imply that notifications reduce awareness and acquisition costs by allowing investors to ex ante allocate resources to process the EA. Chapman (2018) finds increased abnormal volume and EDGAR search around the earnings notifications, suggesting that notifications reduce investors' awareness costs of the firm and its forthcoming EA. However, Chapman (2018) notes that the additional findings of positive returns around notifications followed by lower EA premiums could be consistent with behavioral explanations.

Finally, dissemination bundling potentially increases or decreases processing costs. On the one hand, combining multiple disclosures could create processing efficiencies. On the other hand, if marginal processing costs increase with quantity, bundled disclosures may be costlier to process than separate disclosures. For example, bundling requires investors to select which to process first, which is a costly decision in itself. Chapman et al. (2019b) find that when disclosures occur more evenly across days, the firm has greater liquidity, lower stock volatility, and more accurate analyst forecasts, consistent with less concentrated dissemination decreasing processing costs. Similarly, Atiase et al. (2005) find greater price responsiveness when management guidance is stand-alone rather than bundled with earnings. In contrast, the findings in Twedt (2016) indicate that bundled disclosures have lower awareness and acquisition costs. The conflicting predictions and difficulty identifying investor attention to specific items within a bundle make this a challenging but fruitful area for future research.

4.3.4 Peer firm disclosure transfers

Several papers find delays in price responses to peer firms' disclosures, indicating that across-firm disclosure transfers have high processing costs (e.g., Ramnath 2002; Thomas & Zhang 2008; Cohen & Frazzini 2008). Wang (2014) finds faster peer firm price responses when both firms use IFRS, consistent with comparable reporting standards reducing processing costs. Hilary & Shen (2013) find that analysts with more experience covering a firm produce more accurate and timely forecasts for other firms in the industry, suggesting that experience mitigates processing costs of peer disclosures. Madsen (2017) finds that information transfers between customers and suppliers are more promptly incorporated into price just before the suppliers' EA, consistent with investors allocating limited resources to peer firm disclosure processing in anticipation of the EA.

4.3.5 Conclusion and Directions

The literature provides ample evidence of disclosure characteristics affecting processing costs and capital market outcomes. However, because multiple disclosure characteristics can change at the same time, isolating the effect of one characteristic is a significant challenge. In addition, even if a disclosure characteristic can be isolated, it is difficult to control for management's choice function. Papers using improved research designs to reexamine almost any of the findings above would contribute to the literature, especially those that are able to disentangle specific sources of variation in processing costs.

The amount of observable variation in disclosure creates many research opportunities, but the biggest contributions are to be made by studies that identify common underlying constructs across disclosure characteristics rather than focusing on minor adjustments. As discussed above, there is also room to reexamine prior findings to explicitly consider processing costs as a potential driver. For example, are increased investor responses to reiterated information driven by potentially irrational behavior as discussed in Schrand & Walther (2000), or are processing costs a factor? In addition, new technologies bring opportunities to test classic research questions with new data, and test new predictions relevant to modern markets.

Finally, much of the literature focuses on written disclosures or transcripts of spoken disclosures. A few studies move beyond verbal characteristics to examine nonverbal characteristics during manager presentations, such as vocal affect, facial features, and body movement (e.g., Mayew & Venkatachalam 2012; Blankespoor et al. 2017). These studies find information in nonverbal cues, and leave open questions about investors' costs of nonverbal analysis and whether nonverbal analysis affects the cost of processing verbal disclosure data.

4.4 Market technologies

This section discusses reporting and trading technologies that affect investors' disclosure processing costs and decisions. Technologies affecting intermediaries are discussed in Section 5.

4.4.1. Financial reporting technologies

Technological advances in how firms construct and disseminate disclosures can significantly affect investors' processing costs, even holding constant the information being disclosed. Mandatory (i.e., regulator-required) reporting technologies have been the focus of academic research, likely because the implementation dates and functionalities of private technologies are difficult to observe. In the US, the SEC's EDGAR system and XBRL have received the most academic attention.

The SEC introduced EDGAR in 1994 as an electronic repository for regulatory filings. Before EDGAR, the only central, public sources of SEC filings were reference rooms at select SEC offices. Studies find evidence of EDGAR reducing awareness costs and acquisition costs, leveling the playing field for small investors, increasing trading volume, improving analyst forecast accuracy, and improving price responsiveness and informativeness (Asthana & Balsam 2001; Qi et al. 2000; Asthana et al. 2004; Gao & Huang 2019).

XBRL, first required in 2009, enables machine-readable financial statement data and was expected to reduce investors' disclosure acquisition and integration costs (SEC 2009; Blankespoor 2019). Bhattacharya et al. (2018b) find that XBRL improves the trading efficiency of small institutions more than large institutions, presumably because large institutions were not as hindered by processing costs prior to XBRL. However, Blankespoor et al. (2014a) find decreased liquidity after initial XBRL adoption, suggesting increased information asymmetry between individual and institutional investors, perhaps because individual investors were not immediately able to process XBRL data (e.g., Debreceny et al. 2010; Debreceny et al. 2011). Thus, while XBRL appears to have benefited one class of investor, initial evidence indicates that XBRL disadvantaged small investors on a relative basis.

Other studies also indicate that mandatory reporting technologies can have adverse effects on leveling the playing field between investors, at least temporarily. In the 1980's, procedural inefficiencies at SEC reference rooms meant that commercial data providers were provided copies of corporate filings faster than the filings were made available to the public (GAO 1989).

Rogers et al. (2017) find that many EDGAR Form 4s from 2012-2013 were inadvertently released to paying subscribers of the SEC's data service before the filings were posted on EDGAR. When subscribers had an advantage, the head start translated into price, volume, and spread movements 15 to 30 seconds prior to the public EDGAR posting.

In sum, evidence from EDGAR and XBRL indicate that mandatory financial reporting technologies have the potential to reduce processing costs and improve liquidity and price discovery, at least for some investors. However, there is little evidence on whether the benefits of these regulations outweigh the costs of implementation and enforcement. Also, it is not clear that findings from EDGAR and XBRL would generalize to other technologies, many of which might have smaller benefits than EDGAR and XBRL. A perennial avenue for future research is in evaluating the benefits and costs of financial reporting technologies. In addition, as technological solutions to information frictions become more prevalent, there is continued need to assess how technologies affect different investor groups. If increasingly sophisticated technologies reduce processing costs primarily for large institutions, increased asymmetries between investors could negatively affect liquidity and other market outcomes.

4.4.2. Algorithmic trading

Algorithmic trading (AT), and the subcategory of high-frequency trading (HFT), have multiple and complex effects on disclosure processing. AT uses "computer algorithms to automatically make certain trading decisions, submit orders, and manage those orders after submission" (Hendershott et al. 2011, p1). Virtually all institutions and brokers use algorithms to manage and execute orders in recent years, so it is a misnomer to think of AT as a distinct type of investor. For research on disclosure processing, an important distinction is whether the algorithm itself makes the trading decision, versus an algorithm that executes orders from human traders.[39] Of the algorithms that make the trading decision, some process firms' disclosures and directionally trade based on expected changes in value, others do not process disclosures but use order flow data to free-ride on other investors' disclosure processing, and still others make markets and arbitrage inter-market discrepancies without considering fundamental values (Jones 2013; Cochrane 2013; O'Hara 2015). This heterogeneity in strategies means that AT can have multiple and countervailing effects on disclosure processing and pricing.

On the one hand, using algorithms to quickly monitor, acquire, and integrate disclosures likely lowers marginal processing costs, at least for simpler disclosures that do not require manual processing.[40] More efficient disclosure processing should improve disclosure pricing efficiency. Efficiency is likely further enhanced by AT that provides liquidity for market-making and inter-market arbitrage, and potentially by AT based on order flow data (Hendershott et al. 2011; Brogaard et al. 2014). Working papers by Chordia & Miao (2018), Bhattacharya et al. (2018a), and Chakrabarty et al. (2019) all find evidence of more efficient disclosure pricing in the presence of AT, as measured through larger ERCs, smaller PEAD, faster analyst forecasts, and reduced analyst forecast dispersion. However, these papers face empirical challenges from: (i) endogeneity of which firms and disclosures are algorithmically traded; (ii) noisy proxies for AT and HFT; and (iii) small sample sizes when using better-specified proxies.

On the other hand, there are at least two reasons why AT may negatively affect disclosure processing and pricing. First, AT that free-rides or "piggybacks" on order flows or front-runs informed trades reduce the profits to informed trading, and therefore plausibly deter disclosure

[39] Of course, human traders often use algorithms to inform valuations and trading decisions. Still, the direct involvement of a human in the trading decision dramatically slows the process relative to autonomous algorithms.
[40] While algorithms likely reduce the marginal cost of processing each disclosure, they do require substantial costs to design and maintain. Further, algorithms likely increase systematic risk that from processing errors that affect large numbers of firms and trades at the same time. Thus, algorithmic disclosure processing is certainly not costless.

processing (Cochrane 2013; Stiglitz 2014). AT is associated with reduced pre-EA price drift, reduced pre-EA EDGAR searches, and increased price synchronicity, suggesting that AT deters investors from researching firms before EAs (Weller 2017; Lee & Watts 2018). A plausible implication is that AT deters sophisticated investors' disclosure processing at the EA itself; i.e., if informed trades are immediately identified and mimicked, there is reduced incentive to become informed. Second, by capturing most of the profits to processing simple disclosures, AT may make it unprofitable for non-AT investors to process the remaining, more complex disclosures that algorithms cannot process. For example, AT may be ineffective in processing infrequent, idiosyncratic disclosures such as restructurings, but humans find it unprofitable to continually follow the firm only for the payoff from processing restructurings when they occur. Thus, complex and idiosyncratic disclosures could be priced less efficiently when AT is high.

