

The Proximate Cause Principle of Causality in Organizations: How the Structure of Reality Produces Incorrect and Divergent Understandings Under the Division of Labor

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The most up-to-date version of my job market paper can be found here:

https://mhsingell.github.io/files/Singell_JMP_current.pdf

INTRODUCTION

Causal inference, or determining whether observed associations reflect actual cause and effect relationships between events, is a core problem of organizational actors (Rubin, 2010; Ryall & Sorenson, 2021). To understand how to rectify a failure or repeat a success, employees inside organizations must observe events that have occurred and determine the causal pathways that led to them (McIver & Lengnick-Hall, 2017; Lippman & Rumelt, 1982; Schon, 1995; Ryall & Sorenson, 2021), making correct causal understandings the antecedents to successful strategy. While reaching a correct understanding of past events is important for organizational performance, the process of developing the correct causal model of events from employees' observation of events in an organization is rife with difficulty (see work in causal ambiguity, e.g. King, 2007; King & Zeithaml, 2000).

Consider the failure of Kodak in the digital film market. While a Kodak engineer invented digital film technology, Kodak's management was concerned with the potential of the digital technology to cannibalize the company's profitable traditional film business and decided not to pursue it (Lucas & Goh, 2009). Ultimately other companies, recognizing the consumer demand for the more flexible and powerful photography, developed digital film technology, which generated a decline in the traditional film business and led Kodak to eventually file for bankruptcy. While researchers have noted many potential contributors to Kodak's failure, including a lack of foresight (Vecchiato & Roveda, 2010) and poor leadership (Prenatt et al., 2015), I suggest another source of Kodak's, and many other organizations', failure to form successful strategy: the structure of causal reality. Given that organizations must divide work and thus the experience of their employees, the formation of incorrect causal understandings could result directly from the structure of the true causal pathway between events.

I start by suggesting that the division of labor in organizations leads employees to form causal understandings of events consistent with what I call the Proximate Cause Principle. Because organizations divide work, they divide employee experience, leading employees to over-sample on events related to their work focus (Joseph & Gaba, 2020; Levitt & March, 1988; Heath & Staudenmayer, 2000; Clement, 2023). This leads events in an employee's work focus to seem the most central to causality in the organization, making whatever cause that is the most proximate to the employee's work look like the causal origin of events (what I will call the 'root cause') in the organization.

While potentially myopic in nature, the understandings generated under the Proximate Cause Principle need not be incorrect, and thus this inference principle need not drive performance differences. In fact, an employee is only likely to infer an incorrect understanding of organizational events using the Proximate Cause Principle if the most proximate cause to her work is not a root cause, or not a unique root cause, of events. Because causal realities differ in whether they contain these non-root causes, the structure of causal reality may help explain why organizations differentially come to correct versus incorrect understandings of the events generating organizational performance.

A MOTIVATING EXAMPLE

In order to illustrate how the Proximate Cause Principle of causal inference in organizations may lead to incorrect causal understandings as a function of the structure of causal reality, I will use the example of Kodak's failure in navigating the switch to digital photography. In the 1970s, an employee of Kodak's, electrical engineer Steven J. Sasson, invented digital photography (Deutsch, 2008). The technology was not production ready by any measure, but the ability for this technology to cannibalize Kodak's current film business was recognized early on, and thus management's reaction was "that's cute, but don't tell anyone about it" (Deutsch, 2008). Underlying this statement was the management team's causal understanding of the development of digital technology for Kodak's key film business. If they developed digital technology, they would generate demand for the technology and cannibalize their film business. I formalize this causal understanding in Figure 1 below.

FIGURE 1: Kodak Management's Causal Understanding of Digital Photography
Consumer Demand for Digital ← Develop Digital Technology → Cannibalize Film Business

Mr. Sasson, however, in focusing on the development of digital photography, felt that digital technology might well replace film at some point because of the incredible demand potential for a technology that increased the flexibility and quantity of pictures taken (Deutsch, 2008). Thus, from the engineer's perspective, the causal understanding of digital photography in Figure 2 may have been more likely.

FIGURE 2: Kodak Engineer's Causal Understanding of Digital Photography
Consumer Demand for Digital → Develop Digital Technology → Cannibalize Film Business

Ultimately, despite the engineer's excitement about the possibility of the technology, Kodak's management decided to protect its key business interests and continued its strategy with a heavy emphasis on its film business, which eventually led the company to bankruptcy. When reflecting on the failure, an interview with Carly Fiorina observed that:

"Kodak sat on a mountain of cash and profitability in their traditional photography business and I believe their thinking was **digital photography will eat into my traditional most profitable business**. I don't want that to happen. What I think **Kodak miscalculated about was they weren't in charge of whether that would happen. Consumers were in charge**. Individuals were in charge. And an individual will always choose... what gives them greater control, flexibility, freedom, choice. ... So suddenly consumers had a new way of taking pictures that gave them more control, more freedom, more flexibility and more choice. The consumer became in charge of how fast Kodak's traditional business would be eaten away. And Kodak unfortunately didn't see that in time." (Carly Fiorina interview, Batavick and Lucas, 2008, emphasis added by author)

In other words, the managers at Kodak had the incorrect causal understanding of the development of digital photography. In observing their engineer's new technology, they inferred that if they continued to develop the digital technology, then Kodak would jointly increase the consumer demand for digital solutions and cannibalize their film business. But in reality, the consumer demand for digital solutions ended up driving the development of the technology across the photography market, which cannibalized the film business of not only Kodak, but of

every organization. I formalize this true causal reality of the development of digital photography into a causal model in Figure 3.

FIGURE 3: The True Causal Reality of Kodak's Digital Photography Failure
Consumer Demand for Digital → Develop Digital Technology → Cannibalize Film Business

What can explain why the managers at Kodak incorrectly understood the causal relationships in the digital photography space until it was too late? The Proximate Cause Principle of causal inference in organizations, combined with the structure of the true causal reality for the development of digital technology, provides the following explanation. Kodak's management team was focused on the potential threat that digital technology posed to their core business, and this focus caused management to over index on this portion of reality. Because the development of digital technology was the most proximate cause to the loss of profit in Kodak's key business, this technology looked the most central to causality, leading Kodak's management to infer that as long as digital technology was not developed, demand for the technology which would cannibalize their current business would not manifest.

However, the structure of true causal reality contained a root cause outside of Kodak's focus on the proximate cause of the cannibalization of their traditional film profits. While digital technology was likely to cannibalize Kodak's film business, the reason why this was likely to happen is because consumers wanted a technology that afforded them more freedom and control over their photography. Kodak managers, in focusing on a part of reality that did not contain this root cause of the development of digital photography, incorrectly concluded that as long as they did not develop the technology, their film business would remain safe.

Two points of wisdom about the structure of causal reality and the Proximate Cause Principle of causal inference in organizations result from this example. First, when the structure of causal reality contains a cause that is not a root cause, or not a unique root cause, the Proximate Cause Principle of organizational inference generates incorrect understandings. Consistent with the Proximate Cause Principle, the Kodak managers concluded that the root cause of the cannibalization of their film business was the development of digital technology, but because this proximate cause was not the root cause of the digital photography causal reality, this causal understanding was incorrect.

Second, when employees do not share a proximate cause, the Proximate Cause Principle generates divergence in causal understandings. Work in Kodak was divided, such that the Kodak engineer's focus on digital photography was on the development of the technology, whose most proximate cause was the potential for consumer demand. On the other hand, the division of work focused the Kodak management team on the film business and its most proximate cause, the development of digital technology. Because the divided work of Kodak's engineer and managers led to them not sharing a proximate cause, they did not share a causal understanding of the digital photography space.

In the sections that follow, I develop a theoretical model for how, under the division of labor, causal realities that have a non-root, or non-unique root, cause are likely to generate both incorrect and divergent causal understandings like those held in Kodak's failure to pursue digital photography. The basis of the argument is that because some causal realities contain non-root, or non-unique root, causes and others do not, the potential for incorrect and divergent causal understandings, and the performance consequences of these understandings, varies by the structure of causal reality. To develop the intuition for which types of causal realities contain

non-root, or non-unique root, causes, I outline all possible causal realities for three events and indicate which ones contain a non-root or non-unique root cause in Table 1.

**Table 1: All Possible Causal Realities Between Events A, B, and C
And Whether the Reality Contains a Not Root Cause**

	Example Graph	Non-Root Cause(s)
No Cause	A B C	No
One Cause	A->B C	No
Repeller	A<-B->C	No
Collider	A->B<-C	Yes ¹
Linear	A->B->C	Yes
Cycle	A->B->C->A	Yes
Acyclic Loop	A->B<-C->A	Yes

¹ Collider realities have two root causes, such that they contain non-unique root causes. All other graphs with a “Yes” in column 3 contain a non-root cause.

In considering the implication of my theory for the incorrect and divergent understandings formed by managers and engineer at Kodak, my work suggests that in order to disambiguate the disagreement of understandings, and ultimately select the correct causal understanding to build a successful strategy on, it is essential to think about both the underlying process generating events and the underlying organizational division of work influencing their experience of events. My work provides a set of theoretically grounded propositions and hypotheses for how causal inference occurs under the division of experience in organizations, and how this division is likely to matter for the formation of causal understandings as a function of the structure of causal reality.

THEORY

A Roadmap for Where We Are Going Together

In this theory section I develop my argument for how the systematic division that organizations place on the observation of reality for their employees interacts with the true causal reality to determine whether causal understandings correctly converge. The argument is structured such that I develop the intuition for a series of assumptions I make, and then show that the results of my argument based on these assumptions are likely to generate the Proximate Cause Principle of causality in organizations. The theory section progresses by answering a series of questions in order generate this argument, which I provide in a list below to give you (the reader) a sense for where we are going together.

- What is a causal understanding and why is it important for organizations?
- What is the nature of the true causal reality and an individual’s ability to form a causal understanding of it?
- How do individuals form causal understandings from event observation?
- How do organizations impact the observation of causal reality for their employees?

- How does the structure of causal reality interact with employees' divided observation of this reality in an organization to generate incorrect or divergent causal understandings?

What is a causal understanding and why is it important for organizations?

A causal understanding is an individual's cognitive representation of the true causal relationships that exist between events (Carey, 1995); or, in other words, a causal understanding is an explanation for why events happened the way they did (Juarrero, 2011). In addition to being core to psychology and cognitive science's work on human reasoning (see Carey, 1995; Goodman et al., 2011; Chen & Bornstein, 2024), causal understandings are central to the function of organizations. This is because forming a successful organizational strategy requires a correct causal understanding of events.

One way to view a strategy is as a proposed set of causal relationships between events, where a strategy is really a theory of how the world works based on a causal understanding (Lazzarini & Zenger, 2023; Carroll & Sorensen, 2021). For example, consider the Kodak managers in our motivating example above, who are concerned about the cannibalization of their traditional film business. If Kodak's strategy is to stop development on digital technology in order to preserve film business sales, then implicit to this strategy is the causal understanding that the development of digital technology is what is ultimately going to disrupt the sales of traditional film. Thus, forming a strategy of what to do next relies on a causal understanding of what has happened previously.

If we accept that strategy formation is based on a set of causal understandings, then forming a successful strategy will be contingent on employees having a correct causal understanding. Continuing with our example, Kodak's strategy to stop the development of digital technologies in order to preserve film profits will only be effective if digital technology is a part of what caused the poor performance. If the causal understanding of the relationship between events is incorrect, the strategy formed is unlikely to be effective. This conceptualization of strategies as theories based on causal understandings is consistent with research that finds that managers that have a correct causal understanding of events are more successful at resolving problems when they arise (Milgrom & Roberts, 1992; Ryall & Sorenson, 2021).

Finding the correct causal understanding in order to generate successful future strategy for an organization may sometimes be a straightforward task. For example, returning to IBM's failure to be successful in the personal computer market, IBM's causal understanding that their failed performance in the personal computer market meant they should shift away from the personal computer market and back to other business units that had previously generated profits was logically straightforward (Cortada, 2019). However, if there are consistent factors that generate either incorrect or divergent causal understandings, and these causal understandings are core to the formation of successful strategies, then organizations ought to be uniquely concerned with uncovering these determinants.

