Complex Learning: Evidence from U.S. Manufacturing[1]

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ABSTRACT:

When solving ongoing operational problems, organizations choosing more complex solutions face a tension in managing the costs from complexity and potential benefits from learning. While complexity is likely to raise costs, organizations with experience managing complexity may learn to manage these costs and improve performance. Using the setting of U.S. manufacturing facilities handling toxic waste from 1991 to 2014, we examine how learning and complexity interact to jointly influence operational performance. Results show that although complexity has a direct negative effect, experienced facilities are able to gain learning benefits from managing complexity, which leads to improved operational performance. These results suggest that the costs of complexity are neither static nor uniformly detrimental when solving operational problems, and complexity may result in long-term benefits for adaptation.

Keywords: organizational learning, complexity, problem-solving, operational performance, experience

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INTRODUCTION

Organizational learning processes—most critically, learning from experience (Argote and Epple, 1990; Edmondson, 2002; Pisano, Bohmer, and Edmondson, 2001)—operate at the core of how organizations adapt and improve over time. In particular, learning often results in adaptation in the form of incremental strategic renewal at the activity or process level of the firm (Agarwal and Helfat, 2009). Although learning is recognized as a critical component of maintaining a sustained competitive advantage, empirical evidence highlights persistent heterogeneity in learning outcomes (Eggers, 2012; Lapre, Shankar Mukherjee, and Van Wassenhove, 2000; Larsen, Manning, and Pedersen, 2013; Lawrence, 2018; Levinthal and Posen, 2007). While many factors have been shown to influence learning rates, the effect of complex activities—that is, activities that are broader in scope and thus more challenging—is as yet unresolved. Complexity has been shown to be detrimental to short-term performance (Becker and Murphy, 1992) but beneficial for the development of long-term capabilities (Natividad and Rawley, 2016; Rockart and Dutt, 2015; Stan and Vermeulen, 2013). In this paper, we focus on disentangling the interaction between organizational learning and internal complexity, subsequently examining their joint influence on operational performance.

Studies of learning and internal complexity—where complexity is a function of the number of different components required to execute a single activity—suggest that the two typically have opposing impacts on organizational performance. While increasing levels of both direct and related experience generally improve performance through learning, past work has shown internal complexity to impede performance improvements through an increase in coordination costs (Becker & Murphy, 1992; Csaszar & Siggelkow, 2010; Gulati & Singh, 1998; Rawley, 2010; Zhou, 2011). Some recent studies, however, suggest that complexity may lead to longer term beneficial outcomes for the firm. Specifically relating complexity to organizations' performance, Rockart and Dutt (2015) find that taking on experiences that are more complex in terms of size and scope allows organizations to improve their capability capacity. Similarly, Stan and Vermeulen (2013) find that IVF clinics taking on more difficult cases improve their ability to solve simpler cases, boosting their overall success rate as compared to clinics that screen out the more challenging cases. Finally, Rawley and Natividad (2016) show how organizations that have adapted to complexity incur a performance loss when forced to reduce complexity, as they are better at managing greater complexity and relatively worse at managing lower levels of complexity. All three of these studies highlight the potential performance benefits of complexity in the longer term but do not examine the mechanism by which the detrimental effect of complex activities is moderated. We propose that the linkage between these findings is the effect of learning to manage complexity, where learning is a beneficial shift in performance.

To understand how learning and complexity interact and jointly influence performance on the focal complex activity, we focus on organizations solving operational problems, which we define as routine ongoing challenges that impede performance improvements (Berchicci, Dowell, and King, 2017; Christmann, 2000; Coelli *et al.*, 2005; MacDuffie, 1997). Operational problems are common across many settings yet are understudied in strategy research because of measuring difficulties (Lawrence, 2018; Reichstein and Salter, 2006). Further, we focus on the type of complexity that, as opposed to arising in the external environment, arises as an outcome of organizational choices: internal complexity. We assume that an activity that possesses a larger number of components will be more difficult to execute successfully and thus represents a higher level of complexity than the same activity with fewer components (Larsen *et al.*, 2013; Rawley and Simcoe, 2010; Zhou and Wan, 2017). In line with prior work, we assume that complexity may be costly in the short term, but, if, through the accumulation of experience, it is able to improve learning, complexity should improve long-term performance.