In sum, AT and HFT potentially both reduce direct processing costs and also reduce investors' incentives to incur processing costs. The net effect of AT and HFT on disclosure processing and pricing is not yet understood. Further, while research has begun to investigate the effects of AT on earnings processing, effects are potentially different for more complex or qualitative disclosures that are harder for algorithms to interpret. Understanding the effects of AT on disclosure processing and pricing is a critical avenue for future research, especially given recent moves by security exchanges to curb HFT speeds (Osipovich 2019).

4.4.3. Technology advances in trading platforms and investment vehicles

Several new technologies could alter investors' disclosure processing decisions by affecting expected benefits rather than costs.

One advance is off-exchange dark pools, in which trades are electronically matched with limited pre- and post-trade transparency. Dark pools accounted for roughly 30% of Dow 30 stocks' trading volume as of 2014 (Menkveld et al. 2017). In dark venues, transaction costs can be lower and trades can be executed with less risk of revealing an investor's information, which potentially increases their incentives to process disclosures. However, the absence of market makers means that trades will not be executed if a counterparty does not exist, potentially decreasing the incentives for disclosure processing. There is limited and mixed evidence as to whether dark venue trading volume increases or decreases around disclosures (Menkveld et al. 2017; Gkougkousi & Landsman 2018), and about the effects of dark venue trading on disclosure processing and pricing (Brogaard & Pan 2018).

Passive electronically-traded funds (ETFs) and mutual funds that track an index for a low fee have the potential to change the types of investors who trade in single stocks, which in turn plausibly affects the processing and pricing of firms' disclosures. French (2008) finds that the typical investor would earn higher profits by switching from an active to passive portfolio, but caveats that a widespread shift to passive investing could undermine price efficiency. Israeli et al. (2017) argue that if ETFs reduce active noise trading, then: (i) the risk of adverse selection for remaining investors increases; (ii) they protect via wider spreads and lower depth; and (iii) these higher trading costs reduce the expected returns to disclosure processing. Consistent with these predictions, Israeli et al. (2017) find associations between higher ETF ownership and reduced disclosure pricing efficiency. While an interesting first step in the literature, these results are subject to concerns about endogenous shareholder composition (see Section 4.2.2.1), and passive ownership likely has interrelated effects on systematic risks that should be considered (Anadu et al. 2018). As passive index fund investment now exceeds active fund investment and continues to grow (Lim 2019), understanding the effects of passive investment on disclosure pricing efficiency (as well as corporate governance) are critical areas for future accounting research.

A final unresearched area is the effect of new trading platforms such as m1finance.com, which reduce small investors' explicit trading costs to nearly zero. Reduced trading frictions are likely to increase small investor market participation and speed their trading on firm disclosures. Whether and how this trading will affect disclosure processing and pricing is yet unknown.

4.4.4. Conclusions and directions

The unifying conclusion from this section is that technology is radically and rapidly changing how disclosures are prepared, communicated, processed, and traded upon. These technologies have significant effects unto themselves, and likely have interactive effects that the literature has not yet considered. To date, most of the papers in this literature focus on expensive technologies that are beyond the reach of retail and other small investors. However, more recent advances in technology have the potential to help small investors with disclosure processing (e.g., Cardinaels et al. 2018; Blankespoor et al. 2018). Overall, there is ample room for research on disclosure processing and pricing in modern technological environments.

5. The effects of intermediaries on disclosure processing costs

This section discusses the roles of intermediaries in mitigating disclosure processing costs. Journalists, analysts, data providers, and social media have emerged as intermediaries to serve three capital market functions: (i) reduce awareness and acquisition costs by monitoring, curating, and republishing public information; (ii) reduce integration costs by synthesizing and interpreting the implications of public information for firm value; and (iii) uncover private information. We discuss these first two functions, focusing on information from firm disclosures. Bradshaw et al. (2017) survey the literature on analysts' roles in interpreting and disseminating firms' disclosures, so we exclude analysts from our review.[41] This section is organized by type of

[41] Also see Michaely & Womack (2005), Ramnath et al. (2008), Bradshaw (2011), and Kothari et al. (2016). We exclude credit rating agencies and debt analysts given our focus on equity markets.

intermediary, but the lines between types have blurred in recent years.

Studies of intermediaries grapple with at least three significant empirical challenges. First, intermediary coverage often occurs simultaneously with the firm disclosure and other intermediaries' coverage, making it difficult to isolate the market effects of any one intermediary. Second, the existence, speed, and contents of intermediary coverage is often determined by the characteristics of the disclosure and firm, introducing selection problems. Third, journalists and social media often discuss multiple topics, making it difficult to isolate coverage of a particular disclosure. As the intermediary literatures mature, addressing these empirical issues is increasingly important.

5.1. Data providers

Data providers republish information from disclosures without significant curation or interpretation. They range from Moody's Manuals in the early 1900s that collated firms' financial reports to modern providers such as Capital IQ. Modern data providers also offer alert, search, and extraction tools to further reduce awareness and acquisition costs, such as tools to calculate the sentiment of qualitative information. Some data providers such as Compustat standardize disclosures to facilitate comparisons across firms, which is a processing service that falls at the cusp of acquisition and integration.

Investors' willingness to pay for data subscriptions indicates that they mitigate disclosure processing costs, with the price of a subscription being a lower bound on the expected cost savings. Schaub (2018) and Akbas et al. (2018) support this inference by finding that delayed dissemination of earnings information in First Call and IBES is associated with delayed price and volume reactions, suggesting investors rely on the intermediary rather than directly accessing disclosures. Delayed dissemination is also evidence that data providers themselves are subject to processing costs and capacity constraints. Consistent with data providers rationally assessing processing costs and benefits, studies find that they prioritize disclosures of greatest interest to subscribers (D'Souza et al. 2010; Akbas et al. 2018; Schaub 2018).

Governments are also a data provider, under the argument that disclosure data provide public benefits (SEC 2005). The Securities Acts of 1933 and 1934 mandate that the SEC disseminate firm filings to the public. The SEC initially did so with public reference rooms, but these rooms were far from most investors and used primarily by commercial services (SEC 1936; GAO 1989). The SEC introduced the free EDGAR website in 1994, and improved EDGAR with a public dissemination service ("PDS") in 1998 and XBRL in 2009. As discussed in Section 4.4.1, EDGAR, PDS, and XBRL significantly affect investors' disclosure processing costs.

5.1.1. Conclusions and directions

Data providers affect volume and price reactions to firm disclosures and affect processing costs even for sophisticated investors. Little is known about how data providers standardize data from heterogeneous accounting reports, or the possible information loss from standardization. Another research avenue is investigating the accuracy and completeness of databases (e.g., Ljungqvist et al. 2009; Chuk et al. 2013; Chychyla & Kogan 2015; Karpoff et al. 2017), and the market effects of database errors (e.g., von Beschwitz et al. 2015, Rogers et al. 2017).

5.2. Traditional media and journalists

In a traditional media outlet, journalists monitor firm disclosures, curate important information, distill and interpret that information in an article, and deliver the article to readers. The literature often distinguishes between the media's role in packaging and republishing information ("dissemination") versus interpreting that information (Bushee et al. 2010). Disseminating information from firm disclosures reduces awareness and acquisition costs, while journalists' interpretations affect integration costs.[42]

One approach to isolate media articles from contemporaneous events is to examine articles that come out days after the disclosure and contain only stale information. Using this approach, Dopuch et al. (1986) find insignificant market reactions to qualified audit opinion filings, followed by negative returns around *WSJ* articles on those opinions. These results are consistent with articles reducing processing costs and informing investors. Similarly, Stice (1991) finds returns correlated with earnings surprises around *WSJ* articles of stale 10K/Q filings. Li et al. (2011) find volume and returns reactions to *Dow Jones'* delayed alerts of SEC filings.

Other papers (many of which are discussed further below) use a variety of creative approaches to address the endogeneity of media articles (e.g., Huberman & Regev 2001; Bushee et al. 2010; Engelberg & Parsons 2011; Lawrence et al. 2018; Blankespoor et al. 2018). Together, the literature provides convincing evidence that the media reduce disclosure processing costs and affect trading volume, liquidity, and returns, even when articles do not include private information.