Indeed, work on organizations has addressed several possible antecedents to incorrect and divergent causal understandings. For example, under causal ambiguity, where causal relationships are difficult to infer, trustworthiness is likely to matter for how much information and understandings are shared (Szulanski et al., 2004). Hidden events and factors may also make it difficult for managers to reach a correct causal understanding (Ryall & Sorenson, 2021). And while not necessarily directly based in causal relationships, a large body of work addresses how

differences in mental representations may make the search for and formation of strategy less than ideal (Csaszar & Levinthal, 2016; Santos et al., 2021; Joseph & Gaba, 2020).

However, in considering the broad set of factors that might impact the ability for employees to converge on correct causal understandings, organizational scholars have yet to study in detail the structure of the true causal reality. To the extent that causal reality has been considered in work on organizational understandings, it has often been dismissed, with work citing that employees' interpretations and true events can never be disentangled, and that employees can even hold understandings that are in direct contrast to their experience (Weick et al., 2005; Levitt & March, 1988). While there are no doubt pathways of motivated reasoning and interpretation that generate causal understandings (i.e. see Tappin et al., 2020), work in causal induction suggests that one of the central reasons that causal models diverge when being inferred from observation is because of the underlying structure of the causal reality (see d-separation, Pearl, 2009).

In the next section I turn to this work in causal induction, introducing the structure of true causal reality and a series of assumptions about this reality, which I will build into a theoretical argument for why and how the structure of true causal reality is likely to matter for the inference of causal understandings in organizations.

What is the nature of the true causal reality and an individual's ability to form a causal understanding of it?

A true causal reality is the underlying process that generates the events that individuals, such as employees within an organization, experience. If there is a true causal reality that generates events, then an employee's causal understanding of the world can be defined as this individual's cognitive representation of the underlying true causal reality. While some work within organizations has asserted that there is no true causal reality (i.e. see Skoldberg, 1994; Rhodes & Brown, 2005), the argument in this research generally relies on the fact that humans can never observe the true causal reality independent from their interpretation or perception of this reality (see Weick et al., 2005). While I also assume that the true causal reality cannot be observed, it is analytically useful in my argument to distinguish between the existence of a true causal reality and the ability to observe it. These two first assumptions of the existence, but unobservability, of the true causal reality are formalized below.

Assumption 1: There is a true causal reality, i.e. there is a true causal process that generates events.

Assumption 2: The true causal reality is unobservable to individuals.

It follows from these two assumptions that individuals can seek to find the true causal reality but must infer the true causal relationship between events based on their observation of the events, and not the observation of the process directly. Thus, the act of an individual forming a causal understanding, or a cognitive representation of the true causal reality, is an act of inference from the observation of events.

Proposition 1: When an individual forms a causal understanding, she uses her observation of a set of events to infer the causal relationship between them.

How do individuals form causal understandings from event observation?

If individuals must form causal understandings through inferring the true causal relationships between events based on their observations of them, the natural next question is how individuals perform this inference. To start, I differentiate between event occurrence and event observation. An event occurring means that an event has been generated by the true causal reality. An event observation means that an individual has observed the event that has occurred. While I differentiate between event occurrence and event observation, crucial to my argument is that individuals who are observing events do not differentiate between the occurrence of events and their observation of them. This is a simplifying assumption, but it is consistent with work on theories of causal induction, where inference of causal relationships based on the observation of even small sets of data is a uniquely human endeavor (Griffiths & Tennenbaum, 2009).

Assumption 3: An employee forming a causal understanding assumes that event occurrence is consistent with her observation of events.

With assumption 3 in hand, that individuals assume that their observation of events is consistent with actual event occurrence, I now turn to how individuals go from observing events to inferring relationships between them. General causal inference proceeds with basic principles about how causality should work. One such principle is that a cause can occur without its effect, but an effect cannot occur without its cause. While this is in some ways a strict assumption in our multi-modal complex world, it is also an assumption ingrained in the definition of the terms cause and effect. Simply put, a cause must occur before its effect, or else the labels of cause and effect are not analytically useful or correct (Gale, 1965). However, effects need not occur with their causes. For example, consider the relationship that a cloud causes rain. A cloud must be present in the sky for it to rain, but it need not be raining for a cloud to appear in the sky. I formalize this assumption below:

Assumption 4: A cause can occur without its effect, but an effect cannot occur without its cause (or causes).

The above assumption helps individuals who are seeking to form causal understandings, but cannot observe the true causal reality directly, make correct inferences about the causal relationships between events. However, we are not just interested in individuals forming causal understandings generally, but in employees forming causal understandings in the structured context of organizations. In considering what causality is like in organizations, and what principles of inference might help employees converge on correct causal understandings, I make one further assumption about the nature of causality. Specifically, while much work in causal induction thinks about deterministic causality, I suggest that the causality in organizations is most likely to be probabilistic.

Deterministic causality means that if A causes B, when A happens B happens. Probabilistic causality means that if A causes B, A occurring increases the likelihood that B occurs. In the context of organizations, we generally say that effective coordination is likely to increase performance (Okhuysen & Bechky, 2009) or that complex problems generally require more coordination (Heath & Staudenmayer, 2000). In fact, much organizational research has come to the conclusion that while there are things we generally believe to be the case, the complexity and variation in organizations yields very few absolutes and very many 'it depends'. Thus, when considering causality in the context of organizations, I assume that employees,

consistent with the body of organizational research, will form causal understandings of causal processes that are probabilistic. I formalize this assumption below.

Assumption 5: If a cause occurs the likelihood of its effect occurring is S , where $S < 1$.
(Note: S denotes the causal strength of the relationship between a cause and its effect)

A proposition about the formation of causal understandings by employees follows from these assumptions. Since an effect cannot occur without its cause (assumption 4), an effect must occur at a rate lower than its cause (assumption 5), and employees assume that their observation of events is consistent with the occurrence of events (assumption 3), it follows that causes should be observed occurring more often than effects.

Proposition 2: For an employee forming a causal understanding consistent with causal inference principles, causes should be observed occurring more often than effects.

How do organizations impact the observation of causal reality for their employees?

With a series of assumptions and a proposition developed for how employees might infer a causal understanding based on their observation of events, I now turn to how organizations might impact these employees' observation of the true causal reality. A key element of organizations is the division of labor; in order to complete the complex and information intensive tasks of an organization, work must be divided between employees (March & Simon, 1958; Mintzberg, 1989). While the division of labor improves an organization's ability to complete its necessary tasks, work on modularity and organizational design frequently points to the potentially unintended consequence of this division: the division of event experience in the organization (Clement, 2023; Dearborn & Simon, 1958; Joseph & Gaba, 2020).

In considering how to specifically operationalize the way in which organizations divide the event observation of their employees, I consider two dimensions along which organizations are likely to vary the work, and thus the event experience, of their employees: scope and frequency. First, the division of work is likely to generate an event experience for employees that is reduced in scope. When employees are given a set of related tasks that represent a subset of tasks the organization performs, they are also likely to have a reduced scope of visibility into events corresponding to the tasks that these employees are not performing. Thus, organizations are likely to provide employees with experience of events that are related to each other, but limited in that the event experience may not fully represent a complete set of events occurring in the organization. As Simon says, "structural boundaries and the division of labor reflect how the organization represents its problems and affect how individuals filter information" (Dearborn & Simon, 1958; Joseph & Gaba, 2020).

The structure of the organization then, which limits the scope of work to a small set of related tasks, may also limit the scope of events that an employee is likely to see at any given time, which in turn serves to create this employee's causal understanding of events in the organization as a whole. Thus, the core feature that I consider in operationalizing the way that organizations impact the observations of events for their employees, is the way in which organizations limit employees from getting a bird's eye view of the organization, limiting observation of events at any time. I formalize this assumption below:

Assumption 6: Organizations divide the scope of observation of the true causal reality for their employees, such that while many events may occur in the organization, employees in the organization will only ever observe a subset of related events occurring. 2

Footnote 2: To formalize this assumption for the model specifically, I constrain the observation of the scope of events to pairs of related events only, which greatly simplifies the calculations needed. However, theoretically, the scope of the observation of events need only be consecutive and one event fewer than all causes occurring in the organization, in order for this logical argument to hold.

This is the strongest assumption of my work, and it is also the most consequential. To consider why this assumption may be accurate for organizations, I return again to the motivating example. At Kodak, both the managers and the engineer are forming causal understandings of digital photography. The problem that both sets of employees face in trying to understand digital photography is that they cannot focus on the whole set of events. Because the organization silos experience (whether by time, role, or department), neither the engineer nor the management team at Kodak is likely to observe the consumer demand changes directly with the cannibalization of the film business. This could in some ways help the engineer and the management team form correct causal understandings, because they are unlikely to identify spurious relationships between events, like general consumer demand directly causing the decline in film profits (a common problem in the divergence of causal models, see d-separation in Pearl, 2009). However, it also means that when observing events in the organization, the engineer and the managers at Kodak both had the difficult task of connecting their observation of sets of events into a larger model of causal reality to generate their own causal understandings.

The second way in which the organization's division of labor is likely to impact the observation of events for employees is by modifying the frequency of observation of events. Specifically, because organizations tend to have employees specialize on specific tasks and not others (Dearborn & Simon, 1958; Heath & Staudenmayer, 2000; Thompson, 1961), employees are likely to observe events related to their assigned work at a higher frequency than those events outside the scope of their work. Returning to our motivating example, the management team and the engineer are responsible for different tasks in the organization, which likely leads them to experience different sets of events at different frequencies. Kodak's managers may be responsible for maintaining profits of Kodak, which were majority driven by traditional film, and thus may have experienced this event and its causes more frequently than the other events in the organization. The engineer, on the other hand, is uniquely concerned with the development of the digital technology, and thus may experience this event and its causes more and more saliently than other events. I formalize this below:

Assumption 7: Organizations focus employees on events related to their work focus, such that while employees may observe events that are not associated with their work focus, employees in the organization will observe sets of events in their work focus more frequently.³

Footnote 3: To formalize this assumption for the model specifically, the constraint of the observation of the scope of events to related events only, generates a pair of events equation such that, employees in an organization will observe the pair of events that they are responsible for at a rate higher than that of all other pair of related events, where the focus pair of events e_1 and e_2 ,

for an employee i is observed at a rate $f_{i,focal}(e_1 \& e_2)$ and all other events are observed at a rate $\frac{(1-f_{i,focal}(e_1 \& e_2))}{k_r-1}$, such that focus on all pairs of events sums to 1, and $f_{i,focal}(e_1 \& e_2) > (1 - f_{i,focal}(e_1 \& e_2))$.

From this set of assumptions about how organizations limit the scope and frequency of event experience through the division of labor, it is possible to see how organizations may impact the formation of correct causal understandings for their employees. If, in limiting the scope of experience to related events only (assumption 6), and in increasing the frequency of observation of events within the scope of work focus (assumption 7), the observation of events for employees becomes inconsistent with event occurrence of the causal reality, it is likely that employees will form incorrect causal understandings of events. However, functionally, the modification of the scope and frequency of observation of events by organizations could either exacerbate or attenuate the formation of incorrect causal understandings, depending on both which set of events an employee is focused on and the structure of the causal reality. I generate a set of hypotheses for when the combination of focus on events and structure of causal reality are likely to generate either incorrect or divergent causal understandings for employees below.

How does the structure of causal reality interact with employees' divided observation of this reality in an organization to generate incorrect or divergent causal understandings?

In this theory section, I've developed a series of assumptions about how employees will infer causal understandings from their observation of events and how organizations will influence these employees' observation of events. In the introduction, I have also referenced the Proximate Cause Principle of causal inference in organizations, where because organizations limit the scope and modify the frequency of observation of events, the proximate cause within the focused scope of an employee's work is likely to look like a root cause. In this final section of theory, I connect the assumptions and propositions made about employees inferring causal understandings under the divided observation of events in organizations to the Proximate Cause Principle of causality, in order to generate two hypotheses about when employees are likely to come to incorrect or divergent causal understandings in organizations.

Because the division of labor in organizations limits the scope of event experience and modifies the frequency of event experience for employees, an employee's observation of an event will be a function of whether an event is within view of their focus of work or not. Events that are within the scope of the employee's division of work will be observed more frequently (assumption 7), and events that are observed more frequently are determined to be causes (proposition 2). Since causes do actually occur more often than their effects (assumption 5), the proximate cause within the employee's focus of work will be observed occurring the most often of all events and will be thus inferred as the root cause of all other events.