To test our predictions about how learning and complexity influence operational performance, we use a detailed production-level dataset, the Toxic Release Inventory (TRI), that captures the waste-related activities of all U.S. manufacturing facilities over a 24-year period from 1991 to 2014. Within these facilities, we focus on operational activities aimed at reducing toxic waste. Toxic waste reduction is a priority for all U.S. manufacturing facilities for two reasons: first, the emission of toxic waste is monitored by the U.S. Environmental Protection Agency (EPA) and facilities can be penalized for inaccurately reporting waste levels. Second, the cost of toxic waste disposal is expensive; facilities can cut costs, as well as insurance premiums, by lowering waste output. Each facility must report its level of toxic waste, as well as all disposal activities for each toxic chemical being used or produced in the facility annually. Accordingly, the unit of analysis is the facility-chemical-year and we are able to observe the relationship between changes in experience and complexity on disposed waste levels for a specific chemical within a specific facility over time. This dataset is particularly well suited for examining learning and complexity jointly because it allows us to examine a routine activity at a granular level of analysis over a relatively long time-period. Additionally, because facilities receive annual feedback on their prior performance and choices, they have the opportunity to implement changes, allowing us to track year-to-year performance and infer learning with respect to toxic waste reduction.

The results suggest that complexity has both direct and indirect effects on performance—beneficial for long-term learning but problematic for short-term performance improvements. Both greater direct and greater related experience managing the focal chemical's waste leads to greater improvement in operational performance, consistent with our expectation of learning. Greater complexity in the management of that waste has a direct negative effect on performance. However, most importantly, greater direct experience managing the focal chemical's waste reduces the direct detrimental effect of complexity on performance improvement. In other words, our results suggest that firms learn to manage complexity in their routine operational tasks such that greater complexity is less detrimental in the long run. However, the benefits to experience from related activities is lessened under complexity, suggesting that greater diversity in the nature of the accumulated experience, in conjunction with complexity in the focal activity, is less beneficial.

Our findings provide three contributions. First, we enrich the literature on complexity and diseconomies of scope by highlighting how the specific mechanism of organizational learning diminishes the detrimental effect of complexity on performance. These findings contribute to a nascent area of research on the benefits of complexity for organizational performance. Although much of the research on complexity suggests that organizations should eliminate or reduce complexity, in many settings and for many types of organizations—for instance, multi-divisional firms—complexity may be an enduring feature of their business model. Thus, by highlighting how managers can garner benefits from complexity, we highlight alternatives to its elimination. Second, by theorizing, measuring, and testing the learning benefits that arise from complexity, we also enrich our knowledge of how learning occurs. Because our analysis examines the effect of two distinct learning mechanisms—learning by doing and learning from related efforts—on performance, we compare findings for each type of learning. Although both have a beneficial association with performance, only direct experience has a beneficial effect when managing complexity. Third, although common to many settings, and critical for sustaining competitive advantage (Rosenberg, 1982; Vivero, 2002), research on operational problems is limited in management and strategy research. Our study sheds light on strategies to tackle routine, incremental challenges that arise on a regular basis and that can yield performance-enhancing improvements.

Overall, we find that prior experience and complexity have significant effects on facilities' abilities to improve performance over time. In examining complexity in management of waste at a granular level, we believe we have found evidence of learning to manage complexity in the routine operational tasks faced by firms. Our study extends our understanding of when managers should embrace complexity and how managers should allocate resources to solving ongoing, routine challenges that can significantly improve firm performance.

THEORY

Research on complexity—defined as either interdependence or diseconomies of scope—highlights how complex tasks generate coordination and integration costs (Becker and Murphy, 1992). For instance, Ethiraj and Levinthal (2009) show that managing multiple goals, local and global, even in the case of a simple organization with independent employees will lead to goal conflict, and employees will be unable to identify optimal solutions. Gulati and Singh (1998) demonstrate how contracts with complex governance structures are more difficult to manage and thus less likely to arise. Zhou and Wan (2017) show how increasing levels of product variety amplify the challenges of managing scale and scope benefits for firms. Rawley (2010) shows how, in the taxicab industry, firms that diversify have smaller margins than non-diversifying firms. Finally, Larsen *et al.* (2013) show how greater levels of complexity in offshoring activities are similarly associated with diminished performance in terms of higher implementation costs. Consistent across these studies, which span different empirical contexts and theoretical streams of research, is the notion that greater levels of complexity—in terms of multiple goals, governance structures, input, or product variety—are generally detrimental to performance.

