ALGORITHMIC ROUTINES AND DYNAMIC INERTIA:

HOW ORGANIZATIONS AVOID ADAPTING TO CHANGES IN THE ENVIRONMENT

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ABSTRACT

Organizations often fail to adequately respond to substantive changes in the environment, despite widespread implementation of algorithmic routines designed to enable dynamic adaptation. We develop a theory to explain this phenomenon based on an inductive, historical case study of the credit rating routine of Moody's, an organization that failed to adapt to substantial changes in its environment leading up to the 2008 financial crisis. Our analysis of changes to the firm's algorithmic credit rating routine reveals mechanisms whereby organizations dynamically produce inertia by taking actions that fail to produce significant change. Dynamic inertia occurs through bounded retheorization of the algorithmic model, sedimentation of assumptions about inputs to the algorithmic model, simulation of the unknown future, and specialized compartmentalization. We enable a better understanding of organizational inertia as a sociomaterial phenomenon by theorizing how—despite using algorithmic routines to improve organizational agility—organizations dynamically produce inertia, with potentially serious adverse consequences.

Keywords: Organizational Inertia; Routines; Algorithms; Artifacts; Financial Crisis; Sociomateriality; Performativity

INTRODUCTION

Organizations often struggle to adapt to environmental changes, displaying paralyzing inertia in the face of substantive threats (Hannan and Freeman, 1984). For example, technology firms such as Xerox and Polaroid failed to adapt to a dynamically shifting technological environment by continuing to focus attention and resources on developing their core technologies (e.g., Tripsas and Gavetti, 2000). Similarly, financial firms such as Bear Stearns and Washington Mutual failed to adapt to changes in the economic environment by adhering to existing practices (Lounsbury and Hirsch, 2010; Pozner et al., 2010). The consequences of failing to adapt to environmental changes are significant, often leading to organizational collapse, and in the case of the financial crisis, considerable harm to society.

Scholars have developed several explanations for organizational inertia. First, entrenched patterns of activity are difficult to change because they generate structural inertia by creating "competency traps" (Levitt and March, 1988) or "core rigidities" (Leonard-Barton, 1992). Second, firms may follow established organizational resourcing patterns that fail to prioritize investments in new technologies or capabilities (Christensen and Bower, 1997; Gilbert, 2005). Third, organizational decision-makers can be constrained by existing cognitive frames that prevent them from either observing or effectively responding to a changing environment (Lant et al., 1992; Tripsas, 1997; Tripsas and Gavetti, 2000). However, these "social" explanations often neglect evidence that artifacts constrain, shape, and guide organizational processes and routines (Pollock and Cornford, 2004; Schulz, 2008).

This lack of focus on sociomaterial dynamics is particularly problematic when considering recent trends of organizations deploying a specific kind of artifact—namely, algorithms—to respond to dynamic environmental conditions (Faraj et al., 2018) in the daily enactment of their routines. Unlike other artifacts such as tools or cultural symbols, artifacts that rely on mathematical algorithms and models can rapidly incorporate environmental changes as they unfold and stimulate "adaptive action" (Simon, 1970). For instance, organizations use digital data to represent the environment by analyzing sentiments in social media to understand reputational changes in the market in real time (Moe and Schweidel, 2017). Online service providers like Tripadvisor, LinkedIn, or Last.fm rely heavily on algorithms to monitor customers and the broader environment in real time and develop new value

propositions for stakeholders (Alaimo and Kallinikos, 2017, 2021). These organizations use predictive models to account for dynamic environmental changes when making tactical and strategic organizational decisions (Davenport, 2014, 2018).

Logically, organizations that use algorithmic routines—sociomaterial assemblages of actors, artifacts, theories, and actions that utilize algorithms to perform repetitive, recognizable patterns of interdependent actions—to automate decisions and perform sociomaterial calculations (Feldman and Pentland, 2003; Glaser, Pollock, et al., 2021) should be able to effectively respond to changes in the environment. Typically, organizations are aware of such changes (e.g., Gilbert, 2005; Sull, 1999) and thus should be able to modify algorithmic models to address them. Yet, inertia often prevails in organizations, suggesting that algorithmic routines may generate organizational inertia through the design and enactment of algorithms within the performance of such assemblages (Deleuze and Guattari, 1987; Orlikowski and Scott, 2008). Thus, we ask: *How do organizations produce inertia despite using algorithmic routines that take environmental changes into account?*

To investigate this question, we conducted a historical case study of Moody's, a credit rating agency that uses algorithmic models to represent and react to environmental changes. Moody's exemplifies an extreme case (Pettigrew, 1990) of inertia produced using algorithmic models, in that the firm failed to account for environmental changes in its credit rating routine in the years leading up to the 2008 financial crisis and had to significantly downgrade many highly-rated securities. The Financial Crisis Inquiry Commission (FCIC) provided us with extensive, accurate data about the design and use of Moody's algorithmic credit rating models and the firm's corresponding credit rating routine. Specifically, we studied Moody's credit rating routine for residential mortgage-backed securities (RMBSs) and its evolution over the years leading up to the financial crisis. We zoomed in (Nicolini, 2009) on the design and use of two algorithmic credit rating models between 2000 and 2007 to show how changes to the model and the credit rating routine produced inertia.

Our findings show how inertia developed dynamically as Moody's implemented algorithmic routines that enabled the firm to absorb environmental changes while continuing to pursue its goals. Our theoretical model of dynamic inertia includes four mechanisms: bounded retheorization (i.e., making minor modifications to the original algorithmic model in response to substantive environmental

changes); sedimentation of assumptions (i.e., recognizing change, but failing to change data inputs); simulation of the unknown future (i.e., relying on algorithmic models to account for environmental changes in the predicted future environment); and specialized compartmentalization (i.e., actors in distinct organizational roles taking responsibility for different parts of the algorithmic model). As changes in the environment unfold, these mechanisms and the algorithmic routine may absorb them, just as a spring absorbs a stretch. However, as tensions escalate, the algorithmic routine becomes increasingly stretched, ultimately leading to a dramatic breakdown akin to a coil snapping.

We contribute to the management literature by elaborating a theory of dynamic inertia that explains how inertia develops not only through cognitive frames, resourcing patterns, or structural rigidities, but also dynamically through the performance of algorithmic routines. Specifically, we trace the origins of inertia to the design and use of algorithms in the daily enactment of organizational routines in contexts involving substantive environmental changes. Our findings have significant implications for modern organizations trying to overcome inertia while relying on algorithmic routines. We also contribute to literatures focused on routine dynamics and the 2008 financial crisis.

THEORETICAL BACKGROUND

Organizational Inertia as a Social Phenomenon

Organizational inertia is broadly defined as the inability to enact internal changes in the presence of significant external changes (Gilbert, 2005). Such inertia is a result of path dependency due to organizational success (Leonard-Barton, 1992; Lieberman and Montgomery, 1988; Miller, 1994) based on a formula that shapes processes, competencies, relationships, values, and resource investment patterns (Burgelman, 2002; Sull, 1999).

Some authors have discussed how inertia develops in the face of environmental dynamism due to structural rigidities. Past organizational success may give rise to what Levitt and March (1988) called competency traps, whereby core competencies that yielded favorable outcomes in the past hinder a firm's ability to respond to new environmental challenges. Once a reliable source of action, core competencies may become core rigidities that impede responses to emerging challenges (Leonard-Barton, 1992). For example, Burgelman (2002) showed that although Andy Grove's strategy of

focusing almost exclusively on core microprocessors enabled Intel to dominate the PC market for over a decade, it also generated inertial forces that, like a creosote bush which poisons the surrounding ground, constrained business development in other areas and hampered the company's responsiveness to changing market demands. Scholars (e.g., Gilbert, 2005) have introduced the concept of routine rigidity—whereby "patterns of behavior stabilize as formal structures and routines become institutionalized over time" (Sørensen and Stuart, 2000, p. 86)—as a core mechanism that explains structural inertia. Such accounts resonate with the notion in institutional theory that path dependency impedes organizations from making meaningful changes to their practices and processes (eg. Collinson and Wilson, 2006; Sydow, 2009, 2020).

Other scholars have argued that organizational resources may create inertia by locking firms into commitments that are hard to change. Organizations with greater stocks of historic resources are less likely to engage in adaptive change (Kraatz and Zajac, 2001). For example, Christensen and Bower (1997) argued that in the presence of radical environmental changes, resource investment patterns persist as firms continue to search for resources that are compatible with what they own (see also Greve, 2011; Lant et al., 1992). Unwilling to risk their careers, managers perpetuate existing resource allocation patterns (Gilbert, 2005). Therefore, paradoxically, critical resources are not diverted to new business areas that may help mitigate threats to the core business (Burgelman, 2002).

Finally, managers' established cognitive frames may result in inertia even when corrective measures are taken in response to environmental threats. Well-documented evidence suggests that cognitive frames provide "mental templates that individuals impose on an information environment to give it form and meaning" (Walsh, 1995, p. 281). Amidst uncertainty and a changing environment, actors may experience anxiety and mobilize learned responses (Greve, 2011). Managers may treat environmental changes as temporary and use scarce resources as buffers against changes that they deem unfavorable (Miller, 1994). Subsequently, responses to environmental dynamism, such as scanning, search, and experimentation (Lant and Montgomery, 1987; March, 1991), and organizational adaptation (Levinthal, 1991) become limited. For instance, examining the case of Polaroid, Tripsas and Gavetti (2000) showed how commitments to mental models associated with the

previously successful business strategy prevented the firm from adapting to fundamental technological changes and developing much-needed new capabilities.

Although traditional understandings of inertia seem to suggest a failure to perceive environmental changes, findings show that organizations do make attempts to adapt. Rather than assuming path dependency (Vergne, 2013), some scholars have explored how inertia is generated while organizations vigorously enact changes in response to environmental dynamism. Challenging the view that companies avoid change or only commit to changes that are compatible with their existing resourcing patterns, mental frames, and/or structures, some scholars have argued that even organizations that invest in new resources and technologies in the face of substantive environmental changes may be subject to inertia. Stieglitz et al. (2016, p. 1862) even suggested that inertia can be seen as an "outcome of an adaptive learning process in dynamic environments." Nevertheless, the prevailing argument is that inertia emerges because actors remain committed to their worldviews and environmental perceptions. For example, Gilbert (2005) argued that despite actively investing in new resources associated with digital printing (thereby avoiding resource rigidity), publishing companies failed to adapt because they remained committed to pre-existing core business practices. Similarly, Sull (1999) argued that despite Firestone's substantial investments in radial technology, processes and competencies associated with the organization's culture and past success produced inferior results in the new environment.

Organizational Inertia, Artifacts and Routine Dynamics

Whereas traditional understandings of inertia offer valuable insights, they primarily rely on social accounts that highlight the role of cognitive frames or subjective structural influences on extant patterns of decision-making when responding to environmental changes. However, insights offered by actor-network theory (ANT), sociology of finance, and information system theories seriously challenge these purely social explanations and call for attending to materiality in explaining any social phenomenon (D'Adderio, 2021; Feldman and Orlikowski, 2011).