An important question is whether market reactions elicited by media articles are driven by efficiency-enhancing reductions in processing costs or by misguided investors who do not realize information is stale. If the latter, then media-driven returns should reverse. For example, if additional trading is from retail investors focused on buying, media articles may cause positive price pressure that reverts afterward (Frank & Sanati 2018). Using a case study approach, Huberman & Regev (2001) find that media coverage of a stale disclosure elicits price and volume reactions, and that roughly 50% of the price reaction persists. Huberman & Regev also

[42] Given the focus of our review, we discuss papers that examine media coverage of firm disclosures as opposed to investigative journalism or coverage of other information events. Further, given the size of the media literature we restrict our discussion to representative papers rather than provide a comprehensive review. See Engelberg (2018) for complementary discussion of econometric challenges in media research.

find stock price reactions by peer firms to the stale news. This latter result is interesting because it would take an investor who is “well informed in cancer research and its commercial applications” (p392) to identify peer firms for contagion effects, which indicates that peer firm returns to stale news are driven by sophisticated investors who are apparently still affected by processing costs. Tetlock (2011) and Bushee et al. (2019) find that media coverage elicits trading and price pressure by small investors followed by returns reversals, while Li et al. (2011) find no reversals and no differences in trades between large and small investors. Overall, the evidence suggests both forces are at work: media articles reduce processing costs and improve disclosure pricing, but can also lead investors astray and cause temporary mispricing.

Awareness, acquisition, or integration costs?

Some studies investigate which specific processing costs are reduced: awareness and acquisition costs through media dissemination, or integration costs through interpretation or signaling? Several papers find that dissemination on its own affects market outcomes. Bushee et al. (2010) use control variables to eliminate journalists’ interpretation and find that broader dissemination of earnings news is associated with lower information asymmetry, measured by spread and depth. Blankespoor et al. (2018) further eliminate concerns about journalists’ interpretation by examining algorithmically-generated earnings news articles, finding increases in liquidity and volume for firms that begin receiving algorithmic news coverage, but no effect on earnings price responses. The lack of effect on earnings pricing is explained by the finding that the investors responding to algorithmic articles do not do so using earnings information, but rather appear to trade on the trailing returns mentioned in the articles (Blankespoor et al. 2019). These results highlight the point that integration costs can continue to impede investors even after awareness and acquisition costs are reduced.

Other papers isolate the effects of media on awareness and acquisition costs by examining simple dissemination of insider trades. Chang & Suk (1998) examine *WSJ's* Wednesday listing of the prior week's 10 largest insider transactions, which is stale news with few concerns about contemporaneous events and journalist interpretation. They find insignificant returns between the SEC filing and *WSJ* dissemination, and then significant reactions upon the *WSJ* release, with no reversals. Rogers et al. (2016) find similar results in a more recent setting; they analyze *Dow Jones'* dissemination of insider trade disclosures and find price and volume reactions within seconds of the *Dow Jones* publication, despite prior digital availability on EDGAR.[43]

Several papers examine "news flashes," or nontraditional articles that provide snippets of information from firms' disclosures (e.g., United Technologies 2Q EPS $1.84 >UTX) and are often released within seconds of the SEC filing. Drake et al. (2014) find the news flashes mitigate cash flow mispricing but not accruals mispricing. Twedt (2016) finds that news flashes are associated with more efficient price responsiveness to management forecasts. Twedt (2016) also finds that the existence of news flashes is determined by the nature of the firm and forecast, indicating that selection biases are a concern for news flashes.

Fewer studies isolate the effects of media coverage on integration costs, abstracting from awareness and acquisition costs. Guest (2018) finds that journalist interpretation in *WSJ* articles is associated with more efficient earnings pricing. Although not specifically limited to firms' disclosures, Dougal et al. (2012) find that *WSJ* columnists' personal writing styles affect returns, which indicates that journalistic interpretation affects investors' integration and trading.

Capacity constraints and incentives

Journalists, like all market participants, are subject to capacity constraints. Journalists'

[43] An interesting note about Rogers et al. (2016) is that these publications are unfiltered coverage in a machine-readable format, providing an example of a blurring of media and data provider services.

constraints have tightened in the internet era as media outlets struggle to protect and monetize content, which could lead journalists to produce biased content to appease advertisers (Gurun & Butler 2012), attract readers with certain preferences or political views (Gentzkow & Shapiro 2010), or cater to the preferences of corporate owners (e.g., Gilens & Hertzman 2000).

5.2.1. Conclusions and directions

The literature provides compelling evidence that media coverage affects market outcomes by decreasing awareness, acquisition, and integration costs. While much of the literature indicates that the media improves market efficiency, there is evidence that media coverage can also lead to misguided trading by both small and large investors.

An important topic for future research is the effect of declining traditional media. What is the effect of having fewer journalists, to what extent can journalism technology mitigate those effects, and what biases and weaknesses are introduced by new technology? For example, algorithmic journalism depends on its input dataset and algorithm. To date, it is executed simply and with highly reliable input data (Blankespoor et al. 2018), but as algorithms evolve and data sources expand, questions about reliability and neutrality become increasingly important.

5.3. Social Media

The defining feature of social media platforms is user-generated content, typically with few restrictions on who can participate. The platform features vary widely, from Seeking Alpha's in-depth articles to Twitter's brief messages. Some social media sites focus on investing information (e.g., StockTwits), while others are more general (e.g., LinkedIn). One use of social media is by firms as a dissemination channel, as discussed in Section 4.3.3. This section discusses the use of social media platforms by investors acting as intermediaries for each other.

Unlike the traditional media literature, studies on social media have made little progress in examining whether and how user activity on social media affects disclosure processing costs. Early studies on social media and EA processing find mixed results: Curtis et al. (2016) find that social media activity is associated with faster EA price responses and Gomez et al. (2018) find that SeekingAlpha content in advance of EAs is associated with reduced information asymmetry around EAs. In contrast, Drake et al. (2017) find that coverage by the least sophisticated online blogs is associated with slower EA price responses. A central concern in this research area is the selection issue mentioned in Section 5.0: that both market responses and social media activity are driven by the nature of the earnings news. The social media literature has made less progress overcoming endogeneity concerns than have studies of traditional media and data providers.

Still, many papers find that social media platforms like message boards, Seeking Alpha, Twitter, and Glassdoor contain value relevant earnings forecasts (Bagnoli et al. 1999; Jame et al. 2016), messages (Antweiler & Frank 2004; Chen et al. 2014; Bartov et al. 2018; Tang 2018), and even employee workplace reviews (Hales et al. 2018; Huang et al. 2019). Further, while social media content is subject to more quality and credibility concerns than other intermediaries (e.g., Dewally 2003; Antweiler & Frank 2004), evidence indicates that platform features can help social media users discern high- versus low-quality content (Chen et al. 2014; Bartov et al. 2018). Thus, social media activity has the potential to significantly affect processing costs around disclosures themselves.

5.3.1. Conclusions and direction

Social media provides a platform for individuals to distribute their interpretations of disclosure and to interact with one another, with the diversity of thought underlying crowdsourced interpretations providing valuable information to capital markets. Future studies of social media, processing, and market outcomes can continue to improve research designs to control for the underlying event and correlated intermediaries' activities.

A particularly interesting consideration for future research is social media's lack of traditional oversight and potential for misinformation. In addition, social media blurs the line between traditional and non-traditional outlets, and potentially influences longstanding incentives and effects of other intermediaries. For example, competitive pressure from social media potentially increases traditional journalists' incentives to cater to advertisers or to produce more sensationalized news.

Finally, the variety of features across social media platforms provides opportunities to test new and existing theories on the costs and benefits of processing user content and interactions. For example, social media sites vary in their verification and monitoring of users, which provides opportunities to test how credibility and reputation affect processing costs. Or, social media sites vary in how easy it is to identify content for specific firms or events, providing variation in awareness and acquisition costs.[44]

6. The effects of processing costs on managers' actions

This section reviews studies that examine how managers strategically adjust their disclosure choices and other corporate actions because of (expected) investor disclosure processing costs. Managers and their investor relations (IR) departments expend considerable effort in crafting the contents and delivery of disclosure (Brown et al. 2019), so presumably they expect their efforts to influence investor processing and decisions. Still, research is just beginning to examine whether and how managers' expectations of investor disclosure processing costs affect

[44] For example, Seeking Alpha allows anonymous contributors but approves articles prior to publishing, while LinkedIn verifies individuals' employment but does not filter comments. Twitter has optional cashtags (e.g., $MSFT) to identify firms in a standardized way. Comments on Seeking Alpha articles are clustered together below the related article, while responses to Twitter messages can be directed at the account-level rather than message-level, making it more difficult to find all related comments.

managers' strategic choices.