A smaller subset of studies has suggested that the costs of complexity may be lower for certain types of tasks and organizations. These studies focus on two moderating factors: modularity of the product or activity and careful organizational design choices. At the product or activity level, the factor that seems to influence complexity costs most instrumentally is modularity or the degree to which a unit can be broken down into independent parts (Baldwin and Clark, 2000). Because modularity provides independence between the different parts of a product or activity (Ethiraj and Levinthal, 2004), it is associated with lower integration and coordination costs (Rawley and Simcoe, 2010).

At the level of the organization, however, design choices are a more significant driver in managing complexity-related costs (Gulati, Puranam, and Tushman, 2012; Helfat and Campo-Rembado, 2016; Mintzberg, 1980). Common interventions are the use of hierarchy and divisionalization, which reduce interdependence and coordination while keeping the sources of synergies—for example shared inputs and/or outputs—within the organization. Zhou (2011) shows how a balance between coordination costs and scope synergies is more likely to be achieved if a firm can share inputs across multiple products; however, the balance is less possible if the existing businesses are complex. Zhou (2013) suggests that organizational hierarchy can mitigate some costs by putting more complex tasks and products under the purview of a single division. Relatedly, Zhou and Wan (2017) show how firms producing a wide product variety face challenges in managing the costs of production scale and distribution scope; those managing the best tend to have a hierarchical structure. These studies suggest that the costs of complexity may be compensated for by scope and other synergistic benefits, but the best approaches often include a mix of activity and/or product modularity and hierarchical organizational design. Although such interventions can reduce the negative impact of complexity, complexity still causes an increase in net costs. This outlines our baseline expectation:

Hypothesis 0 (H0): Organizations managing more complex tasks will experience worse operational performance.

While most prior research has focused on the costs of complexity—both how they arise and how to mitigate them—rather than the benefits, there are some notable exceptions which suggest a more positive effect of complexity over time. Natividad and Rawley (2016) show how organizations that experience greater complexity adapt to it over time and face higher adjustment costs after complexity reduces. In Larsen *et al.*, (2013), we see that organizations taking a systematic approach to the design of organizational processes are able to withstand greater levels of complexity. Similarly, Stan and Puranam (2017) show how the presence of managers focusing on promoting coordination across organizational subunits can improve how the organization adapts to changes in complexity. Studies of diversification have also shown how prior diversification experience, by transferring relevant knowledge and capabilities to new units, allows firms to benefit more easily from future diversification (Mayer, Stadler, and Hautz, 2015). These findings highlight heterogeneity in the degree to which complexity diminishes organizational performance.

Further, these findings suggest that beyond interventions that reduce coordination costs, some organizations may learn from certain types of experience, which would allow them to adapt to higher levels of complexity. Accordingly, we develop hypotheses to understand when and how learning moderates the negative effect of complexity on operational performance. While all organizations aim to improve performance, they will exhibit heterogeneity in learning outcomes.

To decompose heterogeneity in learning, we examine how two relevant learning processes influence improvements in operational performance: direct experience and related experience.

Learning-by-Doing: Direct Experience

A robust finding in the literature on organizational learning is the positive influence of experience on learning. As organizations accrue experience, all else being equal, they typically improve performance (see recent review by (Argote, 2013)). The basic principal underlying this effect is that experience creates a growing stock of knowledge which is applied toward the goal of improving the performance of the organization. This improvement generally takes one of two forms within the organization. First, repetition of a given task is associated with development of and improvement in the existing routines associated with that task (Nelson and Winter, 1982). This updating of routines may be akin to the incremental adaptation of firms as a result of experience. Second, performance improvements result from an improved ability to execute the given routine with experience. This latter type of improvement, known most often as learning-by-doing (Arrow, 1962), has been pervasively captured across manufacturing (Argote, Beckman, and Epple, 1990; Benkard, 2000; Wright, 1936) and services (Darr, Argote, and Epple, 1995; Pisano *et al.*, 2001; Reagans, Argote, and Brooks, 2005) settings.