One way artifacts can induce inertia is by establishing the "power of default," which prevents the adaptation and customization of routines (Pollock and Cornford, 2004) and results in their "stay[ing]

on track" (Schulz, 2008). Artifacts can also constrain and enable routine performances by representing espoused patterns of action (Bertels et al., 2016; D'Adderio, 2008). For example, D'Adderio (2008) showed that artifacts both represent and prescribe routine performance, as actors who pursue specific agendas inscribe their community-specific worldviews into artifacts to reinforce desired actions in future iterations of the routines; Cacciatori (2012) showed how designing a new system of artifacts in a design firm can safeguard the status quo by absorbing organizational changes to preserve extant truces; and Lazaric and Denis (2001) found that adopting ISO norms and introducing new technological artifacts hinders future restructuring and reconfiguration by establishing a long-lasting organizational memory (D'Adderio and Safavi, 2021).

Organizational inertia may also result from materiality through what may be referred to as "scene-setting" (Steele, 2021). One may argue that Polaroid failed not only due to prevailing mental frames but also because the material configuration of its business model revolved around instant physical photos and the associated technological ecosystem (Tripsas and Gavetti, 2000). Similarly, the failure of traditional publishing companies to adapt to new environments (Gilbert, 2005) may be ascribed to how certain machinery is used and how production is sequenced in the publishing industry, which may hinder or slow down responses to environmental changes.

With its roots in ANT and structuration theory, routine dynamics theory (D'Adderio, 2008, 2021; Glaser, Valadao, et al., 2021) provides a promising avenue for exploring how dynamics between the social and the material produce organizational inertia. As a unit of analysis, routines cut across humans and non-humans relationally, where actions or narrative fragments entangled with humans and non-humans are the basis for analysis (e.g., software support specialists enact routines through materials such as telephones and call-tracking databases; Pentland and Rueter, 1994). Rather than viewing actors as ontologically separate from artifacts—i.e., humans who do things with artifacts— routine dynamics scholars study sociomaterial assemblages of actors, artifacts, theories, and actions (D'Adderio, 2008; D'Adderio et al., 2019; Glaser, 2017; Glaser, Valadao, et al., 2021; Pentland et al., 2017). These artifacts can alternately or distinctly function as either passive intermediaries or active mediators in routine enactment (Aroles and McLean, 2016; Sele and Grand, 2016).

Algorithmic Routines, Environment, and Performativity

Algorithms are artifacts that are particularly germane for understanding, predicting, and responding to environmental changes and uncertain futures (Alaimo and Kallinikos, 2017; Glaser, Pollock, et al., 2021). By exploiting big data and deploying sophisticated analytical techniques, organizations are increasingly relying on algorithms to predict the future (Davenport and Patil, 2012; Pachidi et al., 2021) in many domains, including purchasing (Alaimo and Kallinikos, 2017, 2021), consumer behavior (Faraj et al., 2018), and criminal activity (Glaser, 2017). Algorithmic models are particularly fundamental to how organizations deal with environmental risk and uncertainty. Organizations actively evaluate and manage risks (Hardy and Maguire, 2016; Maguire and Hardy, 2012) while attempting to tame open and disruptive futures (Wenzel et al., 2020). To avoid incalculability and determine the best course of action, "rational" actors in the financial market develop measures, methodologies, and models to calculate risk (Carruthers, 2013; see also Beunza, 2019; Cabantous et al., 2010). For example, financial institutions have developed credit rating models that predict actors' future behavior and the future performance of financial products (Fourcade and Healy, 2017; Kiviat, 2019).

Importantly, models do not simply represent, but also perform and enact social reality (Orlikowski and Scott, 2008). As Barad (2003) demonstrated, any attempts to represent social reality are flawed, as "apparatuses are not mere static arrangements … but rather … dynamic (re)configurings of the world, specific agential practices/intra-actions/performances through which specific exclusionary boundaries are enacted. Apparatuses have no inherent 'outside' boundary" (p. 816). Through these artifacts, actors realize, imagine, engage, and even make the future (Comi and Whyte, 2018; Wenzel et al., 2020). They "give form to an immaterial future through lines, materials and shapes that can be interrogated in response to present and past constraints" (Comi and Whyte, 2018, p. 1078). Whereas artifact design is often a political process that may privilege select social actors (D'Adderio, 2008), artifacts constantly evolve and remain exposed to interpretation and change while in use (Ewenstein and Whyte, 2009). As such, algorithmic artifacts are not a neutral representation of the environment. Rather, they engage with data, "perceive" and "represent" the environment, and predict the future in ways that are largely intertwined with their design and use (Alaimo and Kallinikos, 2021).

Consequently, artifacts create possibilities for actors in complex ways (D'Adderio, 2011). Whereas artifacts enable social actions by creating certain pathways for actors' conduct through framing, actors may diverge from the prescribed objective or even reject it through overflowing. Jones (1998, p. 299) called this relationship between the social and material "double-mangling" whereby "the outcome of technology development and use cannot be reliably predicted, as both the technical and social are mangled together in the process to produce specific, situated instantiations."

Because the design and enactment of algorithms are entangled in organizational routines (Glaser, Valadao, et al., 2021; Pentland and Feldman, 2008), organizations can use algorithms to incorporate measures of environmental change into their decision-making routines. For instance, in determining whether to check a credit card transaction for fraud, a consumer credit rating model might integrate a variable that measures total unemployment claims in the area, thereby accounting for environmental changes (Siddiqi, 2005). Similarly, Glaser (2017) showed how a law enforcement agency used a game-theoretic algorithm to dynamically randomize patrol routines. Law enforcement officers worked with algorithmic experts to develop a program that prioritized coverage of specific train stations based on environmental changes such as fluctuating passenger volume or increased crime in particular areas. By modeling and mapping parameters, organizations can change their routines in response to the environment, making it challenging to explain inertia. Consequently, we ask: *How do organizations produce inertia despite using algorithmic routines that take environmental changes into account?*

RESEARCH METHODS

We investigated our research question by conducting a historic, inductive case study of Moody's, an organization that develops and sells credit ratings for financial instruments such as RMBSs. Moody's is an ideal extreme case (Pettigrew, 1990) of an organization that generated inertia in the face of substantial environmental changes for three reasons. First, the competitive environment of credit rating organizations changed dramatically between 1996 and 2008 in response to events such as the repeal of the Glass-Steagall Act in 1999, and the introduction of new financial products, such as more complex and riskier securities and novel investment instruments (e.g., collateralized debt obligations or CDOs). Second, beginning in 2000, Moody's responded to these environmental changes by modifying the design and use of an environmental monitoring and modeling algorithm. This artifact

was incorporated into the firm's credit rating routine, enabling organizational actors to consider FICO[1] scores for individual borrowers and simulate the macroeconomic environment. Finally, we were able to access unusually rich historical data in comprehensive investigation records, including an exhaustive inquiry conducted by the FCIC.

Empirical Context

Our empirical context is the secondary financial market for U.S. residential mortgages. In this industry, lenders extend home mortgage loans to borrowers based on assessments of their ability to repay. Often, interest rates and loan amounts are determined by characteristics of individual borrowers (e.g., income level, credit history) and properties (e.g., loan-to-value ratio). Once loans are granted, issuing companies aggregate or "pool" thousands of mortgages together to create investment vehicles known as RMBSs. Below, we describe significant changes in this environment in the period leading up to the 2008 financial crisis. Then, we describe the algorithmic routines used by Moody's, a credit rating agency that generated credit ratings for a significant portion of RMBSs during our study period.[2]

Changes in the Secondary Financial Market

Since the early 1990s, many significant changes have affected the secondary financial market. Prior to 2000, commercial banks were the primary originators of residential mortgage loans. The subprime mortgage market was valued at $70 billion, and only 40% of those loans were securitized. Mortgage pools had two primary tranches: a safer one, which received payments first, was insured, and typically was guaranteed; and a riskier one, which received payments after the first tranche had been paid. The latter tranche was not guaranteed and was usually held by its originator (i.e., was not traded in the market, sometimes called "originate-to-hold"). More than 98% of mortgages had extensive documentation, and there were almost no impairments or defaults (e.g., there were 12 incidents in 1999). However, in 1999, the repeal of the Glass-Steagall Act, which had banned commercial banks and investment banks from entering each other's lines of business, created opportunities for commercial banks to pool and tranche mortgage loans, and for investment bankers to originate loans through refinancing.

As investment banks entered the market for loans, the nature of the subprime mortgage market changed—by 2000, the value of this market had risen to $160 billion, and the percentage of securitized loans had increased to 56%. Low interest rates and the introduction of innovative investment vehicles fueled additional investment and rendered formerly high-risk subprime loans increasingly attractive. For instance, in 2002, CDOs were introduced as vehicles for refinancing riskier RMBSs and played a significant role in the expansion of the subprime market. By pooling and tranching RMBSs, CDOs made highly risky investments seem attractive and safe. There was a mild increase in low- or no-documentation mortgages, and impairment incidents doubled, but remained low. During this period, regulators focused on the Enron scandal; the aim of the Sarbanes-Oxley Act of 2002 was to protect investors from fraudulent financial reporting by corporations.

These trends amplified in the time leading up to the financial crisis. Subprime mortgages became the fastest growing market, reaching $520 billion by 2004 (20.9% of the total market); 66% of these loans were securitized, and originate-to-distribute practices prevailed. Importantly, 27% of mortgages required low or no documentation, and the number of impairment incidents increased to 1,504 by 2007. We summarize these changes in the financial market environment in Table I.

INSERT TABLE I ABOUT HERE

Moody's Credit Rating Model and Credit Rating Routine

Investors rely on credit rating agencies such as Moody's to evaluate the risk associated with complex, aggregated financial instruments (Langohr and Langohr, 2009). Moody's evaluates these securities by enacting a credit rating routine using an artifact: a credit rating model (SIFMA, 2008). First, Moody's receives a "loan tape"—typically, a spreadsheet prepared by issuers, with individual loan-level data underlying an aggregated pool of loans. Second, an analyst inputs the information from the loan tape into Moody's proprietary rating model which generates two values: expected losses for the mortgage pool and the loss coverage protection required for a AAA rating (i.e., the credit enhancement level).[3] Third, using these values, the analyst develops a rating recommendation for the pool, typically by communicating directly with the issuer to clarify details regarding the proposed financial instrument

and to discuss the potential implications of each attribute in the proposed deal. Fourth, the analyst presents the financial instrument to a rating committee composed of other analysts and managers within Moody's who discuss the deal, determine the final expected loss and loss coverage values, and vote on the ultimate letter rating. Fifth, before issuing and publishing the ratings, Moody's asks for an updated loan tape that includes the tranching structure, which is run through the model again to ensure that no material changes were made to the underlying loans during the rating period. Finally, Moody's publicly posts the rating and conducts ongoing surveillance of rated products by monitoring their performance in the market and responding to significant changes by either upgrading or downgrading the original ratings. We summarize Moody's credit rating routine in Table II.