6.1 Processing costs and disclosure choices

6.1.1 Theoretical motivations

Beyer et al. (2010) review analytical studies on the benefits and costs that determine managers' ex post disclosure decisions, and in particular focus on frictions that prevent "unraveling," i.e., prevent market forces from driving full disclosure. Investor disclosure processing frictions are absent from most models reviewed in Beyer et al.[45]

Processing costs likely help create or interact with the unraveling frictions reviewed in Beyer et al. (2010) and could exacerbate or mitigate existing predictions. For example, consider disclosure's effect on stock prices. Most models predict that voluntary disclosures lead to positive market reactions relative to non-disclosure, but the price effects of disclosures are conditional on investors processing those disclosures. Thus, managers must not only consider whether the expected benefits of disclosure exceed the cost (and related costs from litigation and proprietary information), but must condition those expected benefits on the extent to which they expect the disclosure to be processed. A completely unprocessed disclosure provides little price benefit to a firm disclosing good news. The predicted effects of disclosure on stock prices become even more complicated if models allow processing costs to mitigate investor responses to bad news disclosures or to non-disclosures, and likely depend on the assumed nature of the processing costs. For example, if high awareness costs prevent investors from identifying non-disclosure, this alone may create enough friction to sustain an equilibrium with partial non-

[45] Ex post models examine managers' decisions to disclose information after the manager has received it, and are distinct from models that examine managers' ex ante choices about what types of disclosures to produce (discussed further below). Several ex post disclosure models include assumptions that could be reinterpreted as processing costs. For example, Dye's (1985, 1998) assumption that investors do not always know whether managers have information could be reinterpreted as an outcome of investors' awareness costs. Fishman & Hagerty (2003) assume that some investors don't understand disclosures, which could be reinterpreted as investors facing integration costs.

disclosure.

While the analytical literature has explored little of how processing costs interact with or spur ex post disclosure unraveling frictions, a few models incorporate investor processing costs into firms' ex ante choices of disclosure quality. For example, Indjejikian (1991) demonstrates in a competitive setting that, for risk-sharing reasons, the socially optimal level of disclosure quality increases as investor integration costs increase. Fishman & Hagerty (1989) argue that firms overinvest in disclosure precision as they compete for investors' limited processing capacity.[46] Future research can continue to investigate the effects of processing costs on ex ante disclosure design choices, and how processing costs complicate predictions about the effects of disclosure design on market outcomes. For example, disclosure's positive effect on liquidity (Beyer et al. 2010, p.306) would likely be reduced or even turn negative in the presence of processing costs.

More broadly, the effects of processing costs on disclosure decisions is an area where empirical research (reviewed below) has moved substantially beyond the existing analytical literature. In particular, many empirical papers focus on managers' incentives to strategically increase or decrease disclosure processing costs in order to manipulate price responsiveness and other market outcomes. For example, managers and investors, or at least subsets of investors, might prefer slow price responses in order to reduce frivolous litigation from abrupt stock drops, allow time for good news to offset bad news, or allow time for large investors to exploit slow processing by small investors. There are also agency reasons for managers to prefer slow price responses and low market attention, such as to allow time to place insider trades or to reduce negative media attention that can damage career prospects. Or, managers may want to reduce processing costs of good news to improve price responsiveness and benefit from increased

[46] Michaeli (2017) models selective disclosure and disclosure precision, which speaks to how processing costs can affect managers' dissemination decisions.

attention. Similar to manipulating disclosure precision, managers' ability to manipulate investor processing costs blurs the line between mandatory and voluntary disclosure; i.e., mandatory disclosure become somewhat voluntary when managers can manipulate how much investors learn from it.

In sum, there are many opportunities for analytical research to improve our understanding of the effects of processing costs on disclosure choices. Reputation concerns are considered a powerful incentive for managers to forgo disclosure manipulation, so dynamic models may be especially useful to avoid corner solutions and generate predictions that capture realistic repeated interactions between managers and investors. For example, managers in a multi-period game may internalize investors' incentives and withhold information that is exceptionally costly for investors to process, even in the absence of other disclosure frictions.

6.1.2 Empirical evidence

Disclosure quantity, timing, and format can all affect processing costs (Section 4), so managers likely consider all these attributes when making strategic disclosure choices. We discuss empirical research related to each of these in the following subsections.[47]

A challenge with many studies in this research area is that manager intent is unobservable. A typical empirical approach is to examine whether disclosure choice varies with a proxy for managers' incentives. Behavior that is not self-serving is deemed non-opportunistic or helpful, while behavior correlated with misaligned incentives is opportunistic. Some studies go a step further and examine whether strategies are effective at influencing disclosure processing, market

[47] Studies find that IR departments are associated with greater firm visibility (e.g., Bushee & Miller 2012; Kirk & Vincent 2014) and more efficient pricing (e.g., Chapman et al. 2019a). These effects are likely in part due to mitigating disclosure processing costs. However, these studies are not in our scope because they do not focus specifically on disclosures, nor do they isolate the effects of IR on disclosure processing from their effects on compliance and private communications.

outcomes, or CEO career outcomes. However, examining market and career effects is difficult because they can be cumulative and have uncertain timing; for example, it can take multiple periods to build a reputation for transparency, and career benefits can take years to accrue. Also, it can be challenging to control for other actions managers may take along with the strategic disclosure and that also affect outcomes of interest.

Empirical evidence on amount of disclosure supplied

If a reduction in disclosure processing costs increases investors' net benefit to processing, demand for disclosure likely increases and drives an increase in equilibrium disclosure supply. An increase in processing costs would do the opposite. Blankespoor (2019) examines a downward shock to costs of processing quantitative footnote disclosures caused by XBRL, and finds that firms respond by increasing these disclosures. Abramova et al. (2019) and Basu et al. (2019) examine upward shocks to institutional investors' disclosure processing opportunity costs caused by important events elsewhere in their portfolios, and find that firms respond by decreasing the number of forecasts and 8-K filings. Abramova et al. find no evidence that the decline in disclosures affects volume, volatility, or liquidity, indicating that marginal disclosures have small effects.

Other studies examine management choice across disclosure types. Guay et al. (2016) and Park et al. (2019) find that firms provide earnings guidance in response to non-discretionary high processing costs, with the goal of reducing investors' overall processing costs (or, equivalently, to increase the precision gained per unit of processing effort). In Guay et al. (2016) the driver of non-discretionary high processing costs is inherent complexity, measured based on 10K readability. In Park et al. (2019) the non-discretionary high processing costs stems from high opportunity costs due to greater capital market competition from peer firms. Relatedly, Heinle et al. (2018) suggest that managers concerned about proprietary information intentionally obfuscate detailed information in the 10K but offset the increase in processing costs by providing an earnings forecast. Similarly, Chen et al. (2018a) find that managers' tax-avoidance activities increase disclosure processing costs and information asymmetry, and that some managers respond by providing more guidance. Bushee et al. (2003) find that firms with more complex transactions or more retail investors are more likely to open their conference calls to the public, consistent with managers aiming to reduce small investors' processing costs. Open conference calls have more trading volume and volatility, although these effects could be from small investors making better-informed trades or the open call attracting more noise traders.

Empirical evidence on the strategic choice of disclosure characteristics

Several papers find that managers help investors process important information, whether good or bad, by highlighting transitory items or improving the readability of reports (e.g., Riedl & Srinivasan 2010, Curtis et al. 2013; Lundholm et al. 2014). However, there is also substantial evidence of managers opportunistically exploiting processing costs. Managers use a variety of methods to reduce processing costs of favorable information and increase costs for unfavorable information, such as shifting expense classifications, highlighting positive non-GAAP metrics, reminding investors of prior one-time gains but not losses in comparisons to prior performance, or including favorable metrics in headlines despite their lower persistence (e.g., Schrand & Walther 2000; McVay 2006; Bowen et al. 2005; Huang et al. 2018b; Basu et al 2019). Papers on linguistic characteristics find that disclosures of unfavorable information tend to be less readable (e.g., Li 2008), include euphemisms to soften the bad news (Suslava 2019), and manipulate tone (e.g., Allee & DeAngelis 2015; Huang et al. 2018b). For the most part, those papers that also examine market outcomes find that increasing the processing costs of bad news reduces price responsiveness. Finally, Lo et al. (2017) find that firms with greater earnings manipulation tend to have less readable MD&As, consistent with managers manipulating disclosure processing costs to reduce the risk of misreporting detection.

Research examining strategic disclosure choices grapples with several empirical challenges. The first is in isolating the discretionary portion of disclosure characteristics. For example, Bloomfield (2008) notes that the association between bad news and less-readable 10-Ks could be driven by fundamental characteristics such as goodwill write-offs that are inherently complex and difficult to control for, and several papers conclude that 10-K linguistic complexity is substantially non-discretionary (e.g., Guay et al. 2016; Dyer et al. 2017; Chychyla et al. 2019). Papers address this challenge in a variety of ways, such as by controlling for non-discretionary drivers of disclosure characteristics or by looking to non-firm sources for a benchmark of non-discretionary information.

A second challenge is in identifying misaligned incentives. Perhaps good (bad) news is emphasized because it is important (unimportant), in which case it is difficult to distinguish between informative versus opportunistic managers. For example, perhaps managers do not bother decreasing the processing cost of goodwill write-off disclosures because they have few implications for the future.

Empirical evidence on strategic disclosure timing and dissemination

Studies on disclosure timing and dissemination choices again face the empirical challenges of isolating discretionary variation and identifying misaligned incentives. For example, while delayed EAs contain negative news that the market is slow to price (e.g., Bagnoli et al 2002; Johnson & So 2018), we do not know whether EA delays are discretionary or are driven by negative transactions that take longer to account for. As an example of the difficulty in inferring intent, studies dating back to at least 1982 have been unable to agree on whether managers report worse EA news after-hours and on Fridays to provide investors more processing time before trading, or to opportunistically reduce attention to bad news (Patell & Wolfson 1982; Damodaran 1989; Gennotte & Trueman 1996; DellaVigna & Pollet 2009; Doyle & Magilke 2009; deHaan et al. 2015; Michaely et al. 2013, 2016a, 2016b; Lyle et al. 2018).