Proposition 3: The proximate cause within the employee's focus of work will be inferred as the root cause by the employee.

Proposition 3 is the formalization of the Proximate Cause Principle of causality within an organization, and outlines a principle by which causal inference is likely to take place in organizations. However, whether this Proximate Cause Principle of causality will generate incorrect or divergent causal understandings depends on the structure of the true causal reality.

Specifically, when proximate causes are root causes, the proximate cause principle will correctly generate causal understandings consistent with the true structure of causal reality. However, incorrect causal understandings in organizations will occur under the Proximate Cause Principle when the most proximate cause for an employee is not a root cause, or not a unique root cause.

Proposition 4: When the focus of the employee's work does not include a unique root cause (1), the employee will form an incorrect causal understanding of events in the organization.

Footnote 4: or there is no root cause

Second, the Proximate Cause Principle predicts that when employees share a proximate cause, the employees are likely to converge on the same causal understanding of events. Thus, when the division of labor generates non-shared proximate causes between employees, they are likely to diverge in causal understandings.

Proposition 5: When two employees do not share the same proximate cause, their causal understandings of events will diverge.

While Proposition 4 and 5 outline two, perhaps somewhat simplistic, conditions under which employees are likely to reach incorrect or divergent causal understandings, the power of these propositions lies in the fact that different structures of causal reality generate different likelihoods of satisfying them. Specifically, certain causal realities can be divided into slices that have non-root, or non-unique root causes. And, if under the division of labor employees are focused on different sets of events, these causal realities that have a non-root cause also generate non-shared proximate causes between employees with different focuses. For example, consider all possible causal realities between three events as outline in Table 1 (reproduced below for ease of access).

**Table 1: All Possible Causal Realities Between Events A, B, and C
And Whether the Reality Contains a Non-Root Cause
That Under the Division of Labor Generates a Non-Shared Cause**

	Example Graph	Non-Root Cause	Non-Shared Cause
No Cause	A B C	No	No
One Cause	A->B C	No	No
Repeller	A<-B->C	No	No
Collider	A->B<-C	Yes ¹	Yes
Linear	A->B->C	Yes	Yes
Cycle	A->B->C->A	Yes	Yes
Acyclic Loop	A->B<-C->A	Yes	Yes

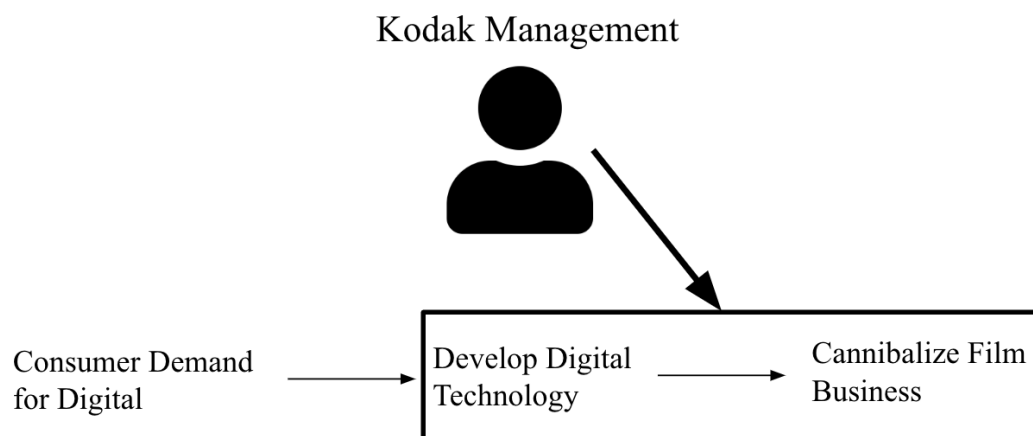
¹ Collider realities have two root causes, such that they contain non-unique root causes. All other graphs with a "Yes" in column 3 contain a non-root cause.

If we consider that the true causal reality represents the scope of events related to organizational tasks over which work is divided, then as long as there is an employee focused on the non-root cause slice of reality (as specified by assumption 6 and 7), causal realities with a non-root cause are likely to generate incorrect causal understandings. Thus, I hypothesize that:

Hypothesis 1: When organizations divide the scope and frequency of employee experience, causal realities with a non-root cause will generate incorrect causal understandings.

To visualize hypothesis 1, I use the motivating example to generate Figure 4 that outlines the expected formation of an incorrect causal understanding by management team at Kodak based on observation of events in the organization generated by a linear causal reality, where the Kodak management team is more focused on the cannibalization of the film business and its antecedent, not the consumer demand.

FIGURE 4:
Causal Realities with Non-Root Cause Will Generate an Incorrect Causal Understanding Because the Division of Work Focuses Employee on a Non-Root Cause Slice of Reality



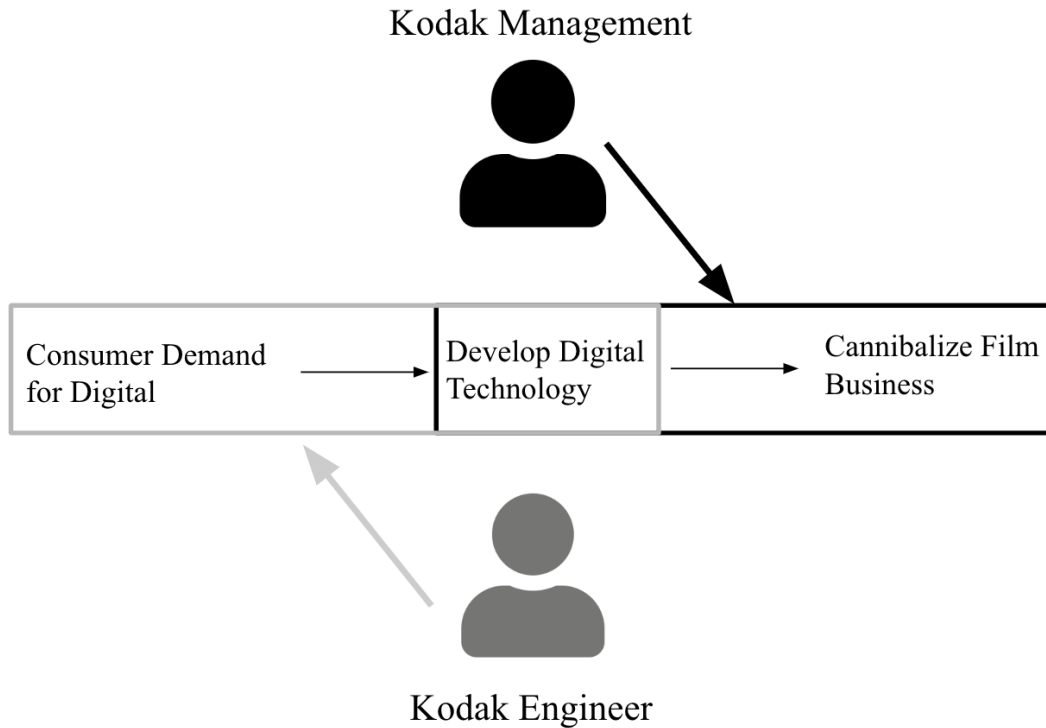
Kodak Management Causal Understanding:
Consumer Demand for Digital \leftarrow Develop Digital Technology \rightarrow Cannibalize Film Business

In considering which causal reality structures will satisfy proposition 5, where non-shared proximate causes are likely to generate divergence, causal realities that contain a non-root cause also tend to generate non-shared proximate causes. If the division of labor is distributed across the causal reality, and the scope of reality cannot contain all causes (assumption 6), such that some employees are focused on a single non-root cause slice of realities and others are focused on a slice of reality with another cause, then divergence is expected. Thus, I hypothesize:

Hypothesis 2: When organizations divide the scope and frequency of employee experience, causal realities with a non-root cause will generate divergent causal understandings.

To visualize hypothesis 2, I use the motivating example to generate Figure 5 that outlines the expected divergence on causal understandings for the Kodak management and the Kodak engineer based on their observation of events in the organization generated by a linear causal reality (non-shared proximate cause, non-root cause reality).

FIGURE 5:
Causal Realities with Non-Root Cause Will Generate Divergent Causal Understandings
Because the Division of Work Focuses Employees on Different Proximate Causes



Kodak Management Causal Understanding:

Consumer Demand for Digital ← Develop Digital Technology → Cannibalize Film Business

Kodak Engineer Causal Understanding:

Consumer Demand for Digital → Develop Digital Technology → Cannibalize Film Business

To test the hypotheses above against my developed assumptions and propositions, and to provide a set of mathematically grounded predictions for the role of causal realities with non-root causes in generating incorrect and divergent causal understandings under the division of experience in organizations, I develop a mathematical model using the set of assumptions I've outlined above.

MODEL

In this section I mathematically test whether non-root cause realities are likely to generate a trade-off between correct causal understandings and division of labor in an organization. To do this, I operationalize my conception of the division of experience in organizations into a causal model and test the likelihood of incorrect and/or divergent causal understandings across different causal realities. The above section outlined and defended several assumptions about the individual inference, organizations, and the true causal reality, which I present in Table 2 below. From these two assumptions, five propositions about how causal understandings will be inferred by individuals followed, which are presented in Table 3. I then present my hypotheses in Table 4, which my model below shows follow from these assumptions and propositions.

My model developed below shows that because non-root cause realities break assumption 3, that an employee's observation of events is consistent with actual event occurrence, proposition 2, that causes should occur more than effects, is not valid. This generates incorrect and divergent causal understandings for employees at high causal strengths, depending on employee focus on non-root cause slices of reality. My causal modeling method provides a proof of concept that when organizations divide experience, realities with non-root cause will generate either incorrect or divergent causal understandings as predicted in hypotheses 1 and 2.

Table 2: Assumptions

Number	Assumption
1	There is a true causal reality, i.e. there is a true causal process that generates events.
2	The true causal reality is unobservable to individuals.
3	An employee forming a causal understanding assumes that event occurrence is consistent with her observation of events.
4	A cause can occur without its effect, but an effect cannot occur without its cause (or causes).
5	If a cause occurs the likelihood of its effect occurring is S, where $S < 1$. (Note: S denotes the causal strength of the relationship between a cause and its effect)
6	Organizations divide the scope of observation of the true causal reality for their employees, such that while many events may occur in the organization, employees in the organization will only ever observe a subset of related events occurring.
7	Organizations focus employees on events related to their work focus, such that while employees may observe events that are not associated with their work focus, employees in the organization will observe sets of events in their work focus more frequently.

Table 3: Propositions

Number	Proposition	Necessary Assumptions
1	When an individual forms a causal understanding, she uses her observation of a set of events to infer the causal relationship between them.	1, 2
2	For an employee forming a causal understanding consistent with causal inference principles, causes should be observed occurring more often than effects.	1, 2, 3, 4, 5
3	Proximate Cause Principle: The proximate cause within the employee's focus of work will be inferred as the root cause by the employee.	1, 2, 3, 4, 5, 6, 7
4	When the focus of the employee's work does not include the root cause (or there is no root cause), the employee will form an incorrect causal understanding of events in the organization.	1, 2, 3, 4, 5, 6, 7
5	When two employees do not share the same proximate cause, their causal understandings of events will diverge.	1, 2, 3, 4, 5, 6, 7

Table 4: Hypotheses

Number	Hypothesis
1	When organizations divide the scope and frequency of employee experience, causal realities with a non-root cause will generate incorrect causal understandings.
2	When organizations divide the scope and frequency of employee experience, causal realities with a non-root cause will generate divergent causal understandings.

Event Occurrence vs. Event Observation

The core distinction that allows me to uniquely apply a causal modeling approach to causal understandings in an organizational setting is the differentiation between event occurrence and event observation. An event occurrence means that an event has been generated by the true causal reality. An event observation means that an individual has observed the event that has occurred. While traditional work in causal modeling would tend to equate event occurrence and event observation, because I assume that organizations structure the experience of employees, limiting the scope of the observation of events, events can occur in the organization without being observed by an employee. For example, engineering resources can be allocated in the organization without the sales manager being aware of it. Thus, my general equation for the probability of an event (e_n) for a given employee (i) in an organization is the likelihood of the occurrence of the event $P(c_{e_n})$ times the likelihood that the event is observed occurring $P_i(b_{e_n})$.

$$P_i(e_n) = P(c_{e_n}) * P_i(b_{e_n}) \quad (1)$$

In the below sections I break down how I calculate the likelihood of both event occurrence and event observation.