INSERT TABLE II ABOUT HERE

Moody's Responses to Environmental Changes and Evidence of Organizational Inertia

During the years leading up to the financial crisis, Moody's made a series of changes to its rating approach. Development of "Moody's Mortgage Metrics" or the M3 algorithmic model began in 2000, with marketing beginning in 2003. Subsequent development of a modified model called M3 Subprime began in 2004, with marketing beginning in 2006. However, in July 2007, Moody's downgraded 399 subprime mortgage-backed securities issued the previous year. Three months later, Moody's downgraded another 2,506 tranches ($33.4 billion); by mid-2008, the firm had downgraded 83% of AAA-rated mortgage-backed security tranches. These downgrades contributed significantly to the financial crash, as they reflected the scale of the crisis in the sector (FCIC, 2011). In 2009, the U.S. government commissioned the FCIC to "examine the causes, domestic and global, of the current financial and economic crisis in the United States" (FCIC, 2011, p. 416). The commission published its report in February 2011, ascribing the crisis to the "collapse of the housing bubble fueled by low interest rates, easy and available credit, scant regulation, and toxic mortgages" (p. xvi).

Data Collection

To investigate our research question, we adopted a historical case study approach to explore how organizational inertia is generated and maintained through routine enactment (Hargadon, 2015;

Kremser and Schreyögg, 2016; Mutch, 2016). First, we collected reports of government investigations of the financial crisis, which provided particularly insightful and detailed information about Moody's and its credit rating routine. Two reports provided particularly rich data: the 662-page report from the FCIC based on testimonies of more than 700 witnesses (FCIC, 2011 p. xi) and a 648-page report from the Senate Permanent Subcommittee on Investigations (2011). We supplemented these data with data from an investigation of select credit rating agencies performed by the U.S. Securities and Exchange Commission (SEC), as well as a report from the Securities Industry and Financial Markets Association (SIFMA) Credit Rating Agency Task Force, which yielded useful information about Moody's credit rating routine (SEC, 2008; SIFMA, 2008).

These investigations revealed multiple types of data that were conducive to our analysis. In most cases, we were able to access written testimonies submitted to the courts, as well as transcripts of oral testimonies. The FCIC also interviewed many employees of leading U.S. financial services firms, including 19 existing or former employees of Moody's. These in-depth interviews ranged from 90 to 180 minutes. Whilst many of these interviews were fully transcribed in public reports, some were only available in audio format, which we then transcribed. These interviews were comprehensive, probing, and detailed, thereby enabling us to effectively reconstruct changes to Moody's credit rating routine during the years leading up to the financial crisis. We also accessed a range of documents from Moody's, including rating committee memos, internal communications, and emails which amounted to more than 600 pages. In both the Senate and FCIC investigations, witnesses predominantly testified under oath, and when interviews took place outside courtrooms, informants were warned about the implications of obscuring the truth, significantly constraining the possibility that they would provide misleading information.

To complement these sources, we gathered historical data about Moody's, including sensegiving materials such as the company's website, annual reports, press releases, etc. We also conducted searches on LexisLibrary (formerly Lexis-Nexis) to capture all articles about Moody's published in the *Wall Street Journal*, the *New York Times*, and the *Financial Times* relevant to our study period. Given their richness in detail, these sources proved extremely valuable to our historical analysis of the

rating routine (Mutch, 2016) and enabled us to retrospectively reconstruct changes to Moody's credit rating model and corresponding routine in the years leading up to the financial crisis.

Data Analysis

Given the importance of developing a customized analytical approach for a specific qualitative research project (Gehman et al., 2018), we followed Langley's (1999) recommendation to obtain a sense of the temporal dynamics associated with our case by constructing a case narrative and timeline of key events. In the first phase, we developed a general timeline depicting two substantial changes in the environment related to Moody's credit rating routine: the repeal of the Glass-Steagall Act in 1999 and the introduction of novel, dramatically different financial instruments with complex tranching structures and risk layering beginning in 2003. These environmental changes stimulated significant growth in the refinancing market and a surge in subprime loans that prompted Moody's to modify the artifacts used in the credit rating routine.

In the second phase, we focused on how two critical artifacts (Nicolini, 2009)—the M3 and M3 Subprime algorithmic models—were developed, modified, and deployed to account for environmental changes during the study period. Through these artifacts, Moody's "modeled" and made sense of its environment and associated changes (Alaimo and Kallinikos, 2021; Hardy and Maguire, 2016). We also analyzed actors' retrospective accounts of the credit rating routine's enactment (Van Maanen, 1979).

In the third phase, we focused on the specific data used by the artifacts to model the environment based on detailed descriptions provided to the FCIC, interviews conducted by social science experts during the FCIC and SEC investigations, and documents and interviews highlighting how these models were used by those who enacted the credit rating routine. We triangulated between interviews and published descriptions to explore different aspects of the design and use of the algorithmic models.

In the final phase, we employed the constant comparative method (Strauss and Corbin, 1990) and engaged in detailed coding to theorize how the algorithmic credit rating routine performances were influenced by environmental dynamics. For both artifacts, we identified similar mechanisms

associated with algorithm design and performance of the algorithmic routine. Driven by insights provided by routine dynamics and assemblage theory (Deleuze and Guattari, 1987; Glaser, Pollock, et al., 2021; Pollock and Cornford, 2004), we aggregated our codes into four themes: bounded retheorization of the algorithmic model, sedimentation of assumptions, simulation of the unknown future, and specialized compartmentalization. Overall, this process enabled us to develop a theory that explains how Moody's dynamically generated inertial outcomes in the face of substantive organizational change, despite using algorithmic routines that considered environmental changes.

FINDINGS

Algorithmic Credit Rating Routine and Adaptation to Environmental Changes

We examined two artifacts developed to systematize and standardize the algorithmic credit rating routine in response to environmental changes. Faced with increased demand for residential mortgages, Moody's increased the efficiency and standardization of the credit rating process and developed the M3 model to rate RMBSs. Later, in response to an unprecedented surge in the subprime market and substantial changes in the composition of market actors, Moody's modified the M3 model and introduced M3 Subprime. We highlight changes to Moody's credit rating model in Table III and describe them below.

INSERT TABLE III ABOUT HERE

Original 1996 Model

Attempting to systematize credit ratings, Moody's introduced a new proprietary methodology called a "factor-based model" in 1996. The objective was to predict an expected loss distribution to help determine the credit rating. Expected loss refers to the overall loss in the mortgage pool in the statistical sense. The model yielded a loan-level default frequency which an analyst would transform into a pool-wide estimate of loss distribution. This estimated loss was used to generate a rating, which was compared with historic data from previously rated pools. This model used historic data (1987–1992) as well as supplementary data from a variety of institutes such as the Mortgage Bankers

Association, Fannie Mae, and Freddie Mac. Predictive factors used in the model emphasized loan-to-value (LTV) ratios less than borrower risk and FICO scores. The rating committee used and periodically updated this model as part of the credit rating routine.

M3 Credit Rating Model

In 2003, in response to growing market needs, Moody's introduced a new artifact into the rating routine: Moody's Mortgage Metrics or M3. Moody's began to develop the algorithmic model in 2000 and introduced it in 2003. Compared to the 1996 model, M3 was a more sophisticated economic model with greater predictive validity. The objective was to generate a pool loss vector using simulation and advanced time series data. Creating simulation models that could project the performance of securities under various economic scenarios was central to how the M3 model worked. M3 incorporated recent historic data on over 500,000 jumbo "A" loans obtained primarily from Loan Performance Inc., enabling Moody's to perform more complex statistical analysis. Moody's believed data quality was better due to increased efficiencies in the industry, particularly in the practices of originators who provided loan-level data. This more sophisticated economic model with greater predictive validity, more fine-grained economic simulation, and refined LTV and borrower characteristics was used to estimate security losses. Outputs included histograms of different characteristics of the pool, expected losses, and loss coverage amounts for loans with AAA ratings. After the algorithmic model was introduced, the credit rating committee increasingly relied on its automated output.

M3 Subprime Model

The M3 Subprime model was based on the M3 model but was specifically calibrated for the idiosyncratic features of subprime loans. Similar to the M3 model, the M3 Subprime model used simulation and advanced time series analysis to generate a pool loss vector for subprime pools "using a unique set of scrubbed data that provide[d] valuable risk metrics at the loan level. The in-depth historic performance data span[ned] 10 years from approximately 2 million subprime loans" (Moody's Archival Document, 2003). Organizational members believed that they "were able to represent causal relationships by modeling each component of loan behavior separately, but integrating them through common economic factors in a simulation" (Roger Stein, 2010, Interview).

The model's multidimensional analysis was believed to better represent the behavior of the mortgage pool by providing "a much more complete picture of the layers of risk present in mortgage portfolios, where the same economic factor can sometimes have competing effects on portfolio losses" (Moody's investor services, 2006 p.1). Credit rating committees used this algorithmic model and M3 for several years.

Although the model initially seemed to work as intended, it eventually failed or "snapped" when it could not effectively respond to environmental changes. We now describe the mechanisms that facilitated the production of inertia.

Mechanisms of Dynamic Inertia

Dynamic inertia occurs when organizations ineffectively adjust algorithmic models to account for substantial environmental changes. Below we present our analysis of the mechanisms that contributed to dynamic inertia: bounded retheorization, sedimentation of assumptions, simulation of the unknown future, and specialized compartmentalization.

Bounded Retheorization

Bounded retheorization occurred as organizational actors made only minor modifications to the algorithmic model in response to substantive changes in the environment. As the environment changed, Moody's continued to model the economy the same way, even during the development of M3. Notwithstanding significant environmental changes (i.e., a growing number of originators and low-quality mortgages, and an unprecedented decline in interest rates), Moody's did not consider the possibility of an economic shock with the magnitude of the financial crisis: "Looking at historical performance through different downturns that had been observed would give some points on a distribution like this [log-normal distribution for losses]" (Jay Siegel, 2010, Interview, p. 72). Moreover, modeling adjustments failed to account for unprecedented growth in the housing market fueled by low interest rates and subprime loans: "Broadly speaking, a full three-year economic history is best at predicting performance in any quarter, with the most recent quarters naturally having the greatest influence" (Moody's Investor Services, 2003, p. 5).

Similarly, analysts made only minor adjustments to the credit rating model based on fluctuations in national house prices. When developing the M3 and M3 Subprime models, Moody's maintained existing causal links between *state-level* housing prices and the estimated probability of a pool-level default without contemplating the possibility of considerable changes in *national* house prices, which had been stable historically. Also, Moody's applied advanced time series modeling to extract predictions about market performance based on historic performance. Despite efforts to standardize, systematize, and streamline the firm's processes, the organization did not fundamentally revise how it modeled the economic environment. For instance, although low interest rates could have resulted in a housing bubble, the use of historic data meant that the model could not capture this possibility as an outlier:

> A first cut for doing a calculation like that would be to look if there's a historical relationship, and then deciding if the historical relationship is one that is robust enough to use as a starting point for the projections going forward. … It's almost like a legal precedent. (Jay Siegel, 2010, Interview)

Moody's responded to changes in the environment by incorporating new quantitative parameters to increase efficiency without questioning or reviewing fundamental assumptions. One major change was the repeal of the Glass-Steagall Act, which enabled different types of financial institutions to enter the RMBS market, magnifying competitive dynamics. For instance, investment banks began offering loans to individual borrowers by introducing new refinancing products, which in turn accelerated growth in the market and demand for additional ratings. These actors fundamentally altered competitive dynamics in the securities market. During the early 2000s, technology and competitive dynamics became increasingly important. As the volume and availability of residential mortgages skyrocketed, lenders and issuers increasingly relied on technology to rate them: "Lenders were producing pool after pool of loans with virtually identical aggregate risk characteristics" (Moody's Investor Services, 2003, p. 1).