Despite empirical difficulties, there is evidence that managers opportunistically adjust disclosure timing to increase the cost of processing bad news. The collective evidence in Hirshleifer et al. (2009), deHaan et al. (2015), and Driskill et al. (2019) is consistent with managers reporting bad EA news on busy days, and that this strategy mitigates attention and price responsiveness. There is also evidence that managers provide less advance warning of bad news EAs to mitigate attention and price responses (deHaan et al. 2015, Boulland & Dessaint 2017). Niessner (2015) finds that managers release bad news 8Ks on Fridays to reduce price responsiveness and implement insider trades. Chapman et al. (2019b) find that managers spread 8K filings over multiple days to allow more time for investor processing, especially for complex or uncertain information, but also find that this smoothing is more common for good news than bad news. Koester et al. (2016) find that managers delay and bundle good news disclosures in order to create large positive earnings surprises that increase investor awareness, institutional ownership, and analyst coverage.

For dissemination, a simple strategy for manipulating processing costs may be to disseminate good news more widely than bad news. Research on dissemination choices is relatively new, likely because managers historically had few dissemination channels to choose from. Further, a challenge is that broader dissemination is often accompanied by additional information, making it difficult to empirically separate dissemination from information, and to confirm its strategic nature. As discussed in Section 4.3, Blankespoor et al. (2014b) examine Twitter usage to help isolate dissemination from information and do not find evidence of strategic usage among early-adopting firms, while Jung et al. (2018) do find that managers are more likely to tweet good news EAs in a more recent sample.

Empirical evidence on managers' consideration of intermediary processing constraints

Studies also find that managers design their disclosure strategies in consideration of processing constraints of intermediaries such as analysts and media. Balakrishnan et al. (2014) find that managers increase disclosure to mitigate information asymmetry between investors caused by analyst closures, and that this disclosure helps improve liquidity. Kim et al. (2019) find that managers increase disclosure after local newspaper closures. Other papers find managers strategically take advantage of intermediaries' constraints. Ahern & Sosyura (2014) find that firms time press releases to manipulate the quantity of news coverage and increase the firm's share price prior to an acquisition, and Blankespoor & deHaan (2019) find that CEOs take advantage of capacity-constrained journalists' tendencies to cut-and-paste quotes from firms' press releases into news articles. Bowen et al. (2005) find that firms with higher media coverage are more likely to use non-GAAP metrics, possibly because cost-constrained media focus on non-GAAP metrics even if they are not the most relevant.

6.2 Processing costs and corporate actions

While our review focuses on investors' valuation and trading decisions, processing costs likely also affect investors' ability to use disclosures for monitoring corporate actions. To date, though, very few papers examine the "real effects" of disclosure processing costs (see Roychowdhury et al. 2019).

One exception is Kempf et al. (2017), who examine whether managers exploit institutional investors' monitoring capacity constraints to take agency-motivated actions. They argue that institutional investors allocate scarce monitoring capacity to firms within their portfolios experiencing the most extreme returns, and find that firms with distracted institutional investors are more likely to make value-destroying acquisitions, cut dividends, have opportunistically-timed equity grants, and are less likely to fire poor-performing CEOs. Most of these actions are announced in timely, public disclosures, so the findings suggest either that institutional investors lack the resources to process those disclosures during high-distraction periods, or that they process the disclosures but lack the resources to take disciplining actions. Their finding that distracted investors are less likely to ask questions in conference calls provides some evidence in support of the former mechanism.

The real effects of disclosure processing costs are also relevant in the earnings management literature. Papers on earnings management often assume that processing costs prevent investors from detecting accrual manipulations or real earnings management (Dechow et al. 2010). There is some evidence that managers manipulate processing costs to mask misreporting (e.g., Lo et al. 2017; Niessner 2015), and managers could plausibly choose to manage earnings more aggressively when processing costs are exogenously higher. However, we are unaware of current evidence supporting this prediction.

There is some evidence that intermediaries play a role in reducing disclosure processing costs for monitoring and governance purposes. For example, investors rely on proxy advisors to reduce the costs of processing compensation data (Ertimur et al. 2013), despite evidence that proxy advisors' recommendations can motivate managers to make value-destroying compensation changes (Larcker et al. 2015). Intermediaries also provide corporate governance ratings that are based largely on firms' disclosures, but there is mixed evidence on the extent to which these ratings improve monitoring (e.g., Daines et al. 2010; Lehmann 2019). There is also mixed evidence on whether media coverage of firms' disclosures improves monitoring and governance of manager actions (e.g., Farrell & Whidbee 2002; Core et al. 2008; Dyck et al. 2008; Kuhnen & Niessen 2012; Dai et al. 2015).

Finally, a potential indirect effect of disclosure processing costs on corporate actions is through their effects on managers learning from prices. Studies find that managers use prices to inform project selection and other internal investment decisions (e.g., Luo 2005; Chen et al. 2007; Bond et al. 2012; Jayaraman & Wu 2019). To the extent that processing costs reduce price informativeness even temporarily, the quality of one of management's signals declines, potentially affecting their ability to make investment choices. For example, Luo (2005) finds that managers learn about M&A deal quality based on the returns to M&A announcements, so if high processing costs cause delayed or volatile price responses, then M&A announcement returns are potentially less informative.[48] To our knowledge, processing costs, price informativeness, and managerial learning has yet to be explored.

<u>*6.3 Conclusions and directions*</u>

Research is just beginning to examine the effects of disclosure processing costs on strategic disclosure and other corporate actions. As a starting point, it would be helpful for analytical research to consider the effects of processing costs on disclosure unraveling and, more broadly, investors' demand for disclosure. Shocks to disclosure demand presumably affect equilibrium supply, but perhaps in nuanced ways that have not been considered in existing research. In addition to disclosure quantity, theory on disclosure timing and characteristics would help guide the empirical literature. Empirical research also has ample room to develop new hypotheses, test

[48] Arya et al. (2017) model a similar scenario in which more precise accounting reports facilitate managers' learning from disclosure price reactions.

predictions coming from analytical research, and reexamine existing findings while better addressing the econometric challenges discussed above.

7. Concluding Remarks

The literature finds that there are significant costs to monitoring, acquiring, and analyzing firm disclosures, even for professional investors. When these processing costs exceed expected trading gains, investors rationally disregard disclosures and the information therein can remain unpriced. This underpricing is a form of efficient inefficiency that permits investors to earn competitive returns on their costly disclosure processing activities. The notion of costly processing means that disclosures can affect price informativeness, price responsiveness, liquidity, volatility, and volume, all within the bounds of the semi-strong efficient market hypothesis.

Researchers have ample room to improve our understanding of the determinants of disclosure processing costs, and why and how processing costs affect trading and market outcomes. Throughout this review we provide specific guidance for future research, and we conclude with several broad critiques. First, existing theory is incomplete, both within the analytical literature and in the hypothesis development of empirical research. Second, research is often imprecise when defining and studying processing costs; studies often speak in generalities, mix costs together, and fail to consider differing or interactive effects across cost types. Third, most empirical research examines earnings surprises, but these are just a fraction of the information disclosed by firms daily. Fourth, processing costs may play a role in driving findings attributed to other mechanisms in research conducted before the idea of processing costs became commonplace. Fifth, new technologies are dramatically changing how processing costs affect investors and markets. All of these critiques provide future research opportunities.

While the focus of this review is on equity investing, another broad set of research opportunities is to examine the effects of disclosure processing frictions on other stakeholders and decision contexts. Lenders, labor markets, auditors, boards of directors, and other contracting parties also face processing costs and capacity constraints, and the effects of processing costs on efficient outcomes may be even greater in settings where arbitrage forces are not as powerful as equity markets. Even among equity investors, the effects of disclosure processing costs may differ for decisions other than stock valuation (e.g., monitoring), and research can examine how disclosure processing costs affect cost of equity capital. Relatedly, research can go beyond examining disclosures to study costly processing of information from many other sources, including managers' processing of information inside the firm.

Finally, we caution readers against assuming that technologies largely eliminate processing costs in modern markets. At the time that Fama (1970) wrote about semi-strong market efficiency, many academics assumed that the processing costs of earnings reports were negligible and, therefore, reports should be immediately impounded in prices. In reality, it took up to 18 business days for filings to make their way from the SEC's mailing room to being available in the SEC reading room, and once there, users were allotted 30 minutes to glean as much information as possible from one of two paper copies (Noble 1982; GAO 1989). In hindsight, it seems evident that processing costs were highly material. In another 50 years, researchers will likely reflect upon today's disclosure processing technologies, and academics' collective understanding thereof, as similarly elementary compared to what is to come.