Event Occurrence: The Likelihood of an Event Given a True Causal Reality and a Probabilistic Causal Strength

Event occurrence in an organization is a function of the true causal reality. One way to understand event occurrence is to conceptualize the possible worlds that a causal reality could create. For all event-generating process with three events (A,B,C) for example, there are eight possible worlds that could occur ranging from all three events not occurring (A:0, B:0, C:0) to all three events co-occurring (A:1, B:1, C:1). I outline all possible worlds for three event causal realities in column 1 of table 2. However, for any specific causal reality with three events, the likelihood of each possible world differs.

For example, consider the true causal reality being a linear graph, as in Figure 3, where Consumer Demand for Digital \rightarrow Develop Digital Technology \rightarrow Cannibalization of Film Business (generalized as $A \rightarrow B \rightarrow C$). If I assume, as I have above, that effects cannot occur without their causes (assumption 4) then for a linear causal reality, some possible worlds will not be possible, because B occurring without its cause A is not possible. In column 2 of Table 5, I identify which of the 8 possible worlds are possible for the linear graph under counterfactual causality.

**Table 5: Likelihood of Event Occurrence for 3 Event Linear Graph (A→B→C)
in the Possible Worlds Framework**

Possible Worlds	Possible for Linear Graph	Likelihood of World for Linear Graph	Likelihood for Linear Graph at S = 0.9
A:0, B:0, C:0	Yes	(1-S)	0.1
A:1, B:0, C:0	Yes	S*(1-S)	0.09
A:0, B:1, C:0	No	0	0
A:0, B:0, C:1	No	0	0
A:1, B:1, C:0	Yes	S*S*(1-S)	0.081
A:0, B:1, C:1	No	0	0
A:1, B:0, C:1	No	0	0
A:1, B:1, C:1	Yes	S*S*S	0.729

After understanding which worlds of event occurrence are possible, the next step of the model is to calculate how likely each world of events is to occur. The assumption that causality in organizations is probabilistic (assumption 5), i.e. that A causing B means that A occurring increases the likelihood of B occurring, is core to executing this calculation. I use the variable causal strength (S) to identify the amount that a cause increases the probability of its effect by. For example, if the causal strength (S) of the relationship between consumer demand for digital and the development of digital technology is 0.7, then consumer demand for digital increases the likelihood that digital technology is developed by 70%. Using this framework, the likelihood of an event occurring given its cause has occurred is S, and the likelihood of an event not occurring given its cause has occurred is 1-S. I assume that the likelihood of an independent cause occurring is also S, which can be interpreted as an unobserved cause of the independent cause occurring. I use this basic logic to generate the likelihood of each possible world for the linear graph in column 3 of Table 5.

Table 5 shows the general intuition that event occurrence in an organization is a function of the structure of the true causal reality and the causal strength between related events. While I show the intuition for these calculations for a linear graph with three events above, this framework can be generalized to any number of events and causal realities, as I formalize in equation 2 below, where the probability of any possible world (w) is a function of the causal strength of the relationship between events (S), the number of events that occur in the possible world (j), the number of independent causes that do not occur in the possible world (i.e. events that do not have a cause in the world, k), and the number of effects of events j that do not occur in the possible world (m).

$$P(w) = S^j * (1 - S)^k * (1 - S)^m \quad (2)$$

With equation 2 formalized to give the likelihood of a possible world given a causal strength (S) and event-generating process (which determines the values of j, k, and m), to find the likelihood of an event occurring $P(c_e)$, I only need to sum all possible worlds where event e occurs, which I formalize in equation 3, where d is the number of possible worlds.

$$P(c_{e_n}) = \sum_0^d w_d[e_n] * P(w_d) \quad (3)$$

I can also calculate the probability of any two events (e_1, e_2) co-occurring together, $P(c_{e_1 \& e_2})$, by summing possible worlds where both events occur, as formalized in equation 4.

$$P(c_{e_1 \& e_2}) = \sum_0^d w_d[e_1] * w_d[e_2] * P(w_d) \quad (4)$$

The above formalization of my model of possible worlds gives me a way to measure the likelihood of event occurrence in an organization $P(c_e)$ given an event-generation process and strength of causal relationship (S). This portion of the model is similar to work developed in causal modeling (i.e. see Pearl, 2009), but adapted to an organizational setting. In equation 2, I also find a calculation supporting our intuition for why realities that contain slices with a non-root cause may generate incorrect causal understandings. These realities are more likely to generate a smaller number of possible worlds, and when causal strength is high, these graphs are most likely to either generate complete co-occurrence or no occurrence of all events. This uncertainty creates the opportunity for errors in causal understandings, which structure of experience is likely to produce.

However, my key assumption about organizations, that they divide the experience of events for employees, is not incorporated into the occurrence of events, but rather into the observation of events that have occurred $P_i(b_{e_n})$, thus I turn to formalizing the observation of events next.

Event Observation: The Likelihood of an Employee Observing an Event Occur Given the Divided Experience in the Organization

Event observation in an organization is a function of the degree to which experience is divided in the context. For example, if the Kodak engineer is tasked with researching alternative film technologies, the organization can be said to have structured the experience of the engineer to focus on this event and its related cause. This means that the engineer is both more likely to see the development of digital technology and the potential for consumer demand for the product occurring, but it also means that he is more likely to see these events not occur. What the structuring of experience functionally means in an organization is that employees are focused on observing specific sections of the event-generating more than others. One nice metaphor to consider this concept through is the tale of the inebriated man searching for his keys only where the lamp had lit up the street, because it was the only place that he could see. Organizations allow for selective observation of events by ‘turning on the streetlight’ for certain people on certain events, creating variance in the observation of events given a set of occurrences of events. To formalize this idea of the structure of experience, consistent with our assumption that organizations limit the scope of experience observable to related events only, the likelihood that an individual observes a pair of events (e_1, e_2) occurring in an organization is simply the likelihood that the employee’s (i) experience in this organization focuses them on observing this pair ($f_{i,e_1 \& e_2}$).

$$P_i(b_{e_1 \& e_2}) = f_{i,e_1 \& e_2} \quad (5)$$

In order to find the likelihood of observing any particular event (e_n) given the siloed, pairwise focus of events in organizations, I can simply sum all the pairwise focuses that include event (e_n), giving equation 6 below.

$$P_i(b_{e_n}) = \sum_{y=0, y \neq n}^N f_{i,e_n \& e_y} \quad (6)$$

This event observation portion of my model formalizes the assumption that organizations divide the event experience of their employees to specific sets of related events, providing a variable of event focus ($f_{i,e_n \& e_y}$) that maps an organization's division of labor to an observation window for individuals to observe events within the organization. (footnote 5). Functionally our event focus variable operationalizes how the division in organizations allows their employees to see only slices of events at any given time, where the engineer may be more likely to experience the development of digital technologies and its associated events, while the management team may be more likely to experience the threat to their film business and associated events.

Footnote 5: As noted in footnote 2, the model formalizes the set of events an employee can observe as a pair of related events only. Making the operationalization of assumption 6 for the model as follows: Organizations divide the scope of observation of the true causal reality for their employees, such that while many events may occur in the organization, employees in the organization will only ever observe pairs of related events occurring. However, as long as the scope of events remains smaller than the number of causes, the argument holds.

In Table 5 I summarize the parameters of my model that I can vary to generate different likelihood of events.

Table 5: Model Parameters

Parameter	Name	Description	Possible Values	Category of Variance
S	Causal Strength	Given that the cause occurs, the likelihood of also observing the effect.	[0,1)	Probabilistic Causality
$f_{i,e_1 \& e_2}$	Event Focus	The proportion of employee i's focus that is directed by the organization onto events e1 and e2.	[0,1]	Division of Labor
j	Events, Occurring	Number of events that occur in a possible world.	[0,N]	Structure of Causal Reality
k	Independent Events, Non-Occurring	Number of events that do not have causes that do not occur in a possible world.	[0,N]	Structure of Causal Reality
m	Effect of Events j, Non-Occurring	Number of effects of events j that do not occur in a possible world.	[0,N-1]	Structure of Causal Reality

Now that I have developed a model to calculate the likelihood that employees within an organization will observe events, I can turn to how these employees will form causal understandings from these events.

Forming a Causal Understanding of Events from Event Observation

In order to form a model about how an employee will form a causal understanding from event observation, I reference several assumptions and propositions generated in the theory section above. Consider proposition 2, which states that for an employee forming a causal understanding consistent with causal inference principles, causes should be observed occurring more often than effects. The first part of proposition 2 specifies that an employee would need to be trying to form a causal understanding consistent with causal inference principles in order for the second piece of the proposition to be relevant. In the model, I formalize this contingency into an additional assumption, which is that employees are seeking to form the correct causal understanding of events, which means that employees will choose the causal understanding that is the most likely to be correct based on the observed probabilities and causal inferences principles.

Assumption 8: Employees seek to find the correct causal understanding of events through the application of causal inference principles (assumption 3-5).

There is much work in organizational research that references motivated or situated interpretation when it comes to making sense of events in organizations (see sense-making literature, i.e. Weick et al., 2005). However, if successful strategies are based on correct causal understandings, and employees are either motivated or incentivized to generate successful organizational outcomes, this assumption may represent a reasonable set of true scenarios in organizations.

Next, the assumptions 1-5 and their implications proposition 1 and 2, plus the newly minted assumption 8, gives the model a clear way to decide how employees will select their causal understandings. The second half of proposition 2 states that causes should be observed occurring more than effects, and assumption 8 says that employees will select the causal understandings that is most likely to be correct given their causal inference principles. Thus, if event 1 is observed occurring more than event 2, then an employee (i) will conclude that event 1 causes event 2.

I formalize this logic into equation 7 below.

$$\begin{aligned} & \text{if } P_i(e_1) > P_i(e_2) \text{ then } e_1 \rightarrow e_2 \\ & \text{if } P_i(e_1) < P_i(e_2) \text{ then } e_2 \rightarrow e_1 \\ & \text{if } P_i(e_1) = P_i(e_2) \text{ then } e_1 \rightarrow e_2 \text{ or } e_2 \rightarrow e_1 \end{aligned} \quad (7)$$

By operationalizing our assumption about employees wanting to find the correct causal understanding and employing causal inference principles to do so, I can form equation 7, which provides a clear way that employees go from observing event co-occurrence to forming causal understandings of these events. In equations 8 and 9, I formalize how the probabilities in equation 7 can be derived from the event probabilities I calculate in equations 1 through 6.

$$P_i(e_1) = P_i(b_{e_1}) * \sum_0^d w_d[e_1] * P(w_d) \quad (8)$$

$$P_i(e_2) = P_i(b_{e_2}) * \sum_0^d w_d[e_2] * P(w_d) \quad (9)$$

Why Proximate Causes Look Like Root Causes in Organizations: How the Frequency Modification of the Division of Labor Makes Proximate Causes be Observed Most Frequently

The structure is now in place to formalize why the most proximate cause in an employee's focus of work ends up looking like the root cause of events in the organization for this employee. In developing the logical argument, I assumed that employees observe the scoped set of events associated with the focus of their work more than events that are further away from their focus (assumption 6 and 7). In the model I formalize this as an employee i observing her focal pair of events e_1 & e_2 at a likelihood of $f_{i,focal}(e_1 \& e_2)$, and observing all other possible pairs of events at a likelihood of $\frac{(1-f_{i,focal}(e_1 \& e_2))}{k_r-1}$, where k_r is the total number of relationships in the causal reality, and where the likelihood of observing of the focal pair of events $f_{i,focal}(e_1 \& e_2)$ is greater than the likelihood of observing all the other pairs of events ($1 - f_{i,focal}(e_1 \& e_2)$). I formalize this into equation 10 below.

$$f_{i,focal}(e_1 \& e_2) > 1 - f_{i,focal}(e_1 \& e_2) \quad (10a)$$

Where $f_{i,focal}(e_1 \& e_2)$ is employee i 's focus on her focal events e_1 and e_2 , and where the sum of all non-focal events is $1 - f_{i,focal}(e_1 \& e_2)$, the focus on the focal events (assumption 7, formalized)

$$f_{i,non-focal}(e_n \& e_y) = \frac{(1-f_{i,focal}(e_1 \& e_2))}{k_r-1} \quad (10b)$$