Moody's viewed these market changes as a growth opportunity. Given Moody's previous success, the changes to the credit rating routine primarily made it more efficient, rather than more accurate. A

Chief Credit Officer testified: "our years of success rating RMBS may have induced managers to merely fine-tune the existing system—to make it more efficient, more profitable, cheaper, more versatile" (FCIC, 2011, p. 210). The company increasingly relied on quantification methods and parameters, i.e. the embedded algorithm, "to the point of delegating the bulk of the determination of these credit support levels to the model" (Moody's Investor Services, 2003, p. 3).

Likewise, as Moody's responded to the skyrocketing number of subprime loans by developing M3 Subprime, actors adjusted parameters rather than rethinking the original M3 model. To assess borrowers' creditworthiness under various scenarios, Moody's used a model which determined how much loss was likely to come from the excess spread, and captured the loss probability of tranches of subprime loans. However, to derive the loss curve, Moody's used a combination of loss curves based on historic data for prime loans:

> We used, actually, a variety of different loss curves. I think we had something like five different sorts of scenarios that would be run. And the basic loss curve was based on historical performance, just on an average of what we've seen. (David Teicher, 2010, Interview)

Extrapolating loss curves for subprime loans from loss curves for other types of loans clearly misrepresented the environment. There was not a clear understanding of rapid changes regarding market players and growth in the share of subprime mortgages. Even the understanding of what was considered "subprime" was ambiguous to market players. Government-sponsored enterprises (i.e., Fannie Mae and Freddie Mac) which historically had issued prime loans, deemed loans subprime if they were "originated by one of [the] specialty lenders or a subprime division of a large lender." Therefore, they categorized only a small proportion of their loans as subprime (0.3%, 0.2%, and 0.1% in 2007, 2006, and 2005, respectively) even though subprime loans comprised a larger proportion of their assets. As a result, approximately 12 million subprime loans were considered prime during rating analysis. The FCIC reported that changing this assumption about the number of prime loans in the market would have resulted in an 86% higher predicted delinquency rate (FCIC, 2011, p. 468).

At Moody's, the mechanism of bounded retheorization manifested as: (a) failing to account for the possibility of economic shock, growth in the housing market, or fluctuations in house prices despite economic changes and potential for more substantive change; (b) viewing changes to the industry

structure inspired by Glass Steagall solely as an opportunity for growth, and not as a trigger to re-examine the algorithmic model; (c) ignoring changes in the personal credit market and continuing to rely on personal FICO scores; and (d) responding to the largest change, the increasing prevalence of subprime mortgages, by incrementally modifying the M3 model rather than re-evaluating the model for the idiosyncracies of the subprime market. These examples suggest that in their retheorizing attempts, Moody's built on previous thinking when modeling the environment, borrowers' behavior, and potential losses, and failed to re-examine fundamental assumptions inherent to the model and its representation of the environment.

Sedimentation of Assumptions

Sedimentation of assumptions occurred as the organization continued to use legacy data inputs for the algorithmic model despite recognizing significant changes in the external environment. For example, Moody's relied on available and imperfect data to generate ratings or predictions about defaults. Specifically, their "analysis benefited from the public availability of performance information from Loan Performance, Inc. (LPI, formerly known as Mortgage Information Corporation) on over 500,000 Jumbo 'A' loans" (Moody's Investor Services, 2003, p. 1). Moody's used data from "A" mortgages when constructing the M3 model used to rate the "Alt-A" loans that had become a considerable proportion of the residential mortgage market:

> When one builds a model, the data is rarely a perfect dataset, have everything you would want to know. And what we would want to predict on a pool backing residential mortgage-backed securities, is the likelihood of a loan leading to a loss. (Jay Siegel, 2010, Interview)

Moreover, Moody's did not change its assumptions regarding how data representing originators' activities was interpreted. Despite changes in the secondary finance market stimulated by the repeal of the Glass-Steagall Act and significant growth, many assumptions about the quality of data provided by market actors remained the same in the credit rating model, and Moody's continued to interpret outputs based on historical data. One key assumption was that technology was enabling originators to more accurately capture underlying mortgage risks:

These streamlined processes, and improved technology infrastructure, ensure tighter control over originations and servicing. Lenders striving to produce pools of uniform risk are able to succeed consistently … we also believe that lenders' efforts toward best practices and uniform risk across deals will create a large subset of pools that can be assessed through a largely quantitative model. (Moody's Investor Services, 2003, p. 2)

Over time, Moody's assumption that mortgages were standard and similar became ossified:

Technology has come to dominate all aspects of "A" residential mortgage finance, starting with the solicitation of business and carrying through credit approval, closing, and servicing. As a consequence, lenders are producing pool after pool of loans with virtually identical aggregate risk characteristics. (Moody's Investor Services, 2003, p. 1)

One informant explained how Moody's perceived originators' practices as similar:

Pools did … tend to become fairly standard. … If you had been a banker, working with Moody's on a variety of deals, you could probably … figure out pretty close where we would come out … They [issuers] had similar underwriting standards, their origination practices didn't vary a lot. So, you wouldn't figure that they'd be playing around a lot with … risk layering and combining risk factors. (David Teicher, 2010, Interview)

These assumptions about data quality proved to be inaccurate, and as shown below, led into considerable discrepancies between predictions and performance.

Similar to M3, sedimentation of assumptions about data occurred and intensified for M3 Subprime algorithmic model inputs. As the subprime market grew between 2003 and 2007, lenders relaxed their criteria for borrowing so that more people could buy homes (U.S. Senate Permanent Subcommittee on Investigations 2011, p. 177). For instance, as shown in Table II, the level of documentation provided by individual borrowers decreased significantly to enable those who were self-employed or had unstable earnings to get mortgages. Despite relaxed borrowing standards, Moody's did not change its assumptions about the data provided by issuers in the loan tape. Prior to 2007, "the feeling was … that it [due diligence data] wasn't necessary for the process … we believed in the accuracy of the

information that we were getting" (David Teicher, 2010, Interview). Moody's thus did not account for the declining quality of the loans being securitized:

> I sat on this high-level structured credit committee, which you'd think would be dealing with such issues [of declining mortgage underwriting standards], and never once was it raised to this group or put on our agenda that the decline in quality that was going into pools, the impact possibly on ratings, other things. . . . We talked about everything but, you know, the elephant sitting on the table. (Jeremy Fons, 2010, Interview)

The sedimentation of assumptions also was evident for data regarding the quality of particular borrowers. Since 1996, Moody's had incorporated FICO scores into its credit rating model. When developing the M3, Moody's continued to model the behavior of borrowers around FICO scores and believed that it was the primary predictive factor in determining default probability, particularly shortly after origination (Moody's, 4/1/2003, p. 7). Although credit risks were increasing, Moody's continued to believe in the predictive utility of FICO scores: "The goal was … to see if a relationship could be established between FICO scores and mortgage performance, particularly default risk, because that's where it's most likely to have an impact" (Jay Siegel, 2010, Interview, p. 83). However, the credibility of FICO scores was starting to decline, as people had learned how to game their scores, and fewer mortgages were requiring full documentation; hence, loan tapes no longer fully captured the reality of environmental changes (Carruthers, 2010; Rona-Tas & Hiss, 2010).

At Moody's, the sedimentation of assumptions mechanism manifested through the continued reliance on: (a) data inputs associated with prime mortgages to reflect assumptions about the quality of origination data, even after sub-prime mortgages skyrocketed in the wake of Glass-Steagall; and (b) FICO scores to reflect assumptions about individual borrowers' default risk even as these data began to change. The continued use of FICO scores is largely attributable to the performative ramifications of the metric's widespread acceptance and the transparency of the FICO methodology. These assumptions about data inputs proved to be wrong, resulting in credit rating models that failed to account for environmental changes. In a speech at the World Economic Forum during the immediate aftermath of the financial crisis, the CEO of Moody's admitted to the sedimentation of assumptions in the company's analytic models: "In hindsight, it is pretty clear that there was a failure in some key

assumptions that were supporting our analytics and our models … both the complete[ness] and veracity [of data were] deteriorating" (Raymond McDaniel, 2008, World Economic Forum).

Simulation of the Unknown Future

Simulation of the unknown future refers to the organization relying on the algorithmic model to account for environmental changes when predicting the future environment. To simulate the future state of the economy, Moody's relied on parameters and hypothetical simulations. In the early 2000s, Moody's embarked on an ambitious, unprecedented initiative to model the behavior of loans under various economic stressors. This was inspired by available historic data and advanced quantitative analysis techniques that had become widespread in the industry. Moody's intended to make ratings more rigorous and to predict instrument performance across a range of scenarios. Multi-path simulation featuring 1,250 macroeconomic scenarios covered economic factors such as inflation, unemployment, and house prices. Analysts considered these macroeconomic insights when evaluating RMBS deals. The quarterly performance of each loan in a pool could be simulated for the entire "universe" of 1,250 potential scenarios. Moody's established "the superiority of considering a distribution of future economic stressors rather than relying on a single historical economy as a presumed worst possible scenario" (Moody's Investor Services, 2003, p. 3).

Moody's believed that the "economic simulations in the credit rating routine captured not only possible distributions of interest rate, unemployment, and real estate market movements but also the correlations of these movements across states" (Moody's Investor Services, 2003, p. 3). Through the simulation engine, Moody's aimed to predict the relationships between economic stressors and the behavior of individual loans.

> The detailed performance histories offer the opportunity to examine with increased precision the causal links between economic stresses and loan behavior. These examinations replace reliance on expected pool loss distributions to examine behavior in stress scenarios, greatly increasing the precision with which we can predict loan behavior in stress situations. (Moody's Investor Services, 2003, p. 2)

However, being divorced from the reality of the market and driven purely by mathematical modeling, algorithmic models failed to accurately represent the macroeconomic environment; even the most stressed scenarios did not predict the sharp downward trend in the economy (particularly house prices) in real time, yielding inconsistent ratings. This issue was raised by an analyst in an internal exchange: "Not recalibrating the prime model and not fixing the simulation will create a growing number of inconsistencies (problems) in the existing models as was the case through most of 2004" (Roger Stein, 2006, Moody's Internal Emails).

A central feature of this simulation model was auto-correlation, whereby the results from one period are determined by the same measures in previous periods; Moody's projections for future scenarios were updated quarterly based on cumulative performance data of similar deals in previous quarters. This feature prevented outliers from being captured in the model since "whatever was automated in the model, as to the look-backs and the curve and the trend, continued to be used" (Jay Siegel, 2010, Interview). Because the scenario simulation engine had built-in autocorrelation, analysts did not consider the possibility that radical changes were occurring, and did not update scenarios accordingly:

> Every quarter, new economic data was acquired from economy.com, and that data formed the basis of the starting point of the next simulation. In the case of the vector auto-regressive model … the first two simulated periods in every path take as input the historical data. After that point, the quote "historical data" is whatever was simulated in the previous period. (Roger Stein, 2010, Interview)

Also, the simulation engine of the M3 Subprime model was taken from the M3 model; the underlying modeling of the macroeconomic situation remained unchanged, despite substantial environmental changes:

> The thinking in doing that was that the same state of the world should obtain for both prime and subprime mortgages with respect to macroeconomic factors. That is, unemployment, for example, in Texas shouldn't be different because I happened to be looking at a prime mortgage versus a subprime mortgage. (Roger Stein, 2010, Interview)

The simulation of unknown futures was not, however, aligned with economic reality under the expansion of the housing market and the subprime market. A key change in the economy during the financial crisis was a 30% decline in house prices. However, "Moody's position was that there was not a … national housing bubble" (Jay Siegel, 2010, Interview) and the new model gave little to no credence to that possibility. Historically, national house price movements had not shown declines. Declines had only been observed in individual states. Therefore, changes in national house prices were not considered worthy of attention (Jay Siegel, 2010, Interview). These expectations proved to be flawed because environmental changes had introduced the possibility of a correlation between states. During the crisis, national house prices declined by nearly 40%, but this stressor was not captured by the model:

> It's fair to say that either the underlying factors were wrong or the economic stress cases were not as stressful as this environment … the 38% national drop, staying down over this short, but multiple-year period, is more stressful than the statistics call for. (Jay Siegel, 2010, Interview)

To account for losses of that magnitude, Moody's had to simulate the future environment differently. However, the simulations did not put significant weight on the possibility of such a dramatic decline. The only era comparable to the financial crash of 2008 was the Great Depression, but the economic landscape had changed considerably since then.