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Figures and Tables

Appendix A: Sample and Variable Definitions

Our sample of US common stocks intersects Compustat, CRSP, and IBES from 2006 – 2016. To reduce noise, we drop firm-quarters without the same earnings announcement ("EA") date in Compustat and IBES, and EAs that occur outside of days [0,90] relative to the fiscal quarter-end (deHaan et al. 2015). We also exclude 6.4% of EAs that occur on Fridays due to selection biases that confound inferences and are difficult to control for in simple analyses (Michaely et al. 2016a). The final sample includes 6,634 firms and 145,529 EAs. Not all variables are available for the full sample.

For market measures, day [0] is set to the following trading day for after-hours EAs. All market variables are measured over days [0,1] unless otherwise noted below. Day [0] is not adjusted for non-market variables due to the presence of after-hours activity. Unless otherwise noted, non-market variables are measured over a one-week period (days [0,6]) to reduce confounds from after-hours EAs and weekends. All continuous variables are winsorized at 1% and 99%.

One motivation for this section is to provide guidance for future empirical research but, of course, we strongly encourage authors to carefully consider their research question and empirical setting when making sample selection and variable construction choices.

We are sincerely grateful to Lucile Faurel, Robin Litjens, James Ryan, Josh Madsen, Shiwon Song, John Wertz, and Christina Zhu for providing data and research assistance. All errors are the authors' responsibility.

Variable	Description	Source
Earnings Surprise	The firm's earnings per IBES less the median consensus, scaled by price two days before the EA. Surprises are sorted into deciles by year to reduce the effects of outliers and noise.	IBES, CRSP
Non-Market Measures		
Abnormal EDGAR Downloads	Log of (one plus the average EDGAR downloads over days [0,6] divided by one plus the average over the trailing eight weeks ending one week before the EA).	EDGAR. Supplied by James Ryan.
Abnormal Google Ticker Searches	Google ticker SVI over days [0,6] minus the average over the trailing eight weeks ending one week before the EA, all scaled by the trailing average. Google investing-specific SVI (see deHaan et al. 2019a) is calculated analogously.	Google. Supplied by Shiwon Song and Robin Litjens
Abnormal Twitter Activity	Tweets is the number of Twitter tweets and retweets containing the firm's ticker preceded by a cashtag on day *t*. Twitter data are constructed as in Bartov et al. (2018). Abnormal Tweets is calculated as the log of (the average Tweets over days [0,6] divided by the average over the trailing eight weeks ending one week before the EA). We require at least one tweet during each of the EA-window and trailing window.	Twitter. Supplied by Lucile Faurel.
Analyst Forecast Delay	For analysts following the firm, delay is the average number of weekdays between the EA and first forecast dates. Following analysts are identified as those that issue or confirm at least one forecast in both the year before and after the EA.	IBES
Analyst Forecast Likelihood	Percentage of analysts following the firm that issue a forecast within days [0,6] of the earnings announcement. Following analysts are identified as those that issue or confirm at least one forecast in both the year before and after the EA.	IBES
IBES System Update Delay	Log of one plus the number of minutes between the EA and when IBES disseminated the earnings news (variable *acttims*). Truncated at 30-days to reduce retroactive firm additions.	IBES
News Articles	Log of one plus the number of EA-related media articles issued within days [0,6] of the EA.	RavenPack Dow Jones Edition
News Flashes	Log of one plus the number of EA-related news flashes issued within days [0,6] of the EA.	RavenPack Dow Jones Edition
Abnormal Bloomberg Attention	Indicator variable equal to one if Bloomberg's measure of abnormal attention has a maximum value of "3" or "4" within days [0,1]. Bloomberg calculates its attention measure based on the number of news article searches and views each hour.	Bloomberg. Supplied by Robin Litjens.

Variable	Description	Source
	Bloomberg then calculates the total attention each eight-hour period relative to the trailing 30 days. A score of 3 (4) is assigned if the recent attention exceeds 94% (96%) of the trailing 30 days. Bloomberg aggregates to the daily level based on the maximum value observed during the day.	
Market Measures		
Abnormal Depth	Daily depth is the average of the time-weighted best bid dollar depth and best offer dollar depth (variable *BestBidDepth_Dollar_tw* and *BestOfrDepth_Dollar_tw*). Abnormal depth is the log of (the average daily depth over trading days [0,1] divided by the average daily depth over days [-41,-11]).	WRDS Intraday Indicators Data.
Abnormal Price Impact	Daily price impact is the average percent price impact of each trade over a 5-minute window (variable *PercentPrice Impact_LR_Ave*). Abnormal impact is the weighted average daily impact over trading days [0,1] divided by the weighted average daily impact over days [-41,-11]). Daily impacts are weighted based on total number of trades during market hours (variable *total_n_trades_m*). Abnormal impact is not logged because the ratio is frequently negative.	WRDS Intraday Indicators Data.
Abnormal CRSP Price Impact	Daily price impact is absolute return divided by total dollar volume, multiplied by 10,000,000. Abnormal price impact is the log of (the average daily impact over trading days [0,1] divided by the average daily impact over days [-41,-11]).	CRSP.
Abnormal Spread	Daily spread is average percent effective spread (variable *EffectiveSpread_Percent_Ave*). Abnormal spread is the log of (the weighted average daily spread over trading days [0,1] divided by the weighted average daily spread over days [-41,-11]). Daily spreads are weighted based on total number of trades during market hours (variable *total_n_trades_m*).	WRDS Intraday Indicators Data.
Abnormal CRSP Spread	Daily CRSP spread is the average of the closing bid minus ask (variables *bid, ask*) divided by the closing price (*prc*). Abnormal CRSP spread is the log of (the average daily spread over trading days [0,1] divided by the average daily spread over days [-41,-11].)	CRSP
Abnormal Trading Volume	Daily volume is the number of shares traded divided by total shares outstanding. Abnormal trading volume is the log of (the average daily volume over trading days [0,1] divided by the average daily volume over days [-41,-11].)	CRSP
Abnormal Retail Trading Volume	Daily retail volume is the number of retail shares traded divided by total shares outstanding. Retail trades are identified using the method developed by Boehmer et al. (2019). Abnormal retail trading volume is the log of ((one + the average daily retail volume over trading days [0,1]) divided by (one + the average daily retail volume over days [-41,-11]), multiplied by 100. We add one to the numerator and denominator due to high frequencies of zero retail trades.	DTAQ. Thanks to Christina Zhu.
Abnormal Volatility	Daily volatility is the sum of squared logarithmic returns for each 5-minute interval for each trading day. Abnormal volatility is the log of (the average daily volatility over trading days [0,1] divided by the average daily volatility over days [-41,-11]).	DTAQ. Thanks to John Wertz.
Abnormal CRSP Volatility	Daily volatility is the squared abnormal return. Abnormal return is the raw return minus CRSP value-weighted return. Abnormal CRSP volatility is the log of (the average daily volatility over trading days [0,1] divided by the average daily volatility over days [-41,-11]).	CRSP
ERC	Coefficient from regressing abnormal returns over [0,1] on the firm's earnings surprise. Abnormal returns are calculated as the firm's buy-and-hold return less the value-weighted return of a portfolio matched on sequential quintiles of size, industry-adjusted book-to-market, and 12-month momentum (similar to Daniel et al. (1997)), and then multiplied by 100. Quintile and portfolio assignments are based on the CRSP-Compustat universe as of the month-end prior to the earnings announcement.	CRSP, IBES
PEAD	Coefficient from regressing abnormal returns over [2,75] on the firm's earnings surprise. Model details are the same as for *ERC*.	CRSP, IBES, Ken French
IPE	Intra-Period Efficiency. Average of $[1 - (\lvert AR_5 - AR_t\rvert)/\lvert AR_5\rvert]$ measured over days [0,5]. AR_t is the buy-and-hold market-adjusted return over [0,t]. Set to missing for $\lvert AR_5\rvert < 0.01$.	CRSP.