Where events n and y are any events but the focus pair and k_r is the number of causal relationships in the causal reality (i.e. possible pairs of events)

Now consider the calculation of the likelihood of events e_1 and e_2 , given the above focus equations above and a true relationship that $e_1 \rightarrow e_2$. Using equation 1, we know that the likelihood of the events ($P_i(e_1)$ and $P_i(e_2)$) is a function of the events' actual occurrence ($P(c_{e_1})$ and $P(c_{e_2})$) times the events' observation ($P_i(b_{e_1})$ and $P_i(b_{e_2})$). Since e_1 causes e_2 and we assume that if a cause occurs its effect occurs at a rate of S , where $S < 1$ (assumption 5), we know that $P(c_{e_1}) > P(c_{e_2})$. In considering the likelihood of observing events e_1 and e_2 , the observation of the events is the focus on all pairs of events that contain the events. Since both e_1 and e_2 are a part of the focal event set, and the focus on the focal event set is greater than the sum of the focus on all the other event sets combined (as specified in equation 10a), all else equal, the difference in the occurrence of events in the focal set will identify event e_1 as the cause of e_2 . I formalize this in equation 11 below:

Given a true causal reality $e_1 \rightarrow e_2$, and that e_1 and e_2 are both in the focal set of observation, such that the focus on the pair of events e_1 and e_2 is greater than the focus of all other event pairs combined $f_{i,focal}(e_1 \& e_2) > 1 - f_{i,focal}(e_1 \& e_2)$, all else equal

$$P(c_{e_1}) * P_i(b_{e_1}) > P(c_{e_2}) * P_i(b_{e_2}) \quad (11)$$

Meaning that employee i is likely to successfully identify e_1 as the cause of e_2 when both events are in the focal set. Thus, those causes in the focus of employee's work (i.e. proximate causes) will successfully be identified by employees as causes.

However, now consider that there is a cause e_0 and an effect e_3 , outside of the focus of employee i 's focal pair $f_{i,focal}(e_1 \& e_2)$, such that $e_0 \rightarrow e_1 \rightarrow e_2 \rightarrow e_3$. In this case, the model will predict that it is likely that employee i will conclude that event e_1 is not only the cause of event e_2 , but also of event e_0 . Intuitively this is because the employee's focus on the pair of events e_1 and e_2 means that employee i is most likely to observe these events either occur or not occur. This increases the frequency of observation of events e_1 and e_2 relative to the observation of event e_0 . Thus, even though event e_0 must occur more than both events e_1 and e_2 due to assumption 5, the relative focus on events e_1 and e_2 compared to all other events makes them appear more frequent.

Mathematically, if the ratio of observation between event e_1 and e_0 is greater than the ratio of occurrence between the two events, employees will conclude that the proximate cause is also the cause of the root cause, such that $e_0 \leftarrow e_1 \rightarrow e_2 \rightarrow e_3$. I formalize this inequality as equation 12:

$$\frac{P_i(b_{e_1})}{P_i(b_{e_0})} > \frac{P(c_{e_0})}{P(c_{e_1})} \quad (12)$$

This inequality is likely to be satisfied when the base rate of occurrence of events is high (i.e. relatively high causal strength (S)) and when there is significant difference between the focus on event e_0 and the focus on event e_1 (i.e. high division of labor).

Thus, simply put, proximate causes in an employee's focus of work look like root causes because the most proximate cause to the employee's focus of work is viewed the most frequently by the employee, and since, consistent with the enactment of causality, causes occur more often than effects (proposition 2), proximate causes look the most cause-y of all, leading to them being identified as root causes.

The Problem with the Proximate Cause Principle: Incorrect and Divergent Causal Understandings Come from True Causal Realities with a Non-Root and Non-Shared Cause

The Proximate Cause Principle, or the idea that employees identify the most proximate cause to the focus of their work as the root cause of events in the organization is almost a given from the model specification. Organizations focus employees on events most related to their work through the division of labor, making these events more likely to be observed, and employees conclude that events that are most frequently observed are causes. Thus, it comes as no surprise that the cause that an employee observes the most frequently is the cause that she deems is the root cause. This is why I present the idea of the proximate cause being determined as the root cause as a principle, and not as a problem, for organizational inference.

What is interesting about the Proximate Cause Principle of causal inference in organizations is that it becomes differentially problematic for organizations who are trying to get their employees to converge on correct causal understandings of events. Particularly, the proximate cause principle suggests that, to the extent that an employee's proximate cause is not a root cause, she is likely to form an incorrect causal understanding. And, to the extent that proximate causes are not shared by employees, employees are likely to form divergent

understandings of events. Whether an employee's proximate cause is non-root or non-shared is a function of the structure of causal reality, which is what I turn to next.

First, building on the section above, consider the formalization of an employee forming an incorrect causal understanding. An incorrect causal understanding occurs when e_1 causes e_2 , but e_2 is deemed more like than e_1 by employee i . I formalize the likelihood of forming an incorrect understanding in equation 13a and 13b below, where equation 13a represents when an incorrect causal understanding would occur given that the true causal reality has the relationship $e_1 \rightarrow e_2$, and equation 13b represents when an incorrect causal understanding would occur given that the true causal reality has the relationship $e_2 \rightarrow e_1$.

$$P_i(b_{e_2}) * P(c_{e_2}) > P_i(b_{e_1}) * P(c_{e_1}), \text{ when } e_1 \rightarrow e_2 \quad (13a)$$

$$P_i(b_{e_2}) * P(c_{e_2}) < P_i(b_{e_1}) * P(c_{e_1}), \text{ when } e_2 \rightarrow e_1 \quad (13b)$$

Both equations 13a and 13b can be rewritten to reflect the relative ratios of event occurrence and event observation for events 1 and 2, where the relative event observation of the two events (represented by $P_i(b_{e_1})$ and $P_i(b_{e_2})$) is not consistent with the actual relative event occurrence of the two events (represented by $P(c_{e_1})$ and $P(c_{e_2})$) incorrect causal understandings are likely to be formed. I rewrite equation 13a and 13b as equations 13a2 and 13b2 in this form below.

$$\frac{P_i(b_{e_2})}{P_i(b_{e_1})} > \frac{P(c_{e_1})}{P(c_{e_2})}, \text{ when } e_1 \rightarrow e_2 \quad (13a2)$$

$$\frac{P_i(b_{e_2})}{P_i(b_{e_1})} < \frac{P(c_{e_1})}{P(c_{e_2})}, \text{ when } e_2 \rightarrow e_1 \quad (13b2)$$

Note that this specification of incorrect causal understandings is a direction contradiction to one of the assumptions that the employee is making in her attempt to form a causal understanding, which is that the employee's observation of events is consistent with event occurrence (assumption 3). Functionally what equations 13a2 and 13b2 formalize is that when an employee assumes that her event observation is consistent with event occurrence, but when event occurrence is not consistent with the employee's event observation, then incorrect causal understandings are likely.

I can now calculate when the pattern of observation of events generated by the division of labor, as specified by assumptions 6 and 7 (formalized above), will be likely to generate incorrect or divergent causal understandings, which I argue will occur when the reality contains a non-root cause that is the focus of an employee's work. To start, I formally define causal realities that contain a non-root cause and the structure of division of labor that generates non-shared cause. Causal realities that contain a non-root cause satisfy equation 14 below.

Formal Definition of a Reality Containing a Non-Root, or a Non-Unique Root, Cause:

Equation 14

A reality contains a non-root cause if and only if there exists a cause (e_c) in the reality, such that the number of effects of t_{e_c} is greater than zero,

$$t_{e_c} > 0 \quad (14a)$$

Where, the event (e_c) is not the root cause, i.e. is caused by another event, such that:

$$z_{e_c} > 0 \quad (14b)$$

where z_{e_c} is the number of causes of the event c as specified by the structure of the true causal reality.

A note that the number of effects of event e_c (t_{e_c}) and the number of causes of event e_c (z_{e_c}) sum together to generate the number of relationships that event e_c has with other events in the true causal reality (l_{e_c}).

$$l_{e_c} = z_{e_c} + t_{e_c} \quad (14c)$$

Separately, a reality that contains a non-unique root cause, which occurs for an edge case of collider graphs only, can be defined as followed. A reality contains a non-unique root cause if and only if there exists two events e_{c1} and e_{c2} , such that:

$$z_{e_{c1}} = z_{e_{c2}} = 0 \quad (14d)$$

Since two root causes can definitionally not be related to each other, the same pattern of observation occurs for non-unique root cause graphs that occurs for the non-root cause realities, which will be detailed in equation 16 and 17 below, where a root cause is left outside of the focus of an employee because of the division of labor, which drives an incorrect understanding of events. To simplify the calculations included in the body of this paper, I formalize the case of non-unique root causes in the appendix.

Hypothesis 1 states that a reality that contains a non-root cause is likely to generate incorrect causal understandings under the division of labor.

Why might realities that contain a non-root cause generate incorrect understandings for employees? My argument is that if an employee focuses on a portion of reality that contain a non-root cause, the Proximate Cause Principle suggests that this employee will form an incorrect understanding. Thus, let's consider the implications of a non-root cause reality for an employee (i) focused on a non-root cause in her work, such that:

Employee (i) Focused on a Non-Root Cause Through the Division of Labor

$$f_{i,focal}(e_1 \& e_2), \text{ where } z_{e_1} > 0 \text{ and } z_{e_2} > 0 \quad (15)$$

Given the assumption that employees see a limited scope of events in the organization (assumption 6), there must at least exist an event e_n that is not observed by employee i in the focus of her work. And if we consider that $e_1 \rightarrow e_2$ in the true causal reality, this also implies that there exists an event e_n that is a cause of event e_1 , in order to satisfy the fact that there exists a cause of e_1 such that the number of causes of event e_1 (z_{e_1}) is greater than 0. Thus, the minimum structure of causal reality that satisfies the non-root cause characteristic given a single causal relationship $e_1 \rightarrow e_2$, must be $e_n \rightarrow e_1 \rightarrow e_2$.

What causal understanding will employee i form given her focus of work and this non-root cause reality?

If employee i is focused on e_1 and e_2 as her focal event, then the likelihood of observing a non-focal event e_n is:

$$P_i(b_{e_n}) = l_{e_n} * \frac{(1-f_{i,focal}(e_1 \& e_2))}{k_r-1} \quad (16a)$$

Where l_{e_n} is the number of events that event e_n is related to in the true causal reality

And the likelihood of event e_1 , which is a part of the focal pair, is:

$$P_i(b_{e_1}) = f_{i,focal}(e_1 \& e_2) + (l_{e_1} - 1) * \frac{(1-f_{i,focal}(e_1 \& e_2))}{k_r-1} \quad (16b)$$

Because equation 10 also specifies that $f_{i,focal}(e_1 \& e_2) > (1 - f_{i,focal}(e_1 \& e_2))$, and the number of relationships between a single event cannot be greater than the number of relationships in the causal graph (i.e. $l_{e_n} \leq k_r$), we know necessarily that:

$$P_i(b_{e_1}) > P_i(b_{e_n}) \quad (16c)$$

However, we also know that given the minimal non-root cause reality structure of $e_n \rightarrow e_1 \rightarrow e_2$, event e_n occurs more than event e_1 (assumption 5)

$$P(c_{e_n}) > P(c_{e_1}) \quad (16d)$$

Equation 13a2 suggests that when the ratio of observed events is greater than the ratio of event occurrence, then incorrect understandings are likely. I reformalize this equation 13a2 into equation 17 below, to identify when incorrect understandings are likely under a non-root cause reality where employee i is focusing on a non-root cause.

$$\frac{P_i(b_{e_1})}{P_i(b_{e_n})} > \frac{P(c_{e_n})}{P(c_{e_1})}, \text{ given } e_n \rightarrow e_1 \quad (17a)$$

$$\frac{f_{i,focal}(e_1 \& e_2) + (l_{e_1} - 1) * \frac{(1-f_{i,focal}(e_1 \& e_2))}{k_r-1}}{l_{e_n} * \frac{(1-f_{i,focal}(e_1 \& e_2))}{k_r-1}} > \frac{\sum_0^d w_d[e_n] * (S^{j_d} * (1-S)^{k_d} * (1-S)^{m_d})}{\sum_0^d w_d[e_1] * (S^{j_d} * (1-S)^{k_d} * (1-S)^{m_d})}, \text{ given } e_n \rightarrow e_1 \quad (17b)$$

Equation 17 then suggests two ways that non-root cause realities with an employee focused on the non-root cause by the division of labor will create incorrect causal understandings:

Condition 1 for Hypothesis 1: As the causal strength (S) approaches 1, such that $P(C_{e_1})$ approaches $P(C_{e_n})$ an employee focusing on a non-root cause slice of a non-root cause reality will form an incorrect understanding.