The algorithmic model yielded predictions that gave organizational actors confidence in their understanding of the future. However, these simulations overlooked potential issues in the theoretical structure of the model and/or the data inputs that compromised the accuracy of predictions, which diverged significantly from reality.

Specialized Compartmentalization

Specialized compartmentalization occurred as responsibilities for the design and enactment of the algorithmic routine were divided and assigned to actors in distinct roles based on their expertise. Moody's did not have an "architect" responsible for artifact design or "big picture consolidation" of the design process, and ownership and use of the model were distributed. Moody's relied on quantitative analysts (i.e., "quants") to develop the simulation engine. These mathematicians, who had

expertise in developing economic models to predict market behavior, developed an algorithm to simulate the macroeconomic environment that was embedded in the M3 and M3 Subprime models: "The technicality of the model was complex to the extent that not many people understood how it worked" (Jay Siegel, 2010, Interview).

Specialized compartmentalization continued and even intensified when the M3 Subprime model was introduced, as analysts used their expert judgment to determine parameters and train the model. Moody's M3 Subprime model had two primary components: a simulation engine to predict the macroeconomic state and a component to model the performance of securities. In the absence of historical data for the second component, the M3 Subprime model relied primarily on expert judgment reflecting analysts' expectations and assumptions. The aim was to yield results that would faithfully represent Moody's view of the risks and analysts' expectations. A developer of the M3 Subprime model explained: "when you have a model that must contemplate events for which there is no data, it's not clear how else one might calibrate that model, besides using an expert's judgment" (Roger Stein, 2010, Interview). For instance, Moody's made some minor changes to the historic parameter for loan prepayments:

> Ultimately, if the analysts' theory about a particular parameter was X and, by setting the parameter by X the losses were not high enough, then we would make other adjustments as necessary. For subprime mortgages during that period, our analysis suggested that prepayment is a big driver of pool-level losses because, if a loan prepays, it can't default. And so if prepayment rates are very high, even very risky borrowers leave the pool early. So by lowering prepayments, we make the conditional probability of default, the conditional loss rate of the pool much higher. (Roger Stein, 2010, Interview)

Due to the lack of ownership and absence of a chief architect for the model, some changes were made randomly. Over time, analysts created ad-hoc rules which compromised the model's consistency: "It seems, though, that the more of the ad hoc rules we add, the further away from the data and models we move and the closer we move to building models that ape analysts' expectations" (Roger Stein, 2007, Moody's Internal Emails).

Specialized compartmentalization also occurred during the enactment of the algorithmic routine. Moody's did not strictly define how to use the models, and rating committees complemented model outputs with other decision-making tools. For instance, until the end of 2006, they continued to use benchmarking as their primary means for rating deals, which had become "standardized" over the years as the market expanded, and thus provided an impression of consistency across various ratings. They also deployed professional judgment to account for deal-specific factors: "One of the reasons why this [benchmarking] approach worked so well for so long … was because … a given lender would tend to produce very similar collateral from pool to pool to pool" (David Teicher, 2010, Interview).

In their benchmarking attempts, "the lead analyst would go and get what we call these stratifications or these histograms for prior pools, to use for comparison purposes, … and after gathering this information, they would prepare a committee memo with their recommendations" (David Teicher, 2010, Interview). However, changes in underwriting standards and the complexity of novel products meant that benchmarking was no longer appropriate because it did not enable a more sophisticated analysis of deals: "You just have the summary characteristics … the summary of the LTVs, the summary of the FICOs" (David Teicher, 2010, Interview).

Distributed ownership among various actors who exercised their professional discretion and deployed multiple versions of the model exacerbated these problems. On various occasions, Moody's made exceptions to how the model was used in the rating routine. As the market grew, Moody's increased the enhancement levels (i.e., the cushion required to cover financial losses) necessary for securities to receive a AAA rating and incorporated these changes into the methodology used in various versions of the M3 and M3 Subprime models.

Similarly, rating committee members exercised professional discretion when making adjustments to model outputs in response to declining underwriting standards and explosive market growth. Because the committee viewed the M3 and M3 Subprime models as decision-making tools to be used in conjunction with the 1996 model, outputs were not considered final. Because each transaction was different, the models provided Moody's analysts with reference points for similar deals. Although the

models helped standardize the enactment of the credit rating routine across committees, rating committee members continued to exercise their professional judgment to adjust model outputs to match their assessments regarding originator quality: "To the extent the model output is a tool, and … if there's an originator where you're often a point higher than the model—then you could say, 'I'm relying on the model and adding a point'" (Jay Siegel, 2010, Interview).

Such reliance on committee members' judgment led to inconsistencies that rendered the models insignificant in the overall rating process by creating discrepancies across various iterations of routine enactment. For example, recommended enhancement levels varied across different committees. In an internal email exchange in 2007, concerns about variance in how committees assign ratings were voiced:

> Over time, different chairs have been giving different guidelines at different points of time on how much over-enhancement we need for a bond to be notched up to AAA, the numbers vary from 10% to 1/3 of bond size. The main reason I sent Tony to you is to get some general guidance on the notching practice, so that people can follow without having to run by you every time the issue comes up. (Yi, 2007, Email)

Extensive reliance on expert judgment sometimes led to favorable adjustments to ratings which proved to be flawed when the economic crisis unfolded. At times, the committee assigned lower enhancement levels (higher ratings) to deals than the model had indicated. An email to Citigroup acknowledged: "the results for M3 subprime … were higher [less favorable] than what committee agreed on for the deal" (Moody's Email, 2007). Many of Citigroup's tranches were downgraded less than a year later.

At Moody's, specialized compartmentalization created fragmentation in and divergence between the design of the algorithmic model and routine enactment. The algorithmic model was designed and modified by actors with varying expertise in the organization; and routine enactment involved a variety of actors, many of whom were not involved in designing and modifying the algorithmic model. These distributed responsibilities created confusion in and around the algorithmic routine.

DISCUSSION

As shown in Figure 1, four interrelated and recursive mechanisms contribute to dynamic inertia as an organization modifies its algorithmic routine to account for environmental changes. Through bounded retheorization, an organization incrementally adjusts the fundamental structure of its model in the face of substantive, qualitative changes in the environment. Theories embedded in the algorithmic routine are not revamped, but marginally altered. Through the sedimentation of assumptions created by available and imperfect data, an organization generates inaccurate ratings or predictions. As data change (in both quality and volume), assumptions about those data in the algorithmic routine remain unchanged. Over time, an organization's simulation of an unknown future becomes misguided, envisioning futures that do not correspond to reality. Finally, through specialized compartmentalization, the development, ownership, and use of algorithmic routines become convoluted, such that an organization loses track of the broader routine within its organizational context when data scientists maintain a nuanced understanding of the model, but others become disconnected from its underlying theories and simulations.

These mechanisms are only partially effective for responding to uncertainties and aligning algorithmic routines with environmental changes, ultimately producing inertia. Insofar as minor environmental changes are incorporated into algorithmic routines, such assemblages remain functional, and our four identified mechanisms enable adequate responses. However, when environmental changes diverge from the goal of the algorithmic routine, the mechanisms become inadequate, resulting in the failure of the algorithmic routine and its ultimate collapse.

INSERT FIGURE 1 ABOUT HERE

As a revelatory case, our examination of how Moody's dealt with environmental changes enhances our understanding of organizational inertia. Examining organizational inertia from a routine dynamics perspective (Pentland and Feldman, 2005), we have analyzed the important role algorithms play in generating and maintaining dynamic inertia by sensing and responding to environmental dynamism (Alaimo and Kallinikos, 2021). Insights from this study complement the dominant structural perspective, which explains inertia as a path dependency mechanism (Burgelman, 2002; Davis et al., 2009; Gilbert, 2005; Hannan and Freeman, 1984; Leonard-Barton, 1992; Levitt and March, 1988), as

well as the cognitive perspective, which explains inertia by examining established cognitive frames (Greve, 2011; Miller, 1994; Tripsas and Gavetti, 2000; Walsh, 1995). The routine dynamics framework adopted herein has enabled us to develop a theory of dynamic inertia that incorporates both the social and material aspects of organizational life. Specifically, we have traced the origins of inertia to the design and use of algorithmic artifacts in the daily enactment of organizational routines in contexts involving substantial environmental changes. We offer three main contributions to the literature.

First, we extend the current understanding of inertia by foregrounding the role of artifacts and algorithms increasingly being used in organizations (Alaimo and Kallinikos, 2017, 2021; Faraj et al., 2018; Glaser, Pollock, et al., 2021) and by revealing inertia as dynamic and evolving, rather than stable and difficult to change. Most existing conceptualizations of inertia are human-centric, framing it as the outcome of (powerful) organizational actors' inability to deviate from their dominant cognitive frames to adequately respond to environmental changes (Fligstein et al., 2017; Kaplan and Tripsas, 2008); likewise, organizations that manage to deviate from their dominant frames are more likely to avoid inertia (Kim, 2021). Accordingly, even when actors recognize environmental dynamism, their responses remain congruent with their existing frames. Dominant explanations for inertia in the presence of mental frames highlight actors' cognitive (Kaplan and Tripsas, 2008; Tripsas and Gavetti, 2000) and emotional (Raffaelli et al., 2019) biases when making decisions.

It is also argued that inertia results from the path dependencies that emerge as organizations age and accumulate experience and resources (Davis et al., 2009; Hannan and Freeman, 1984). This approach implies that through structures, resourcing patterns, and path dependencies, organizations internalize certain ways of responding to environmental changes and continue to respond similarly, with only slight variations across individual actors. Performance feedback theorists (Audia and Greve, 2021) argue that structural rigidities prevent learning and access to feedback loops that can stimulate adequate change in organizations (Cyert and March, 1963; March and Olsen, 1975) or result only in incremental changes which are not proportionate to environmental changes (Quinn, 1978). Learning is "routine-based, history-dependent, and target-oriented" (Levitt and March, 1988, p. 319), and organizational responses to environmental changes are grounded in previous experiences, which are

characterized by path dependencies and core rigidities (Greve, 2011; Leonard-Barton, 1992). Consequently, organizational learning may fail to adequately address challenges introduced by environmental changes.