Figure 1: Paper Organization

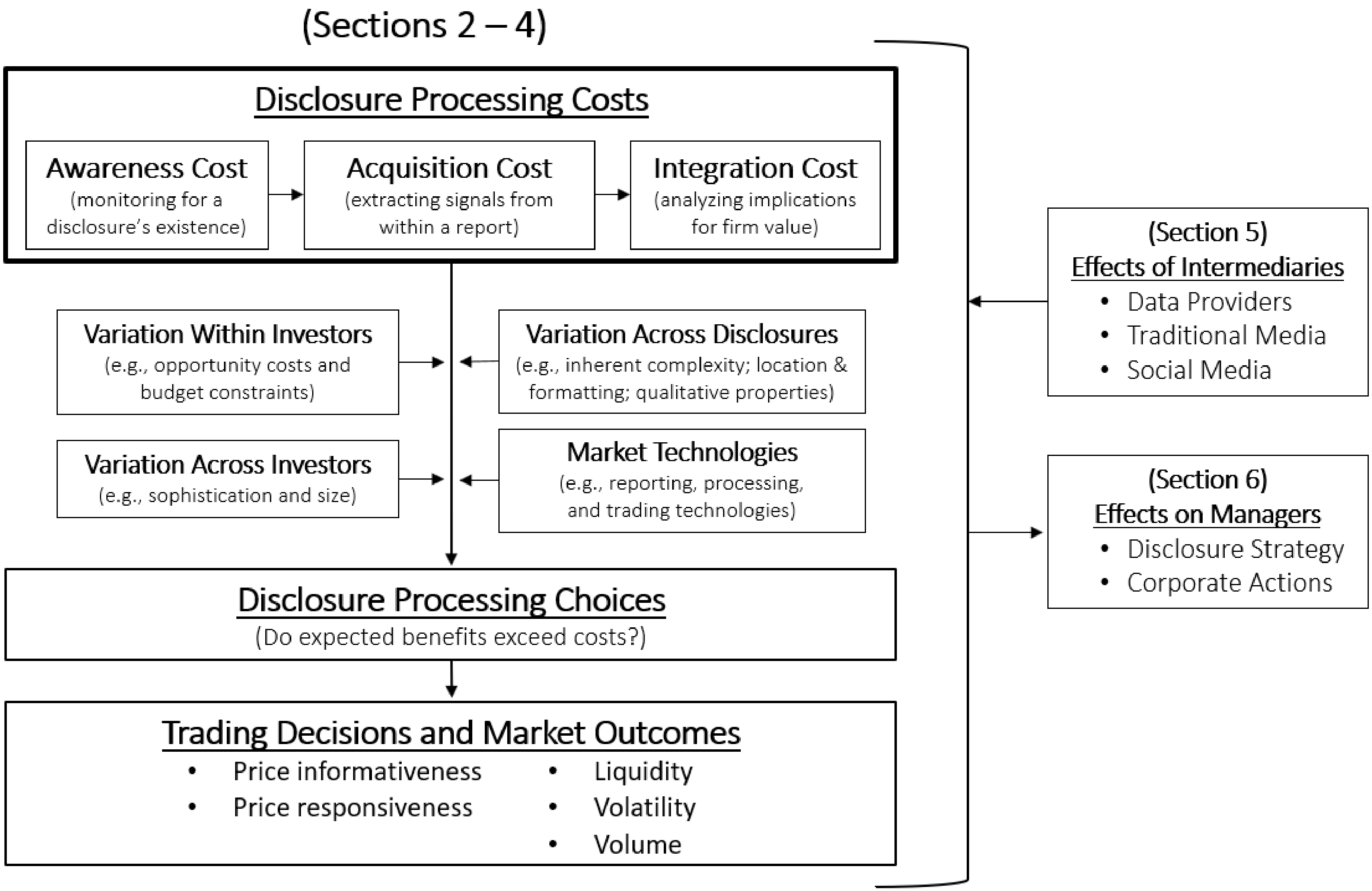


Figure 2: Analytical Studies Relevant to Disclosure Processing Costs

This figure provides key analytical studies relevant to understanding disclosure processing costs and their potential effect on market outcomes. We separate the studies by class of models, first identifying the most related type of processing cost and then the market outcomes the models speak to (whether they explicitly model them or we interpret natural implications). In some cases, the costs in the model have characteristics of multiple cost types.

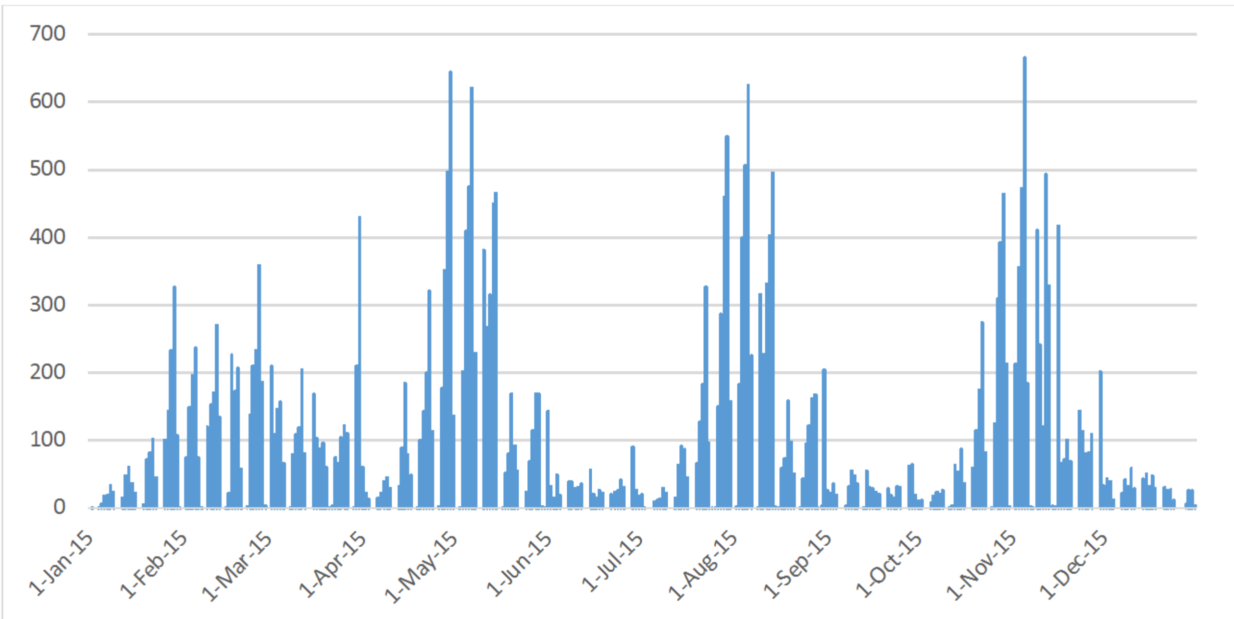
	Classic Rational Models			
	Perfect Competition	**Imperfect Competition**	**Rational Inattention Models**	**Behavioral Models**
Processing Cost				
Awareness				Harrison & Kreps 1978; Harris & Raviv 1993; Hirshleifer & Teoh 2003; Scheinkmann & Xiong 2003; Peng & Xiong 2006; DellaVigna & Pollet 2009; Banerjee et al. 2009; Banerjee & Kremer 2010, Biais et al. 2010; Hirshleifer et al. 2011; Eyster et al. 2019
Acquisition	Diamond 1985; Grossman & Stiglitz 1980; Goldstein & Yang 2017	Kyle 1989; Fishman & Hagerty 1989, 1992; Kim & Verrecchia 1994	Fischer & Heinle 2018; Chen et al. 2018b	
Integration	Hellwig 1980, Verrecchia 1982a,b; Indjejikian 1991; Kim & Verrecchia 1991a,b; Goldstein & Yang 2017	Bushman et al. 1996; Banerjee & Breon-Drish 2018; Avdis & Banerjee 2018	Sims 1998, 2003, 2010; Veldkamp 2006, 2011; Peng 2005; Reis 2006; Van Nieuwerburgh & Veldkamp 2009, 2010; Mackowiak & Wiederholt 2009; Duffie 2010; Kacperczyk et al. 2016; Jiang & Yang 2017; Chen et al. 2018b	
Market Outcome				
Price Informativeness	Grossman & Stiglitz 1980; Verrecchia 1982a,b; Vives 2010; Goldstein & Yang 2017; Andrei et al. 2019	Fishman & Hagerty 1992a,b		Scheinkmann & Xiong 2003
Price Responsiveness	Grossman & Stiglitz 1980; Verrecchia 1982a,b; Kim & Verrecchia 1991a,b; Vives 2010; Goldstein & Yang 2017; Andrei et al. 2019		Duffie 2010; Sims 1998, 2003, 2010; Veldkamp 2006, 2011; Peng 2005; Reis 2006; Van Nieuwerburgh & Veldkamp 2009, 2010; Mackowiak & Wiederholt 2009; Kacperczyk et al. 2016; Jiang & Ming 2017; Fischer & Heinle 2018	Hirshleifer & Teoh 2003; Hong & Stein 2007; DellaVigna & Pollet 2009; Banerjee et al. 2009; Biais et al. 2010; Hirshleifer et al. 2011
Liquidity	Glosten & Milgrom 1985; Vives 2010; Goldstein & Yang 2017	Kyle 1985; Kyle 1989; Fishman & Hagerty 1992a,b; Kim & Verrecchia 1994; Bushman et al. 1996; Avdis & Banerjee 2018		

Volatility	Vives 2010; Goldstein & Yang 2017	Kyle 1985; Kyle 1989; Fishman & Hagerty 1989, 1992; Kim & Verrecchia 1994; Avdis & Banerjee 2018	Fischer & Heinle 2018	Banerjee et al. 2009; Banerjee 2011; Eyster et al. 2018
Volume	Kim & Verrecchia 1991a,b; Vives 2010	Kim & Verrecchia 1994; Avdis & Banerjee 2018		Harrison & Kreps 1978; Hong & Stein 2007; Banerjee et al. 2009; DellaVigna & Pollet 2009; Banerjee & Kremer 2010; Hirshleifer et al. 2011; Banerjee & Green 2015
Other Relevant Papers	Hellwig 1980; Diamond 1985	Kyle 1985; Myatt & Wallace 2012		

Figure 3: Earnings Announcement Firms' Trading Volume on Busy Announcement Days

See the Appendix for sample and variable specifications. Panel A shows the number of Compustat firms announcing quarterly earnings each day in 2015. The left axis of Panel B plots abnormal firm-level trading volume for firms over 2006 through 2016 based on quintiles of EAs per day for all firms, S&P 500 firms, S&P 100 firms, and Dow Jones 30 firms. Quintiles are calculated by year. Data for Panel B are provided in Table 1. The right axis of Panel B (i.e., dotted line) plots average daily total market trading volume, in $billions, for days in each quintile.