Condition 2 for Hypothesis 1: As the division of labor increases, such that the focus of employee i on the non-root cause slice of reality $f_{i,focal}(e_1 \& e_2)$ approaches 1, employee i will form an incorrect understanding.

I will show these conditions for the formation of incorrect causal understandings with an employee focus on a non-root caused reality based on this equation in an example with three events in the section below.

For now, I turn to the second hypothesis, which suggests that causal realities that contain a non-root cause are likely to generate divergence in causal understandings, depends on a pattern of division of labor that generates a non-shared cause, where different employees have different proximate causes. I formalize a non-shared cause for employees in equation 18 below.

Formal Definition of the Division of Labor that Creates Non-Shared Cause for Employees, Given a Non-Root, or Non-Unique Root, Cause Reality: Equation 18

Given a non-root cause reality as defined in equation 14, a reality contains a non-shared cause if and only if there exists two employees, employee i and r , where their focal events are not the same, such that:

$$\text{For } f_{i,focal}(e_x \& e_y) \text{ and } f_{r,focal}(e_q \& e_s), e_x \& e_y \neq e_q \& e_s \quad (18)$$

Why might non-root cause realities that contain a non-shared cause due to the division of labor generate divergent understandings for employees under the division of labor? Given that a non-root cause exists in the reality, what the division of labor that generates a non-shared cause ensures is that employees do not share a proximate cause. The development culminating in equation 17 above shows that an employee focusing on a non-root cause of a causal reality is likely to form the incorrect understanding, so let's consider the employee focused on the root cause slice of reality in our example above.

Recall that our non-root cause reality is minimally identified as $e_n \rightarrow e_1 \rightarrow e_2$ given a single causal relationship $e_1 \rightarrow e_2$. Since our definition of non-shared cause specifies that the focus of event of two employees i and r is different, and our assumption 6 specifies that sets of events must be related, if employee i is focusing on $f_{i,focal}(e_1 \& e_2)$, then to satisfy the non-shared cause specification, employee r must be focusing on $f_{r,focal}(e_n \& e_1)$. As outlined above, within her focal set of events, employee r will correctly identify the relationship between events, and conclude $e_n \rightarrow e_1$. However, consider her observation of events e_1 and e_2 . Because $e_1 \rightarrow e_2$, we know event e_1 occurs more than event e_2 (assumption 5), such that,

$$P(c_{e_1}) > P(c_{e_2}) \quad (18a)$$

We also know that based on equation 10 because event e_1 is in the focal set of events for employee r and event e_2 is not that the focus on event e_1 is greater than the focus on e_2 , such that:

$$P_r(b_{e_1}) > P_r(b_{e_2}) \quad (18b)$$

In considering when employee r might form incorrect understandings about event and event based on observations that are inconsistent with event occurrence, as specified in equation 18c below, we see that employee r is always likely to form a correct understanding of events given her observations.

$$\frac{P_i(b_{e_2})}{P_i(b_{e_1})} > \frac{P(c_{e_1})}{P(c_{e_2})}, \text{ given } e_n \rightarrow e_1 \quad (18c)$$

This is because due to equation 18a, the right side of the equation will always be greater than 1 for the causal reality and due to equation 18b, the left side of the equation will always be less than 1 for employee r's observation. Thus employee r, whose focus due to the division of labor leads them to focus on the root cause of the non-root cause reality will always select the correct causal understanding, and employee i will select the incorrect causal understanding at high causal strength and high focus on the non-root cause slice of reality. In considering when the divergence of employee i and r is likely for non-root cause realities, as predicted in hypothesis 2, equation 17 and 18 suggest that:

Condition 1 for Hypothesis 2: When two employees i and r differentially focus on slices of causal reality in a non-root cause reality, as the causal strength (S) approaches 1, such that $P(C_{e_1})$ approaches $P(C_{e_n})$, employee i and r will form divergent understandings.

Condition 2 for Hypothesis 2: When two employees i and r differentially focus on slices of causal reality in a non-root cause reality, as the division of labor increases, such that the focus of employee i on the non-root cause slice of reality $f_{i,focal}(e_1 \& e_2)$ approaches 1, employee i and r will form divergent understandings.

In this section I've formalized when the proximate cause principle of causal inference in organizations is likely to generate incorrect and divergence causal understandings. My calculations show how non-root causes (or non-unique root causes) are likely to generate incorrect understandings for employees focused on the non-root cause, and they also show how non-shared causes, generated by the division of labor across a non-root cause reality, are likely to generate divergence in understandings. Thus, the mathematical model, built on the same assumptions as our theory section, supports both hypothesis 1 and hypothesis 2, and provides two distinct mechanisms relating to the strength of causal relationships and the division of labor for when the outcomes of the hypotheses are likely.

A Three Event Example: Causal Understandings as a Function of the Division of Experience, the True Causal Reality, and Causal Strength

In my motivating example, Kodak's managers and engineers diverge on causal understandings about the development of digital photography, coming to following conclusions in Figure 1 and 2 (reproduced below).

FIGURE 1: Kodak Management's Causal Understanding of Digital Photography
 Consumer Demand for Digital \leftarrow Develop Digital Technology \rightarrow Cannibalize Film Business

FIGURE 2: Kodak Engineer's Causal Understanding of Digital Photography
 Consumer Demand for Digital \rightarrow Develop Digital Technology \rightarrow Cannibalize Film Business

My theoretical development suggests that if the true causal reality generating events contains a non-root and non-shared cause, then because proximate causes are observed occurring more than other causes due to the division of experience in organizations, the divergence of causal understandings in Figure 1 and 2 is likely. My mathematical equations show this is the case at high enough causal strengths and high enough division of labor between employees.

But how does this development matter for how causal understandings are formed in organizations? Calculating the values for the equations above, I show under what level of causal

strength and how much division of experience will generate incorrect or divergent causal understandings between the Kodak managers and engineers given a true causal reality. The results show how only causal realities with a non-root cause generate incorrect understandings and only causal realities with a non-shared cause generate divergent understandings. In Table 6 I show all possible event-generating processes between the three events engineering resources (A), product design (B) and low sales (C), identifying which graphs contain non-root and non-shared causes.

Table 6: All Possible Causal Realities Between Events A, B, and C

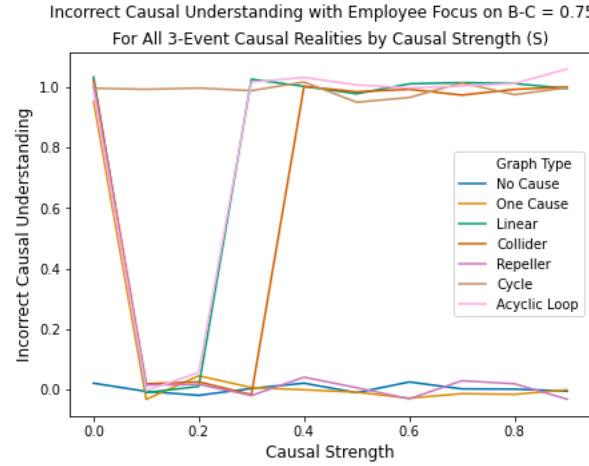
	Example Graph	Number of Graph in Type	Number of Arrows in Graph	Non-Root Cause	Non-Shared Cause	Equations Used
No Cause	A B C	1	0	No	No	NA
One Cause	A->B C	6	1	No	No	13a
Repeller	A<-B->C	3	2	No	No	13b
Collider	A->B<-C	3	2	Yes1	Yes	13a
Linear	A->B->C	6	2	Yes	Yes	13a
Cycle	A->B->C->A	2	3	Yes	Yes	13a
Acyclic Loop	A->B->C<-A	6	3	Yes	Yes	13a
Total		27				

Then, for each possible causal reality listed in Table 6, I first calculate equation 13 for each causal reality, which tells us given a causal strength and focus on a pair of events, when an employee will generate an incorrect causal understanding. The mathematical equations above suggest that there are two variables that contribute to forming an incorrect causal understanding.

First, high causal strength between events (represented by a high value of variable S) are likely to generate an incorrect causal understanding for employees focused on a non-root cause slice of reality. This is because a high base rate of event occurrence decreasing the difference in occurrence between cause and effect, making it easier for small differences in observation to generate incorrect causal understandings. I visualize this in Figure 6, where on the x-axis is the causal strength of relationships between events (S). On the y-axis, for an employee i focused on the non-root cause slice of reality (if it exists) such that $f_{i,focal}(e_B \& e_C) = 0.75$, if the value is 0, employee i forms the correct causal understanding, if the value is 1, employee i forms the incorrect causal understanding of the causal reality. To calculate the 0 and 1 values of the y-axis for each true causal reality, I use either equation 13a or 13b (specified in column 6 of Table 4) depending on whether the true relationship is either $A \rightarrow B$ or $B \rightarrow A$. If equation 13 is satisfied, employees reach an incorrect causal understanding for the true causal reality at that causal strength, meaning a value of 1 on the y-axis.

FIGURE 6:

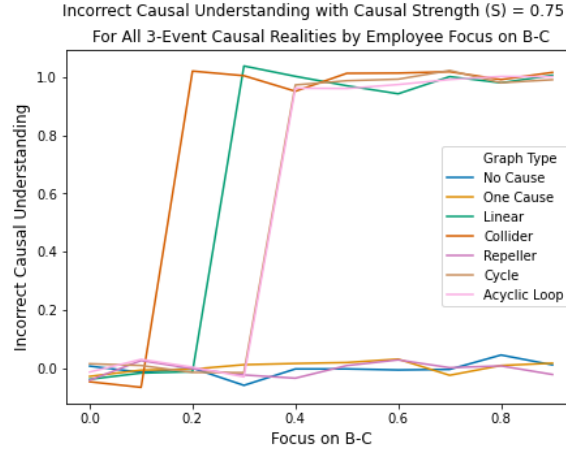
Focus on Events B and C at 0.75 Generates Incorrect Understanding of Relationship Between A and B for Non-Root Cause Graphs at Causal Strength > 0.25 (6)



Footnote 6: A note for all figures that contain multiple graph types. In order to avoid lines completely overlapping so that each graph type's line can be seen, I add a slight bit of noise to the lines, but all values are exactly either 0 or 1.

Second, high division of labor (represented by high focus values on the focus set of events $f_{i,focal}(e_x \& e_y)$) is likely to generate an incorrect causal understanding for employees focused on a non-root cause slice of reality. This is because a high focus on a non-root cause set of events skews the frequency of observation of events, such that employees observe the non-root cause occurring frequently and incorrectly conclude that this cause is the causal origin of events. I visualize this in Figure 7, where on the x-axis is the focus on events B and C for an employee i ($f_i(e_B \& e_C)$). On the y-axis, for a causal strength value of $S = 0.75$, if the value is 0, employee i forms the correct causal understanding, if the value is 1, employee i forms the incorrect causal understanding of the causal reality. To calculate the 0 and 1 values of the y-axis for each true causal reality, I use either equation 13a or 13b (specified in column 6 of Table 4) depending on whether the true relationship is either $A \rightarrow B$ or $B \rightarrow A$. If equation 13 is satisfied, employees reach an incorrect causal understanding for the true causal reality at that causal strength, meaning a value of 1 on the y-axis.

FIGURE 7:
Causal Strength at 0.75 Generates Incorrect Understanding of Relationship
Between A and B for Non-Root Cause Graphs at Focus on Events B and C > 0.25



To show the mechanism for why the results in Figure 6 and 7 occur, for each of the causal realities I generate the observation of events A and B for employees vs. the actual occurrence for event A and B for employees across causal strengths (S) and focus on events A and B by employee i ($f_i(e_B \& e_C)$)), and report them in Figure 8a-g and 9a-g. When the observation and occurrence line remain on the same side of zero to each other, this means that employee observation in the organization is consistent with event occurrence, satisfying the assumption made by employees (assumption 3). However, for non-root cause realities, above causal strength of ~ 0.25 and above focus on events A and B of ~ 0.25 , employee observation and occurrence are no longer consistent, breaking assumption 3, and generating incorrect causal understandings.