In both of these types of changes, learning is captured as a change in the organization's knowledge as a function of experience, which is observed through the modification of some organizational routine. Organizational scholars have typically modelled both forms of learning as a function of cumulative output. These models have in turn accounted for a variety of dependent variables, including total costs per unit (Darr *et al.*, 1995), errors per week (Lawrence, 2018), and survival prospects (Baum and Ingram, 1998). This long history of support for the observation of a positive relationship between direct experience with a focal task and improved performance due to learning provides the logic for the first hypothesis:

> *Hypothesis 1 (H1): Organizations with greater amounts of direct experience solving specific operational problems will experience greater improvements in operational performance.*

Learning-by-Doing: Related Experience

Although learning from direct experience represents a primary avenue for learning, organizations may also learn from experience which is indirectly acquired. Here, we focus on learning which is acquired by the focal organization for an activity that is related but not identical to the focal activity. This form of learning should be considered distinct from indirect learning acquired for the same focal activity by a different organization or set of individuals—which would be considered vicarious learning or knowledge transfer (Baum and Ingram, 1998; Haunschild and Miner, 1997)—or for the same activity but with different timing—namely learning that occurs before or after the focal activity learning (Carrillo and Gaimon, 2000; Pisano, 1994).

Several studies have suggested that variety in types of experience may facilitate overall organizational learning. In a lab experiment with groups playing a strategic game, experience with a related game was shown to improve learning rates by a greater amount than either pure specialization or unrelated variation in game experiences (Schilling *et al.*, 2003). Similarly, Littlepage *et al.* (1997) found that experience with related tasks enhanced group learning by increasing individual member proficiency. In a non-lab setting, Boh *et al.* (2007) found that software teams with diverse experiences across related software systems performed better than those with more concentrated experiences. Also, Lawrence (2018) finds that retail restocking teams composed of employees who have performed a related version of restocking learn the new restocking practice more quickly than other teams without this experience. Learning from diverse but related activities seems to expand a unit's knowledge base, particularly if the related activities are aligned in terms of incentives (Clark, Kuppuswamy, and Staats, 2018).

Studies have also shown that the related experience does not have to be acquired by the same team. There can be knowledge spillovers from other teams who are doing the related activities, which improve learning outcomes for employees engaging in a focal activity (Greenwood *et al.*, 2016). These studies suggest that related experience—either acquired directly or through spillovers from collocated teams—are particularly important in building an organization or unit's knowledge base (Argote and Miron-Spektor, 2011). Thus, beyond the benefits gained from repeating a focal activity, related activities should improve operational performance for the focal activity. This outlines the logic underlying the second hypothesis.

Hypothesis 2 (H2): Organizations with greater amounts of related experience solving operational problems will experience greater improvements in operational performance.

Learning to Manage Complexity

Given that the learning benefits of accruing experience—both from focal and related activities—are largely positive for operational performance, while the impact of complexity is largely negative, it is important to understand how experience interacts with complexity in influencing operational performance. If complexity is uniformly detrimental to operational performance, we should expect firms to avoid and/or reduce complexity. However, if the negative effect of complexity is moderated by experience, we may find more instances where choosing complexity is optimal.

As organizations gain more direct experience, they are exposed to a wider range of potential underlying issues with the current routine or task. Dealing with these issues is likely to result in a deeper understanding of the causes underlying the genesis of different problems (Finkelstein and Haleblian, 1999). A more comprehensive understanding of these issues triggers processes of deliberate learning (Zollo and Winter 2002). Therefore, as organizations gain more and more direct experience, they should develop superior routines and capabilities for dealing with static operational activities or tasks (Nelson and Winter, 1982).

A small subset of studies has examined the performance of organizations performing complex activities. Stan and Vermeulen (2013) show in a study of IVF clinics that clinics which select more challenging IVF cases improve their ability to solve easier cases. The authors argue that the by taking on more challenging cases, clinics experimented with a wider range of techniques and codified their new knowledge, resulting in improved success rates on all cases. The effect of these activities raised overall performance for these clinics relative to clinics that screened out the most complex cases. Similarly, Rockart and Dutt (2015) show how investment banks are able to improve their capabilities—as assessed by a survey of their clients from that year—by taking on more complex projects. They argue that the experience gained in completing the more challenging projects allows organizations to elevate their maximum capability. In turn, these banks provide better services across all projects, resulting in higher evaluations by their clients and a more sustainable competitive advantage. These studies suggest that complex experiences, by being more challenging, force organizations to better understand the causes and consequences of the problems they are solving. Over time, the broader and deeper knowledge acquisition and learning through the acquisition of this type of experience should yield better performance outcomes. This highlights the logic underlying the effect of the interaction between direct experience and complexity on operational performance:

Hypothesis 3a (H3a): Organizations with greater amounts of direct experience solving operational problems that are of higher complexity will experience greater improvements in operational performance.