Panel A: Earnings Announcements Per Day During 2015



Panel B: Firm-Level Abnormal Trading Volume by Quintile of Busy Days

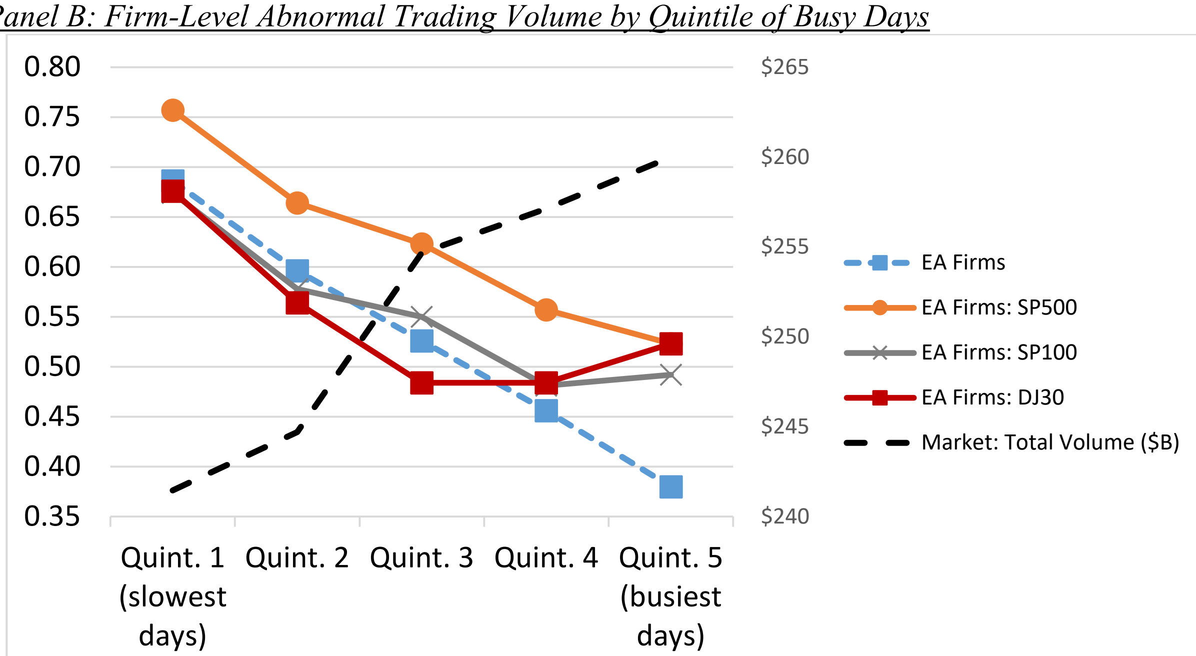


Table 1: Disclosure Processing for Announcing Firms on Busy Earnings Announcement Days

See the Appendix for sample and variable specifications. All analyses are presented by quintile of daily "busyness," defined as the number of Compustat firms announcing earnings on that day. Quintiles are calculated by year. Panel A presents average firm-level abnormal trading volume for the complete sample, S&P 500 firms, S&P 100 firms, and Dow Jones 30 firms. Univariate tests assess the difference between the fifth and first deciles. The last row presents tests of differences including firm and calendar year-quarter fixed effects. Panel B presents analyses of common measures of investor activity. Panel C presents variables based on intermediaries' activities. Panel D presents market outcome measures. ***, **, * indicates significance at 1%, 5%, and 10%, based on standard errors clustered by firm and date.

Panel A: Abnormal Trading Volume

	Sample of EA Firms			
Earnings Announcements Per Day	**All Firms**	**S&P 500**	**S&P 100**	**Dow Jones 30**
Quintile 1 (avg. = 81)	0.686	0.757	0.674	0.676
Quintile 2	0.596	0.664	0.578	0.564
Quintile 3	0.526	0.623	0.550	0.484
Quintile 4	0.456	0.557	0.481	0.484
Quintile 5 (avg. = 569)	0.380	0.523	0.492	0.523
Difference, (Q5 minus Q1):	**-0.306**	**-0.234**	**-0.182**	**-0.153**
	[-13.15]* **	**[-9.20]*** **	**[-4.48]*** **	**[-2.04]** **
Q5 minus Q1, with firm and year-quarter fixed effects:	**-0.207**	**-0.135**	**-0.106**	**-0.075**
	[-15.93]* **	**[-7.54]*** **	**[-3.63]*** **	**[-1.83]* **

Panel B: Measures of Investor Activities (all firms)

EAs Per Day	**Abnormal EDGAR Downloads**	**Abnormal Google Ticker Searches**	**Abnormal Bloomberg Attention**	**Abnormal Retail Trade Volume**
Quintile 1 (avg. = 81)	0.473	0.153	0.824	0.106
Quintile 2	0.353	0.137	0.818	0.078
Quintile 3	0.318	0.107	0.820	0.068
Quintile 4	0.263	0.087	0.777	0.063
Quintile 5 (avg. = 569)	0.245	0.088	0.754	0.058
Difference, (Q5 minus Q1):	**-0.228**	**-0.065**	**-0.070**	**-0.048**
	[-11.73]* **	**[-6.61]*** **	**[-3.23]*** **	**[-10.29]*** **
Q5 minus Q1, with fixed effects	**-0.208**	**-0.033**	**-0.041**	**-0.036**
	[-15.16]* **	**[-4.33]*** **	**[-3.42]*** **	**[-13.62]*** **

Panel C: Measures of Intermediary Activity (all firms)

EAs Per Day	Media: News Articles	Media: News Flashes	Analysts: Forecasting Likelihood	Analysts: Forecasting Delay	Data Provider: IBES Update Delay	Social Media: Twitter Activity
Quintile 1 (avg. = 81)	0.577	1.544	81.290	7.454	4.000	1.377
Quintile 2	0.467	1.497	81.060	7.532	4.150	1.158
Quintile 3	0.399	1.505	81.312	7.455	4.218	1.048
Quintile 4	0.338	1.443	79.006	8.859	4.334	0.797
Quintile 5 (avg. = 569)	0.267	1.403	77.865	9.215	4.570	0.834
Difference, (Q5 minus Q1):	**-0.310**	**-0.141**	**-3.425**	**1.761**	**0.570**	**-0.543**
	[-11.65]* **	**[-6.04]*** **	**[-5.45]*** **	**[6.22]*** **	**[4.41]*** **	**[-7.36]*** **
Q5 minus Q1, with fixed effects	**-0.098**	**-0.024**	**-0.706**	**0.689**	**0.449**	**-0.318**
	[-14.25]* **	**[-3.78]*** **	**[-2.17]** **	**[4.05]*** **	**[12.39]*** **	**[-9.65]*** **

Panel D: Market Outcome Measures (all firms)

EAs Per Day	(i) TAQ Abnormal Spread	(ii) CRSP Abnormal Spread	(iii) TAQ Abnormal Depth	(iv) TAQ Abnormal Impact	(v) CRSP Abnormal Impact	(vi) Earnings Response Coefficient	(vii) Post Earn. Announce. Drift	(viii) Intra-Period Efficiency	(ix) TAQ Abnormal Volatility	(x) CRSP Abnormal Volatility
Quintile 1 (avg. = 81)	0.071	-0.056	0.053	1.264	-0.413	1.020	0.242	0.523	1.081	0.976
Quintile 2	0.079	-0.060	0.049	1.302	-0.342	0.927	0.102	0.526	1.024	0.911
Quintile 3	0.117	-0.026	0.023	1.347	-0.249	0.950	0.307	0.509	1.044	0.917
Quintile 4	0.117	-0.016	0.023	1.335	-0.253	0.919	0.356	0.487	0.973	0.778
Quintile 5 (avg. = 569)	0.130	0.010	-0.006	1.381	-0.235	0.896	0.477	0.467	0.951	0.672
Diff., (Q5 minus Q1):	**0.059**	**0.066**	**-0.059**	**0.117**	**0.178**	**-0.124**	**0.235**	**-0.056**	**-0.130**	**-0.304**
	[3.68]* **	**[4.91]*** **	**[-4.21]*** **	**[2.77]*** **	**[6.30]*** **	**[-3.24]*** **	**[2.43]** **	**[-5.66]*** **	**[-2.77]*** **	**[-5.98]*** **
Q5 minus Q1, with f.e.	**0.049**	**0.055**	**-0.040**	**0.108**	**0.150**	**-0.130**	**0.215**	**-0.019**	**-0.077**	**-0.142**
	[4.41]* **	**[5.57]*** **	**[-5.37]*** **	**[3.23]*** **	**[9.51]*** **	**[-3.30]*** **	**[2.35]** **	**[-3.05]*** **	**[-3.14]*** **	**[-5.69]*** **