FIGURE 8a-g: Mechanism

Observation and Occurrence of Events A and B Become Inconsistent for Realities with a Non-Root Cause when Causal Strength is High

Figure 8a: No Cause Reality

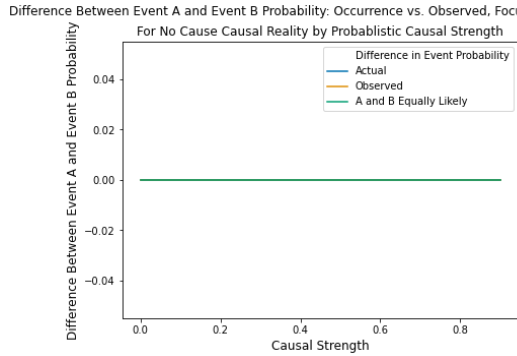


Figure 8b: One Cause Reality

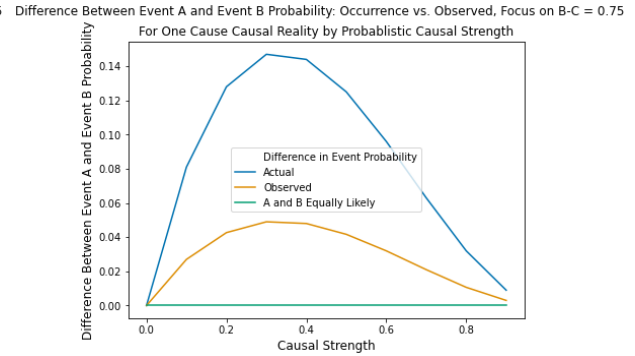


Figure 8c: Linear Reality

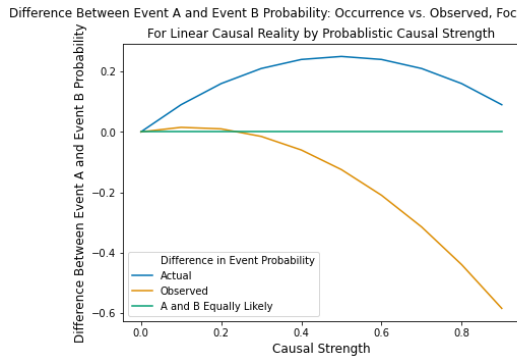


Figure 8d: Collider Reality

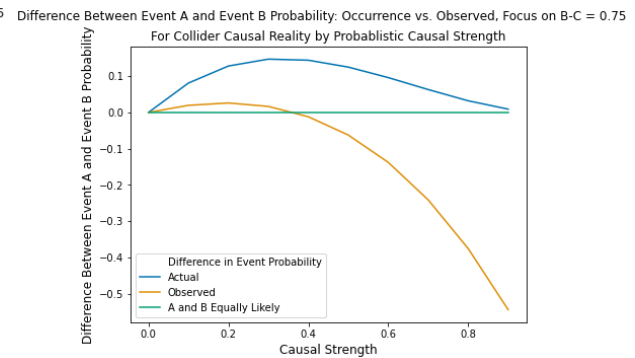


Figure 8e: Repeller Reality

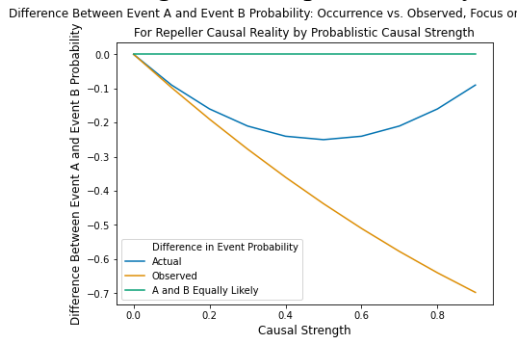


Figure 8f: Cycle Reality

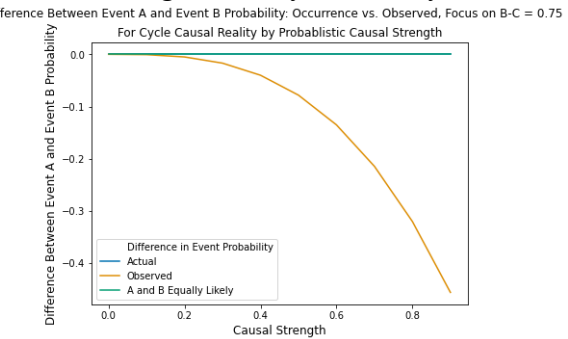


Figure 8g: Acyclic Loop Reality

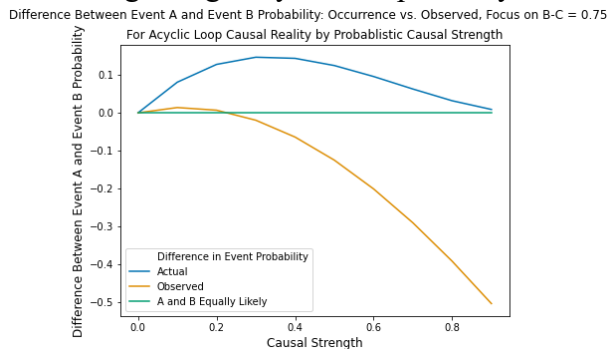


FIGURE 9a-g: Mechanism

Observation and Occurrence of Events A and B Become Inconsistent for Realities with a Non-Root Cause when Division of Labor on Events is High

Figure 9a: No Cause Reality

Difference Between Event A and Event B Probability: Occurrence vs. Observed, Causal Strength = 0.75
For No Cause Causal Reality by Focus on Event B-C

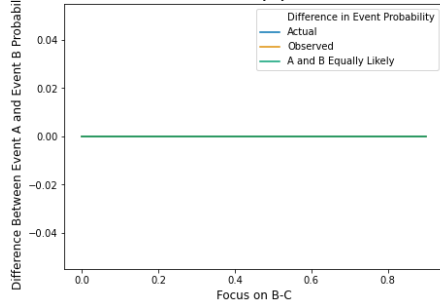


Figure 9b: One Cause Reality

Difference Between Event A and Event B Probability: Occurrence vs. Observed, Causal Strength = 0.75
For One Cause Causal Reality by Focus on Event B-C

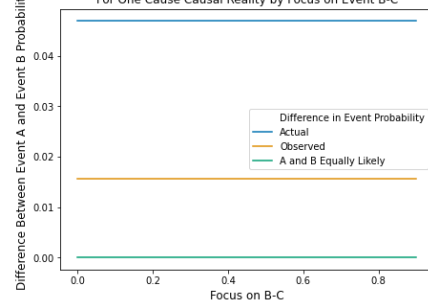


Figure 9c: Linear Reality

Difference Between Event A and Event B Probability: Occurrence vs. Observed, Causal Strength = 0.75
For Linear Causal Reality by Focus on Event B-C

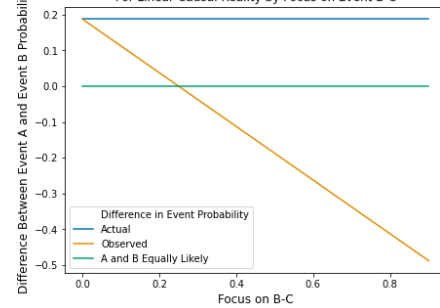


Figure 9d: Collider Reality

Difference Between Event A and Event B Probability: Occurrence vs. Observed, Causal Strength = 0.75
For Collider Causal Reality by Focus on Event B-C

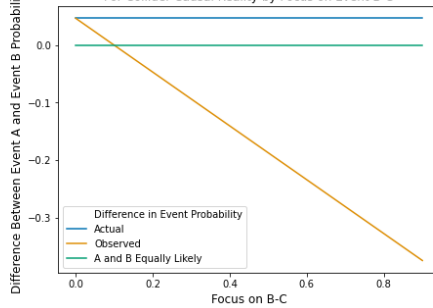


Figure 9e: Repeller Reality

Difference Between Event A and Event B Probability: Occurrence vs. Observed, Causal Strength = 0.75
For Repeller Causal Reality by Focus on Event B-C

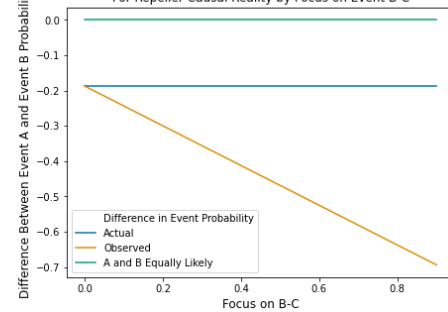


Figure 9f: Cycle Reality

Difference Between Event A and Event B Probability: Occurrence vs. Observed, Causal Strength = 0.75
For Cycle Causal Reality by Focus on Event B-C

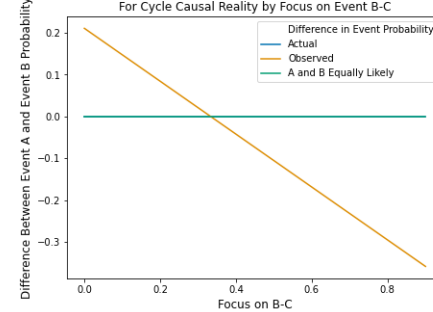
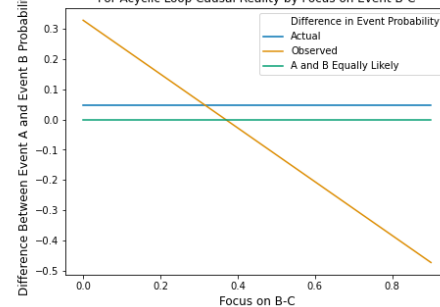


Figure 9g: Acyclic Loop Reality

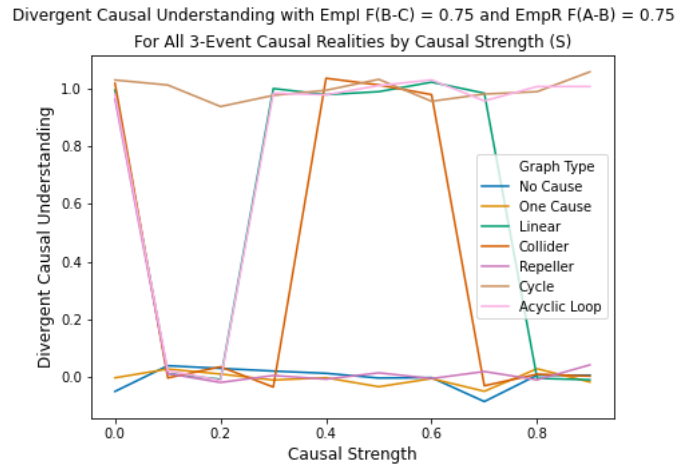
Difference Between Event A and Event B Probability: Occurrence vs. Observed, Causal Strength = 0.75
For Acyclic Loop Causal Reality by Focus on Event B-C



In considering when divergence of causal understandings is likely, I calculate equation 13 for two different employees, employee i and employee r. The same two variables, causal strength and relative focus on events, were highlighted in the mathematical equations above as contributors to the divergence of causal understandings.

First, high causal strength between events (represented by a high value of variable S) are likely to generate divergent causal understandings when employees are differentially focused on slices of a non-root cause reality. This is because a high base rate of event occurrence decreasing the difference in occurrence between cause and effect, making it easier for small differences in observation to generate different causal understandings. I visualize this in Figure 10, where on the x-axis is the causal strength of relationships between events (S). On the y-axis, for an employee i focused on the non-root cause slice of reality (if it exists) such that $f_{i,focal}(e_A \& e_B) = 0.75$ and for employee r focused on another slice of reality such that $f_{r,focal}(e_B \& e_C) = 0.75$, if the value is 0, employee i and r form convergent causal understandings, if the value is 1, employee i and r forms divergent causal understandings of the causal reality. To calculate the 0 and 1 values of the y-axis for each true causal reality, I use either equation 13a or 13b (specified in column 6 of Table 4) depending on whether the true relationship is either $A \rightarrow B$ or $B \rightarrow A$.