Our findings extend these contributions by revealing mechanisms of inertia that dynamically unravel through the design and use of algorithmic routines in response to environmental changes. Inspired by related findings in the strategy-as-practice literature (Burke and Wolf, 2020; Jarzabkowski and Kaplan, 2015), we have shown that inertia may also emerge from algorithmic and material arrangements. Using algorithms, organizations continue to use certain types of data when modeling the market and simulating future economic scenarios through the sedimentation of assumptions; they do not obtain new or updated data because the artifacts determine and shape which data are to be used and how.

We also extend the existing understanding of inertia by attending to the processual nature of inertia as it dynamically unfolds. Our findings challenge the prevalent understanding of inertia as a "state" that determines and limits organizational responses to environmental changes, as suggested by path-dependency and performance feedback theories. The algorithmic model used by Moody's was anything but rigid. It was constantly modified throughout the study period as actors adapted and modified the algorithmic routines in their attempts to respond to the substantive environmental changes. For instance, attending to the material and distributed nature of algorithmic routines, our findings challenge assumptions about decision makers' coherent cognitive frames that induce inertia (Kaplan, 2008; Tripsas and Gavetti, 2000). Cognitive frames imply a coherent worldview among organizational actors, which is static and difficult to change (Raffaelli et al., 2019). We showed how Moody's algorithmic routine was not singularly designed and used, but subject to compartmentalized specialization. Because multiple actors participated in both the design and use of the algorithmic routine, no unique frame underpinned the routine and associated inertial forces, yet the result was devastating inertia.

Second, we contribute to the routine dynamics literature and related discussions about algorithms in practice (e.g. Christin, 2017, 2020) by introducing "algorithmic routines" and unpacking how they address the organizational environment. In studies of organizational routines, researchers have

primarily examined how the immediate context affects routine dynamics by exploring the embeddedness of routines in the organizational structures (Howard-Grenville, 2005), schemata (Rerup and Feldman, 2011), and culture (Bertels et al., 2016). A few researchers who have attended to changes in the wider environment have shown how environmental changes can break organizational truces and lead to subsequent changes to routines and/or resistance to such changes (Safavi, 2021; Safavi and Omidvar, 2016; Zbaracki and Bergen, 2010); however, these researchers did not consider the central role of algorithms through which actors perceive and respond to the environment and make decisions.

We extend these findings by showing how organizations connect to the organizational environment, predict futures, and respond to changes through algorithmic routines. Recently, researchers have explored how futures and future-making practices are developed (Hernes and Schultz, 2020; Wenzel et al., 2020). Kaplan and Orlikowski (2013) argued that actors construct and reconstruct relationships between the past, present, and projections of the future through temporal work. Although questions of time, temporality, and rhythms are well understood in existing research on routine dynamics (Geiger et al., 2021; Turner and Rindova, 2012, 2017), only few of these studies address how routines deal with the future. In an exception, Glaser (2017) showed how design performances help organizations envision potential future needs and enable constant changes in their routines through new sociomaterial assemblages. Studies of narrative networks (Pentland et al., 2011; Pentland and Feldman, 2007) and process multiplicity (Pentland et al., 2020) also have revealed ways of looking at potential paths for routines to emerge. We extend these contributions by showing how the future is perceived and made sense of through algorithmic routines, not only in the reflective sense that emerges during artifact design (Glaser, 2017) and routine enactment (Dittrich et al., 2016) or through the possibilities created by grammars of action (Pentland et al., 2020; Pentland and Rueter, 1994) but also through simulation of the unknown future forged by specialized compartmentalization of algorithmic routines. Our findings reveal that future and future-making (e.g. Wenzel et al., 2020) are integral to algorithmic routines and their associated assemblages; through simulation of unknowns reinforced by specialized compartmentalization, such futures are constructed in algorithmic routines. By unpacking the material dynamics that algorithmic routines offer, we extend recent contributions

that have shown how algorithms establish patterns that remain stable despite the rapid changes in the environment (Feldman et al., 2021).

Finally, our findings have general implications for research related to the financial crisis. Few empirical studies have examined micro-level organizational practices as they unfolded in the years leading up to the crisis. We contribute to this domain of inquiry by exploring how Moody's changed its credit rating routine over the years. Researchers have shown significant interest in examining potential underlying reasons for the crash, including moral depravity (Wang et al., 2011; Wang and Murnighan, 2011; Zhong, 2011), the influence of cognitive frames on organizational activities (Fligstein et al., 2017), arbitrage opportunities created in markets (MacKenzie, 2011), reaffirmation of taken-for-granted assumptions by monetary policymakers during a crisis (Harmon, 2018), and institutional pressures to compete when innovative financial products are introduced (e.g., Kotz, 2009; Lounsbury and Hirsch, 2010; Pozner et al., 2010).

Some authors have highlighted the role played by credit rating agencies in the financial crisis by failing to issue accurate ratings because they commoditized uncertainty and harmonized expectations in the market (Carruthers, 2013). We have shown how inertial mechanisms in Moody's algorithmic routine largely contributed to the subprime crisis. Although attributing the collapse of the entire financial sector to the malfunctioning of a single routine may be simplistic, we contend that such a realization is essential in explaining how the crisis unfolded.

Our analysis of factors that led to the financial crisis reflects Beunza's (2019) view that the practices and incentive systems mediated by models may create moral disengagement. We have taken this one step further by revealing that models can also result in environmental disengagement through four mechanisms—some of which, ironically, relate to elements specifically designed to monitor and respond to environmental changes. Ultimately, this environmental disengagement is what led to the mass downgrading of RBMS ratings. Through bounded retheorization, sedimentation of assumptions, simulation of the unknown future, and specialized compartmentalization, algorithmic routines can limit environmental engagement. Over time, this lack of engagement impedes financial institutions from responding to environmental changes appropriately.

These findings have significant organizational and managerial implications. Because algorithms are intertwined with the daily enactment of routines, organizations perceive reality in the immediate environment through the algorithms they deploy; organizations delegate a significant proportion of interactions with and reactions to environmental changes to these algorithms, which serve as organizational boundary objects (Alaimo and Kallinikos, 2021). Given the widespread integration of algorithmic routines, modern organizations try to overcome inertia by using reliable tools built on the pillars of data science and by analyzing samples of historical data to predict the future. However, we have shown how disastrous failures may still happen when responses to environmental changes converge, absorbing environmental dynamism in the process. This in turn generates inertia, albeit dynamically, ultimately preventing organizations from appropriately responding to environmental changes.

CONCLUSION

Organizations face environmental changes that can generate negative consequences. Scholars have highlighted the cognitive and structural nature of inertia, but our findings reveal how algorithmic routines can produce organizational inertia dynamically. We hope our sociomaterial explanation inspires additional research to help organizations understand how to expose elements of inertia and effectively adapt to environmental changes. By radically retheorizing, departing from existing assumptions, reflexively interrogating representations of the environment and future outlooks, and facilitating conversations across areas of expertise, organizations can avoid producing dynamic inertia, which, as we have shown, may lead to disaster.

NOTES

1. A FICO score is a credit score created by the Fair Isaac Corporation (FICO).

2. Moody's, Standard & Poor's (S&P), and Fitch Group are the largest credit rating agencies (i.e., the Big Three) in the United States.

3. Credit enhancements are risk-reduction techniques designed to reduce the default risk or increase the credit profile of structured financial products. Tranching, or establishing a risk hierarchy, is one of the most popular techniques for credit enhancement. Subordinate tranches function as protective layers for more senior tranches. The tranche with the highest seniority has the first rights to cash flow, whereas the distribution of losses rises from the bottom. The subordinated tranches are, therefore, perceived to carry greater risk and pay higher yields.

REFERENCES

Alaimo, C. and Kallinikos, J. (2017). 'Computing the everyday: Social media as data platforms'. *The Information Society*, **33**, 175–91.

Alaimo, C. and Kallinikos, J. (2021). 'Managing by Data: Algorithmic Categories and Organizing'. *Organization Studies*, **42**, 1385–407.

Aroles, J. and McLean, C. (2016). 'Rethinking Stability and Change in the Study of Organizational Routines: Difference and Repetition in a Newspaper-Printing Factory'. *Organization Science*, **27**, 535–50.

Audia, P. G. and Greve, H. R. (2021). *Organizational Learning from Performance Feedback: A Behavioral Perspective on Multiple Goals: A Multiple Goals Perspective.* Cambridge University Press.

Barad, K. (2003). 'Posthumanist Performativity: Toward an Understanding of How Matter Comes to Matter'. *Signs: Journal of Women in Culture and Society*, **28**, 801–31.

Bertels, S., Howard-Grenville, J. and Pek, S. (2016). 'Cultural Molding, Shielding, and Shoring at Oilco: The Role of Culture in the Integration of Routines'. *Organization Science*, **27**, 573–93.

Beunza, D. (2019). *Taking the Floor: Models, Morals, and Management in a Wall Street Trading Room*. Princeton, NJ: Princeton University Press.

Burgelman, R. A. (2002). 'Strategy as Vector and the Inertia of Coevolutionary Lock-in'. *Administrative Science Quarterly*, **47**, 325-57.

Burke, G. T. and Wolf, C. (2020). 'The process affordances of strategy toolmaking when addressing wicked problems'. *Journal of Management Studies*, **58,** 359-88.

Cabantous, L., Gond, J.-P. and Johnson-Cramer, M. (2010). 'Decision Theory as Practice: Crafting Rationality in Organizations'. *Organization Studies*, **31**, 1531–66.

Cacciatori, E. (2012). 'Resolving Conflict in Problem-Solving: Systems of Artefacts in the Development of New Routines'. *Journal of Management Studies*, **49**, 1559–85.

Carruthers, B. G. (2013). 'From Uncertainty Toward Risk: The Case of Credit Ratings'. *Socio-Economic Review*, **11**, 525–51.

Christensen, C. M. and Bower, J. L. (1997). 'Customer Power, Strategic Investment, and the Failure of Leading Firms'. *Strategic Management Journal*, **17**, 197–218.

Christin, A. (2017). 'Algorithms in practice: Comparing Web Journalism and Criminal Justice'. *Big Data & Society*, **4**, 1-14

Christin, A. (2020). *Metrics at Work: Journalism and the Contested Meaning of Algorithms.* Princeton University Press.

Collinson, S. and Wilson, D. C. (2006). 'Inertia in Japanese Organizations: Knowledge Management Routines and Failure to Innovate'. *Organization Studies*, **27**, 1359–87.

Comi, A. and Whyte, J. (2018). 'Future Making and Visual Artefacts: An Ethnographic Study of a Design Project'. *Organization Studies*, **39**, 1055–83.

Cyert, R. M. and March, J. G. (1963). 'A behavioral theory of the firm'. London: Wiley

D'Adderio, L. (2008). 'The Performativity of Routines: Theorising the Influence of Artefacts and Distributed Agencies on Routine Dynamics'. *Research Policy*, **37**, 769–89.

D'Adderio, L. (2011). 'Artifacts at the centre of routines: Performing the material turn in routines theory'. *Journal of Institutional Economics*, **7**, 197–230.

D'Adderio, L. (2021). 'Materiality and Routine Dynamics'. In Pentland, B. T., Rerup, C., Seidl, D., Dittrich, K., D'Adderio, L. and Feldman, M. S. (Eds), *Cambridge Handbook of Routine Dynamics.* Cambridge: Cambridge University Press.