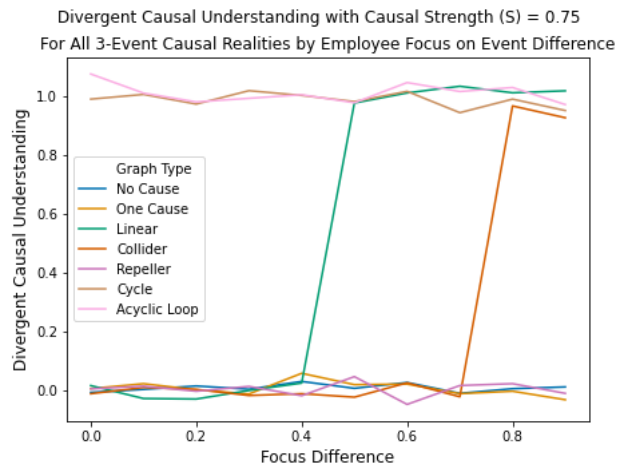
FIGURE 10:
Divergent Causal Understandings Likely for Non-Root Cause Graphs
with Differential Focus on Event ($f_{i,focal}(e_A \& e_B) = f_{r,focal}(e_B \& e_C) = 0.75$)
at Moderate to High Causal Strengths (S)



Second, high division of labor (represented by high focus values on the focus set of events $f_{i,focal}(e_x \& e_y)$) is likely to generate a divergent causal understanding for employees differentially focused on slices of a non-root cause reality. This is because a high focus on a non-root cause set of events skews the frequency of observation of events, such that employees observe the non-root cause occurring frequently and incorrectly conclude that this cause is the causal origin of events, where employees who are not focused on this non-root cause are more likely to land on a correct causal understanding. I visualize this in Figure 11, where on the x-axis is the difference in focus on events A and B for an employee i and r ($f_i(e_A \& e_B) - f_r(e_A \& e_B)$), such that a value of 0 represents $f_i(e_A \& e_B) = f_r(e_A \& e_B) = 0.5$, and a value of 1 represents $f_i(e_A \& e_B) = 1$ and $f_r(e_A \& e_B) = 0$. On the y-axis, for a causal strength value of $S = 0.75$, if the value is 0, employee i forms the correct causal understanding, if the value is 1, employee i forms

the incorrect causal understanding of the causal reality. To calculate the 0 and 1 values of the y-axis for each true causal reality, I use either equation 13a or 13b (specified in column 6 of Table 4) depending on whether the true relationship is either $A \rightarrow B$ or $B \rightarrow A$.

FIGURE 11:
Divergent Causal Understandings Likely for Non-Root Cause Graphs
with High Difference in Focus on Events at Causal Strength (S) = 0.75



Several findings of note result from this three-event example of the mathematical model of causal understandings. First, the three-event model shows the general mechanisms developed in the mathematical model, which is that, for causal realities containing a non-root cause, incorrect and divergent causal understandings are likely at high causal strengths and high division of labor. Second, there are several notable exceptions to this mechanism that provide interesting insights into how the structure of causal reality might be particularly problematic for organizations seeking to form correct causal understandings.

Consider the results displayed in Figure 6, which shows that above causal strengths of around 0.25 incorrect causal understandings are likely for the employee focused on a non-root cause event, combined with the results displayed in Figure 10, that at high causal strengths (above 0.7 and 0.8 respectively) both collider and linear causal realities generate convergence. These results jointly suggest that non-root causes in a reality may drive convergence on incorrect causal understandings at high causal strengths. Similarly, consider the results displayed in Figure 7, which shows that differences in division of labor of 0.1 and 0.2 for collider and linear causal realities respectively make incorrect causal understandings likely for the employee focused on a non-root cause event, combined with the results displayed in Figure 11, that until focus differences of 0.8 and 0.5 respectively, both collider and linear causal realities generate convergence. These results once again suggest that non-root cause realities may not only generate divergence and incorrect understandings, but may actually facilitate convergence on incorrect understandings. I discuss the implications of these results further in the discussion section.

Now that I've outlined the results of the model for three event causal realities, I turn to how these results speak to my hypotheses, and more generally suggest when organizations are likely to experience a trade-off between correct and convergent causal understandings and division of labor. I used the intuition of causal modeling to develop the hypotheses that non-root cause realities are likely to generate incorrect or divergent causal understandings under the

divided experience of organizations. My model shows that this is the case. In considering what this finding means for organizations, I return to the motivating example.

The Kodak managers and engineers are trying to understand digital photography in order to form a successful strategy to approach digital technology development for their organization. In order to generate this solution, employees at Kodak need to understand the space in a way that allows them to come to a correct and convergent strategy of what to do next. But Kodak also has divided the work of their employees, such that the Kodak managers and engineers are likely to have experienced digital photography in different ways. Given this structure of work and experience, when are the managers and the engineers likely to be able to form a correct and convergent causal understanding of what happened? If the true causal reality does not contain non-root cause, the manager and the engineer are likely to agree on the correct causal understanding even under their differences in experience. However, if the causal reality does contain a non-root cause, the manager and engineer are likely to disagree on causal understandings, generating difficulty forming a successful strategy to address development of digital technology in the photography industry.

Overall, my model suggests the importance of the structure of true causal reality for when organizations are likely to face difficulty forming correct and convergent causal understandings under the division of labor.

DISCUSSION & CONCLUSION

Below I summarize the findings of my theoretical and mathematical model, suggest a wide set of contexts that this type of model can apply to, and suggest directions for future research on causal understandings in organizations.

What do we gain from considering causal reality in the formation of causal understandings in organizations?

Organizational research has previously ignored causal reality for reasons both theoretical and practical (i.e. Levitt & March, 1988; Weick et al., 2005; McIver & Lengnick-Hall, 2017). While there are arguments against the consideration of causal reality, my model nonetheless suggests that examining the interaction between an organization's division of work and causal reality provides a powerful way to predict when employees within an organization will reach incorrect or divergent causal understandings. Specifically, when true causal reality contains a non-root cause, employees are likely to form incorrect causal understandings or reach divergent causal understandings, depending on the division of work in the organization.

The application of this model to real world organizations, however, may be stymied by a particularly troublesome and necessary assumption of it, which is assumption 2, that individuals cannot observe the true causal reality. My model provides a proof of concept for how the true causal reality is important, but in order to identify situations where causal understandings are likely to be incorrect or divergent, knowing the structure of causal reality is essential. So how can a model showing that the structure of true causal reality be useful when it assumes that the structure of true causal reality is unobservable?

Practically, my model is likely to be most useful for organizations in three ways. First, in ex post analysis of organizational failures and success, my model suggests that considering the structure of causal reality might help distinguish why Kodak failed, but why a newer competitor in the digital film space who was not so entrenched in traditional film, may have succeeded. My model would provide the hypothesis that the reality that Kodak faced was not only uncertain, but

also structured in such a way that converging on the correct assumptions in order to form the right strategy may have been a difficult task due to Kodak management's focus on traditional film.

Second, my model may be particularly useful to organizations when they are attempting to select the most successful strategy from a set of divergent causal understandings. While motivated reasoning and other factors may be at play in divergent causal understandings, another consistent reason employees in an organization reach divergent understandings of event is because of the division of work, and thus experience in organizations (Dearborn & Simon, 1958; Joseph & Gaba, 2020). However, only certain structures of causal reality are likely to generate divergent understandings from division of labor, non-root cause realities where a cause is not shared. In the case where the structure of causal reality is generating divergent understandings in organizations, my model provides a clear prediction for whose causal understanding will be correct, the employee who observes the root cause and its associated events more.

Because the true causal reality cannot be observed, it may be difficult to directly identify the root cause. However, my model suggests that having a theory for who is most likely to observe the root cause, may help organizations make more principled decisions in choosing a strategy from divergent causal understandings. For example, some work suggests that managers may be closer to the root cause of events, making manager's causal understanding of root cause events more likely to be correct, but potentially generating myopia to the trickle-down effects of higher-order decisions (Hannan et al., 2003). While in other instances, employees on the ground who are doing the work and are closer to the action, may observe the root causes of issues in the organization more saliently, and thus soliciting input, especially divergent input, from employees may generate more successful strategy (Tegarden et al., 2005).

Finally, my model suggests a rather counterintuitive, but hopeful implication for the division of work and divergent causal understandings in organizations. Traditional accounts of modularity in organizations point to how the division of work drives divergence and disagreement, harming coordination and performance (i.e. Clement, 2023; Santos et al., 2021; Heath & Staudenmayer, 2000). This research has an often unified story that, when it comes to making collective decisions, divergence in understandings decreases collective outcomes. While it's likely that the processes to reach a convergent decision will be more difficult under the divergent causal understandings that are formed in my model, the results of division of experience for the likelihood of coming to the correct causal understanding in an organization are uniformly positive.

This is because in non-root cause realities, if employees are not highly differentially focused on different parts of this causal reality, employees would converge on causal understandings, but they would agree on an incorrect understanding. In this light, divergence in causal understandings due to division of work can be seen as a positive outcome of organizational processes. When employees see different slices of reality, then even for non-root cause realities in which it is extremely difficult to infer correct understandings, there is a chance that organizations can reach the correct causal understanding, because some employees do hold this understanding.

Ultimately, while the true structure of causal reality is unobservable, my work suggests that having a theory about the structure of the true causal reality may help organizations consider how to better select which causal understanding to form strategy on when causal understandings diverge. In addition, in ex post analysis of organizational failure and success based on causal understandings, perhaps considering the structure of causal reality can provide a more tangible

input to the uncertainty and causal ambiguity that can generate differences in outcomes for organizations (Raynor, 2007; King, 2007).

Where else do the results of the interaction of division of experience and causal reality apply?

While the work above uniformly focuses on the organizational context, my theory on causal reality applies to any context that consistently divides individual scope and frequency of experience. Societal structures, such as the sociodemographic features of race, gender, and income, may also be likely to systematically structure individuals' experience of event (Healey & Stepnik, 2009). Expanding my model to this wider set of social structures, my theory provides a potential explanation for why, for example, low-income and high-income parents may disagree on causal understandings of raising children (Lareau, 2018). Or even why democrats and republicans, whose experience is often stratified by many social features, may observe the same set of political events and come to different understandings on them (Cutler, 2003; Basta, 2017). Thus, while I believe that organizations are particularly likely to exhibit the particular division of experience outlined in my model above, future work might well consider how other societal groups whose experience of events is also structured, may also reach divergent causal understandings as a function of the division of experience and the structure of causal reality.

Where do we go from here?

The goal of the theory developed in the paper is to help future work in organizations and social science research better identify why incorrect and divergent causal understandings occur. I suggest an additional and often overlooked source of this variance in causal understandings, which is the structure of true causal reality. While the structure of true causal reality is not readily observable to researchers and practitioners alike, my work suggests that having a theory of what the structure of true causal reality is may help us better understand the antecedents of division and make principled selections of causal understandings when divergence exists. Several pathways for future work follow.

First, while the propositions above are developed by following the set of assumptions, the first test of my theory is, in a controlled experimental setting, to see whether under this assumption set, individuals form incorrect and divergent causal understandings. Work on causal narratives in economics has run models and sets of experiments that generally support the idea that the observation of co-occurrence of events generates the types of causal inference errors I identify in my theory above (i.e. Spiegler, 2016; Eliaz & Speigler, 2020). However, this work does not test the set of assumptions about how organizations divide work and event experience, thus future work should explore how the formation of causal understandings under the specific set of divided work we expect to see in organizations is likely to generate the theoretical insights developed here.

Second, a major contribution of this work in organizational contexts is that it may help organizations make principled decisions about which causal understandings may generate successful strategy when there is divergence of causal understandings in the organizations. Future work should explore this theoretical insight by specifically examining organizational context where division in causal understandings arise, testing whether forming a model of the structure of causal reality and which set of stakeholders are most likely to observe the root cause of events, may help organization select better strategies and ultimately perform better.

Finally, organizations' division of experience represent similar division of experience that occurs in many different parts of our society. For any social science scholar who studies populations that diverge on causal understandings, from work on polarization to work on class

differences in parenting, considering the structure of causal reality and division of experience of individuals may help explain the divergence of individuals who may ostensibly observe the same reality.

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