D'Adderio, L., Glaser, V. L. and Pollock, N. (2019). 'Performing Theories, Transforming Organizations: A Reply to Marti and Gond'. *Academy of Management Review*, **44**, 676–79.

D'Adderio, L. and Safavi, M. (2021). 'Truces and routine dynamics'. In *Cambridge Handbook of Routine Dynamics*. 209–228.

Davenport, T. H. (2014). *Big Data at Work: Dispelling the Myths, Uncovering the Opportunities.* Harvard Business Review Press.

Davenport, T. H. (2018). *The AI Advantage: How to Put the Artificial Intelligence Revolution to Work, 1st edition*. Cambridge, MA: The MIT Press.

Davenport, T. H. and Patil, D. J. (2012). 'Data Scientist: The Sexiest Job of the 21st Century'. *Harvard Business Review*, **90,** 70-76

Davis, J. P., Eisenhardt, K. M. and Bingham, C. B. (2009). 'Optimal Structure, Market Dynamism, and the Strategy of Simple Rules'. *Administrative Science Quarterly*, **54**, 413–52.

Deleuze, G. and Guattari, F. (1987). *A Thousand Plateaus: Capitalism and Schizophrenia,* 2nd edition. Minneapolis, MN: University of Minnesota Press.

Dittrich, K., Guérard, S. and Seidl, D. (2016). 'Talking About Routines: The Role of Reflective Talk in Routine Change'. *Organization Science*, **27**, 678–97.

Ewenstein, B. and Whyte, J. (2009). 'Knowledge practices in design: the role of visual representations as 'epistemic objects''. *Organization Studies*, **30**, 7–30.

Faraj, S., Pachidi, S. and Sayegh, K. (2018). 'Working and organizing in the age of the learning algorithm'. *Information and Organization*, **28**, 62–70.

FCIC. (2011). *The Financial Crisis Inquiry Report: Final Report of the National Commission on the Causes of the Financial and Economic Crisis in the United States*. Available At https://lccn.loc.gov/2011381760 .

Feldman, M. S. and Orlikowski, W. J. (2011). 'Theorizing Practice and Practicing Theory'. *Organization Science*, **22**, 1240–53.

Feldman, M. S. and Pentland, B. T. (2003). 'Reconceptualizing Organizational Routines as a Source of Flexibility and Change'. *Administrative Science Quarterly*, **48**, 94–118.

Feldman, M. S., Worline, M., Baker, N. and Lowerson Bredow, V. (2021). 'Continuity as Patterning: A Process Perspective on Continuity'. *Strategic Organization*, in press.

Fligstein, N., Brundage, J. S., and Schultz, M. (2017). 'Seeing Like the Fed: Culture, Cognition, and Framing in the Failure to Anticipate the Financial Crisis of 2008'. *American Sociological Review*, **82**, 879–909.

Fourcade, M. and Healy, K. (2017). 'Categories All the Way Down'. *Historical Social Research*, **42**, 286–96.

Gehman, J., Glaser, V. L., Eisenhardt, K. M., Gioia, D., Langley, A. and Corley, K. G. (2018). 'Finding Theory–Method Fit: A Comparison of Three Qualitative Approaches to Theory Building'. *Journal of Management Inquiry*, **27**, 284–300.

Geiger, D., Danner-Schröder, A. and Kremser, W. (2021). 'Getting Ahead of Time—Performing Temporal Boundaries to Coordinate Routines under Temporal Uncertainty'. *Administrative Science Quarterly*, **66**, 220–64.

Gilbert, C. G. (2005). 'Unbundling the Structure of Inertia: Resource Versus Routine Rigidity'. *Academy of Management Journal*, **48**, 741–63.

Glaser, V. L. (2014). *Enchanted Algorithms: The Quantification of Organizational Decision-Making.* Dissertation, Marshall School of Business.

Glaser, V. L. (2017). 'Design Performances: How Organizations Inscribe Artifacts to Change Routines'. *Academy of management journal*, **60**, 2126–54.

Glaser, V. L., Pollock, N. and D'Adderio, L. (2021). 'The Biography of an Algorithm: Performing algorithmic technologies in organizations'. *Organization Theory*, **2**, 26317877211004610.

Glaser, V. L., Valadao, R. and Hannigan, T. R. (2021). 'Algorithms and Routine Dynamics'. In B. T. Pentland, C. Rerup, D. Seidl, K. Dittrich, L. D'Adderio, and M. S. Feldman (Eds), *Cambridge Handbook of Routine Dynamics.* Cambridge: Cambridge University Press.

Greve, H. R. (2011). 'Positional rigidity: Low Performance and Resource Acquisition in Large and Small Firms'. *Strategic Management Journal*, **32**, 103–14.

Hannan, M. T. and Freeman, J. (1984). 'Structural Inertia and Organizational Change'. *American Sociological Review*, **49**, 149–64.

Hardy, C. and Maguire, S. (2016). 'Organizing Risk: Discourse, Power, and "Riskification"'. *Academy of Management Review*, **41**, 80–108.

Hargadon, A. (2015). 'From What Happened to What Happens'. In K. D. Elsbach and R. M. Kramer (Eds), *Handbook of Qualitative Organizational Research.* Routledge Handbooks Online.

Harmon, D. J. (2018). 'When the Fed Speaks: Arguments, Emotions, and the Microfoundations of Institutions'. *Administrative Science Quarterly*, **64,** 542-575.

Hernes, T. and Schultz, M. (2020). 'Translating the Distant into the Present: How actors address distant past and future events through situated activity'. *Organization Theory*, **1**, 1-20.

Howard-Grenville, J. (2005). 'The Persistence of Flexible Organizational Routines: The Role of Agency and Organizational Context'. *Organization Science*, **16**, 618–36.

Jarzabkowski, P. and Kaplan, S. (2015). 'Strategy Tools-In-Use: A Framework For Understanding 'Technologies Of Rationality' In Practice'. *Strategic Management Journal*, **36**, 537–58.

Jones, M. (1998). 'Information Systems and the Double Mangle: Steering a Course Between The Scylla of Embedded Structure and The Charybdis Of Strong Symmetry'. *Information Systems: Current Issues and Future Challenges*.

Kaplan, S. and Orlikowski, W. J. (2013). 'Temporal Work in Strategy Making'. *Organization Science*, **24**, 965–95.

Kaplan, S. and Tripsas, M. (2008). 'Thinking about Technology: Applying a Cognitive Lens to Technical Change'. *Research Policy*, **37**, 790–805.

Kim, S. (2021). 'Frame Restructuration: The Making of an Alternative Business Incubator amid Detroit's Crisis'. *Administrative Science Quarterly*, **66,** 753-805.

Kiviat, B. (2019). 'The Moral Limits of Predictive Practices: The Case of Credit-Based Insurance Scores'. *American Sociological Review*, **84**, 1134–58.

Kotz, D. M. (2009). 'The Financial and Economic Crisis of 2008: A Systemic Crisis of Neoliberal Capitalism'. *Review of Radical Political Economics*, **41**, 305–17.

Kraatz, M. S. and Zajac, E. J. (2001). 'How Organizational Resources Affect Strategic Change and Performance in Turbulent Environments: Theory and Evidence'. *Organization Science*, **12**, 632–57.

Kremser, W. and Schreyögg, G. (2016). 'The Dynamics of Interrelated Routines: Introducing the Cluster Level'. *Organization Science,* **27,** 698-721.

Langley, A. (1999). 'Strategies for Theorizing from Process Data'. *The Academy of Management Review*, **24**, 691–710.

Langohr, H. and Langohr, P. (2009). *The Rating Agencies and Their Credit Ratings: What They Are, How They Work, and Why They are Relevant,* 1st edition. Hoboken, NJ: Wiley.

Lant, T. K., Milliken, F. J. and Batra, B. (1992). 'The Role of Managerial Learning and Interpretation in Strategic Persistence and Reorientation: An Empirical Exploration'. *Strategic Management Journal*, **13**, 585–608.

Lant, T. K. and Montgomery, D. B. (1987). 'Learning from Strategic Success and Failure'. *Journal of Business Research*, **15**, 503–517.

Lazaric, N. and Denis, B. (2001). 'How and why routines change: some lessons from the articulation of knowledge with ISO 9002 implementation in the food industry'. *Economies et Sociétés,* **6,** 585–612

Leonard-Barton, D. (1992). 'Core Capabilities and Core Rigidities: A Paradox in Managing New Product Development'. *Strategic Management Journal*, **13**, 111–25.

Levinthal, D. A. (1991). 'Random Walks and Organizational Mortality'. *Administrative Science Quarterly*, **36**, 397–420.

Levitt, B. and March, J. G. (1988). 'Organizational Learning'. *Annual Review of Sociology*, **14**, 319–38.

Lieberman, M. B. and Montgomery, D. B. (1988). 'First-mover advantages'. *Strategic Management Journal*, **9**, 41–58.

Lounsbury, M. and Hirsch, P. (2010). 'Markets on Trial: Toward a Policy-oriented Economic Sociology'. *Markets on Trial: The Economic Sociology of the U.S. Financial Crisis: Part A*, 5–26.

MacKenzie, D. (2011). 'The Credit Crisis as a Problem in the Sociology of Knowledge'. *American Journal of Sociology*, **116**, 1778–841.

Maguire, S. and Hardy, C. (2012). 'Organizing Processes and the Construction of Risk: A Discursive Approach'. *Academy of Management Journal*, **56**, 231–55.

March, J. G. (1991). 'Exploration and Exploitation in Organizational Learning'. *Organization Science*, **2**, 71–87.

March, J. G. and Olsen, J. P. (1975). 'The Uncertainty of the Past: Organizational Learning Under Ambiguity'. *European Journal of Political Research*, **3**, 147–71.

Miller, D. (1994). 'What happens after success: The perils of excellence'. *Journal of Management Studies*, **31**, 325–58.

Moe, W. W. and Schweidel, D. A. (2017). 'Opportunities for Innovation in Social Media Analytics'. *Journal of Product Innovation Management*, **34**, 697–702.

Moody's investor services. (2003). *Moody's Mortgage Metrics: A Model Analysis of Residential Mortgage Pools*.

Moody's investor services. (2006). *Moody's expands Moody's Mortgage Metrics to include subprime residential mortgages*.

Murphy, C., Patvardhan, S. and Gehman, J. (2017). 'Moral Accounting by Organizations: A Process Study of the U.S. Financial Crisis Inquiry Commission'. *Journal of Management Inquiry*, **26**, 303–25.

Mutch, A. (2016). 'Bringing History into the Study of Routines: Contextualizing Performance'. *Organization Studies*, **37**, 1171–88.

Nicolini, D. (2009). 'Zooming In and Out: Studying Practices by Switching Theoretical Lenses and Trailing Connections'. *Organization Studies*, **30**, 1391–418.

Orlikowski, W. J. and Scott, S. V. (2008). 'Sociomateriality: Challenging the Separation of Technology, Work and Organization'. *Academy of Management Annals*, **2**, 433–74.

Pachidi, S., Berends, H., Faraj, S. and Huysman, M. (2021). 'Make Way for the Algorithms: Symbolic Actions and Change in a Regime of Knowing'. *Organization Science*, **32**, 18–41.

Pentland, B. T. and Feldman, M. S. (2007). 'Narrative Networks: Patterns of Technology and Organization'. *Organization Science*, **18**, 781–95.

Pentland, B. T. and Feldman, M. S. (2008). 'Designing Routines: On the Folly of Designing Artifacts, While Hoping for Patterns of Action'. *Information and Organization*, **18**, 235–50.

Pentland, B. T., Hærem, T. and Hillison, D. (2011). 'The (N)Ever-Changing World: Stability and Change in Organizational Routines'. *Organization Science*, **22**, 1369–83.

Pentland, B. T., Mahringer, C. A., Dittrich, K., Feldman, M. S. and Wolf, J. R. (2020). 'Process Multiplicity and Process Dynamics: Weaving the Space of Possible Paths'. *Organization Theory*, **1**, 2631787720963138.

Pentland, B. T., Recker, J., and Wyner, G. (2017). 'Rediscovering handoffs'. *Academy of Management Discoveries*, **3**, 284–301.

Pentland, B. T. and Rueter, H. H. (1994). 'Organizational Routines as Grammars of Action'. *Administrative Science Quarterly*, **39**, 484–510.

Pettigrew, A. M. (1990). 'Longitudinal Field Research on Change: Theory and Practice'. *Organization Science*, **1**, 267–92.

Pollock, N. and Cornford, J. (2004). 'ERP systems and the university as a "unique" organisation'. *Information technology & people*, **17**, 31–52.

Pozner, J.-E., Stimmler, M. K., and Hirsch, P. (2010). 'Terminal Isomorphism and the Self-destructive Potential of Success: Lessons from Subprime Mortgage Origination and Securitization'. *Markets on Trial: The Economic Sociology of the U.S. Financial Crisis: Part A*, 183–216.

Quinn, J. B. (1978). 'Strategic change:" logical incrementalism"'. *Sloan Management Review (pre-1986)*, **20**, 7-21.

Raffaelli, R., Glynn, M. A. and Tushman, M. (2019). 'Frame Flexibility: The Role of Cognitive and Emotional Framing in Innovation Adoption by Incumbent Firms'. *Strategic Management Journal*, **40**, 1013–39.

Rerup, C. and Feldman, M. S. (2011). 'Routines as a Source of Change in Organizational Schemata: The Role of Trial-and-Error Learning'. *Academy of management journal*, **54**, 577–610.

Safavi, M. (2021). 'Advancing Post-merger Integration Studies: A Study of a Persistent Organizational Routine and Embeddedness in Broader Societal Context'. *Long Range Planning*, 102071.

Safavi, M. and Omidvar, O. (2016). 'Resist or Comply: The Power Dynamics of Organizational Routines during Mergers'. *British Journal of Management*, **27**, 550–66.

Schulz, M. (2008). 'Staying on Track: A Voyage to the Internal Mechanisms of Routine Reproduction'. In *Handbook of organizational routines*, 228-55.

SEC. (2008). *Summary Report of Issues Identified in the Commission Staff's Examinations of Select Credit Rating Agencies*.

Sele, K. and Grand, S. (2016). 'Unpacking the Dynamics of Ecologies of Routines: Mediators and Their Generative Effects in Routine Interactions'. *Organization Science*, **27**, 722–38.

Siddiqi, N. (2005). *Credit Risk Scorecards: Developing and Implementing Intelligent Credit Scoring*, 1 edition. Hoboken, NJ: Wiley.

SIFMA. (2008). *Recommendations of SIFMA's Credit Rating Agency Task Force for the Credit Rating System*. Available At https://www.sifma.org/resources/general/recommendations-of-sifmas-credit-rating-agency-task-force-for-the-credit-rating-system/ (accessed 27 February 2021).

Simon, H. A. (1970). *The Sciences of the Artificial*, Cambridge, Mass: MIT Press, third edition.

Sørensen, J. B. and Stuart, T. E. (2000). 'Aging, Obsolescence, and Organizational Innovation'. *Administrative Science Quarterly*, **45**, 81–112.

Steele, C. W. J. (2021). 'When Things Get Odd: Exploring the Interactional Choreography of Taken-for-Grantedness'. *Academy of Management Review*, **46**, 341–61.

Stieglitz, N., Knudsen, T. and Becker, M. C. (2016). 'Adaptation and inertia in dynamic environments'. *Strategic Management Journal*, **37**, 1854–64.

Strauss, A. L. and Corbin, J. (1990). *Basics of Qualitative Research, techniques and Procedures for Developing Grounded Theory*. Newbury Park, CA: Sage publications.

Sull, D. N. (1999). 'The Dynamics of Standing Still: Firestone Tire & Rubber and the Radial Revolution'. *The Business History Review*, **73**, 430–64.

Sydow, J. (2009). 'Organizational Path Dependence: Opening the Black Box'. *Academy of Management Review*, **34,** 689-709.

Sydow, J. (2020). 'Path Dependence and Routine Dynamics'. In *Cambridge Handbook of Routine Dynamics*. Cambridge University Press.

Tripsas, M. (1997). 'Unraveling the Process of Creative Destruction: Complementary Assets and Incumbent Survival in the Typesetter Industry'. *Strategic Management Journal*, **18**, 119–42.

Tripsas, M. and Gavetti, G. (2000). 'Capabilities, Cognition, and Inertia: Evidence from Digital Imaging'. *Strategic Management Journal*, **21**, 1147–61.

Turner, S. F. and Rindova, V. (2012). 'A Balancing Act: How Organizations Pursue Consistency in Routine Functioning in the Face of Ongoing Change'. *Organization Science*, **23**, 24–46.

Turner, S. F. and Rindova, V. P. (2017). 'Watching the Clock: Action Timing, Patterning, and Routine Performance'. *Academy of Management Journal*, **61,** 1253-80.

Van Maanen, J. (1979). 'The Fact of Fiction in Organizational Ethnography'. *Administrative Science Quarterly*, **24**, 539–50.

Vergne, J.-P. (2013). 'QWERTY is Dead; Long Live Path Dependence'. *Research Policy*, **42**, 1191–94.

Walsh, J. P. (1995). 'Managerial and Organizational Cognition: Notes from a Trip Down Memory Lane'. *Organization Science*, **6**, 280–321.

Wang, L., Malhotra, D. and Murnighan, J. K. (2011). 'Economics Education and Greed'. *Academy of Management Learning & Education*, **10**, 643–60.

Wang, L. and Murnighan, J. K. (2011). 'On Greed'. *The Academy of Management Annals*, **5**, 279–316.

Wenzel, M., Krämer, H., Koch, J. and Reckwitz, A. (2020). 'Future and Organization Studies: On the rediscovery of a problematic temporal category in organizations'. *Organization Studies*, **41**, 1441–55.

Zbaracki, M. J. and Bergen, M. (2010). 'When Truces Collapse: A Longitudinal Study of Price-Adjustment Routines'. *Organization Science*, **21**, 955–72.

Zhong, C.-B. (2011). 'The Ethical Dangers of Deliberative Decision Making'. *Administrative Science Quarterly*, **56**, 1–25.

TABLE I. CHANGES IN THE FINANCIAL MARKET ENVIRONMENT

Factor	1996–2000	2000–2003	2004–2007
Main originator of loans	Commercial banks	Commercial banks and investment banks	Commercial banks and investment banks
Subprime mortgages	Small part of the market ($70 billion in 1996)	Growing part of the market ($160 billion in 2000)	Fast growing part of the market ($520 billion in 2004)
Securitized subprime mortgages	40% (1996)	56% (2000)	66% (2004)
Configuration of deals	Two tranches: a safer, guaranteed one, and a riskier, unguaranteed one	Complex structure with multiple tranches (usually six), each with different risk levels and payment streams	Complex structure with multiple tranches (usually six), each with different risk levels and payment streams
Dominant origination practice	Originate-to-hold	Originate-to-distribute	Originate-to-distribute
Documentation	Less than 2% of mortgages required low documentation or no documentation	Around 2% of mortgages required low documentation or no documentation	More than 27% of mortgages required low documentation or no documentation
Impairment incidents	0 (1996) 12 (1999)	23 (2000) 34 (2003)	24 (2004) 1,504 (2007)
Regulatory events	Repeal of the Glass-Steagall Act (1999)	Sarbanes-Oxley Act (2002) protected	Credit Rating Agency Reform Act (2006)

removed the separation between investment banks and depository banks	investors from fraudulent financial reporting by corporations	created a registration scheme for credit rating agencies to be treated as nationally-recognized statistical ratings organizations

TABLE II. MOODY'S CREDIT RATING ROUTINE

Element	Description
Objective	To provide a credit rating (i.e., a letter grade ranging from AAA to C) that reflects the riskiness of an RMBS
Actors	Issuing firm investment bankers, the Moody's focal analyst directly responsible for evaluating the security, and a Moody's rating committee of more distant analysts and managers
Artifacts	Loan tape generated by the issuing firm describing characteristics of the mortgage pool The rating model generated by Moody's that calculates the expected loss and enhancement level
Action pattern	1. Obtain information about the RMBS 2. Use the rating model to estimate expected loss and the loss coverage protection requirement 3. An analyst provides a rating recommendation using the model outputs 4. The rating committee generates a final recommendation 5. Information about the mortgage security is updated, the tranching structure is applied, and—assuming there are no material changes to the security—final credit ratings are published 6. Moody's personnel monitor the performance of the mortgage security over time

TABLE III. MOODY'S CREDIT RATING MODELS

Element	1996 original model	2003 M3 algorithmic model	2006 M3 subprime algorithmic model
Objective/ goal	Predict an expected loss distribution to be used to determine the credit rating	- Create a simulation model that projects performance based on specific loan characteristics in different economic environments - Use a simulation model and advanced time series analysis to generate a pool loss vector	- Create a simulation model that projects performance based on specific loan characteristics in different economic environments - Use a simulation model and advanced time series analysis to generate a pool loss vector for subprime pools
Data sources	Historical pools (1987–1992) Supplementary data from: - Mortgage Bankers Association - Fannie Mae/Freddie Mac - Private mortgage insurers - Database of rated loan pools tracked by Moody's - Historical home price data - Time-to-foreclosure estimates - Economic indicators	- More recent historical data - Belief that the quality of data is better due to efficiencies in the industry - Loan Performance, Inc. (LPI, formerly known as Mortgage Information Corporation) on over 500,000 Jumbo 'A' loans	- A unique set of scrubbed data - In-depth historic performance data spanning 10 years from approximately 2 million subprime loans

Predictive factors (- or ¯ in importance)	- Loan-to-value ¯ - Borrower risk - - Originator practices - - Amortization schedule and loan seasoning - Loan characteristics - Regional economic outlook - Pool size	- More sophisticated economic model with greater predictive validity - Economic indicators modeled in much more detail with increasing sophistication - Refinement of LTV, borrower characteristics	- The credit impact of layered risks where the same economic factor can sometimes have competing effects on portfolio losses - Multidimensional analysis to better represent the behavior of the mortgage pool
Routine practices	- Ratings committee meetings - Periodic updating of the model - Monitoring	- Increased reliance on the automated output of the algorithmic rating model	- Using both M3 and M3 subprime algorithmic models in ratings

FIGURE 1. A THEORETICAL MODEL OF DYNAMIC INERTIA