The learning processes triggered by acquiring related experience are different from those associated with learning from direct experience. As organizations gain more related experience, their knowledge base expands, but instead of gaining knowledge specific to the focal task, they are expanding the types of knowledge they possess. Increasing knowledge breadth is associated with many positive outcomes, including the development of a greater number and higher quality of new products and patents as well as the ability to solve novel problems (Fleming and Sorenson, 2001; Nelson and Winter, 1982). In particular, related experience should help organizations better respond to changes in their environment and adapt more effectively (March, 1991).

At the same time, a broader range of knowledge is also likely to introduce greater costs. There are two reasons for this increase. First, as organizations draw from a wider range of knowledge, they increase the scope of their search activities, the cost of which correspondingly increases (Katila and Ahuja, 2002). Second, integrating different types of knowledge engages a greater cognitive load than deploying a single type of knowledge (Grant, 1996). In some cases, a broader search allows for the identification of better solutions. However, given that operational problems are not novel but rather ongoing challenges, an increase in breadth would increase costs but not benefits (Christmann, 2000).

In large part, operational problems are ongoing, routine challenges, so it remains unclear whether or not they benefit from a wide breadth of knowledge. Therefore, between the higher coordination costs of undertaking greater levels of complexity and higher costs and uncertain benefits of increasing knowledge scope for solving operational problems, organizations that have accrued a greater amount of related knowledge as well as high complexity are likely to experience smaller improvements in operational performance than those organizations with lower complexity. This underlies the logic of our final hypothesis, which considers the effect of the interaction between related experience and complexity on operational performance:

> *Hypothesis 3b (H3b): Organizations with greater amounts of related experience solving operational problems that are of higher complexity will experience lower improvements in operational performance than those solving problems with lower complexity.*

The learning mechanisms outlined in these hypotheses above are likely particularly relevant for settings where firms are addressing operational problems that are recurrent, incremental, and require the implementation of ongoing solutions. Further, the learning from experience outlined above may be a result of changes to the routines themselves or improvement in the ability to execute the routine with greater experience. In the case of our setting, which includes a long panel of data, we acknowledge that both types of learning from experience may be the underlying drivers of our results. However, since we propose that firms learn to manage complexity over time, we believe both types of changes due to learning support our argument. We also recognize that the mechanisms proposed here may not apply either if the organizations are facing radical, one-time problems or if the sources of the complexity are external. We consider these limits explicitly in the discussion section. At the same time, because our setting captures the population of all manufacturing facilities in the U.S. from 1991–2014, and routine operational problems are prevalent across multiple settings, we believe this is a compelling and generalizable problem that deserves attention.

DATA AND METHODOLOGY

Data

Our data are primarily drawn from waste reporting by manufacturing facilities in the U.S. between 1991 and 2014. This dataset is collected by the Environmental Protection Agency (EPA) in the Toxic Release Index (TRI) database, which has been published annually, since 1987, in reports that account for 612 routinely processed chemicals. These data reliably measure the key variables of interest starting in 1991; for instance, there is no variation in the complexity measure prior to 1991; correspondingly, our analysis examines the data from 1991 onwards. The TRI gathers information from facilities that possess more than 10 employees and generate chemical waste above threshold levels (usually 10 to 25,000 pounds depending on the chemical); this does mean that some facilities that emit waste are not captured by the data, but this dataset still captures the vast majority of manufacturing facilities by number and production volume in the U.S. We combine these data with data from the National Establishment Time Series (NETS) to be able to account for facility size, sales, and profits. The resulting dataset contains facility-level information about establishment location, size, industry affiliation, and managing personnel and has been used for research by management and economics scholars (Berchicci *et al.*, 2017; Doshi, Dowell, and Toffel, 2013; Li and Zhou, 2017). Because each reporting facility must submit a different form for each toxic chemical it is generating or using, we are able to examine how changes in waste management activities at the facility-chemical level influence changes in facility-chemical waste output by examining chemical-level and facility-level choices by year. Correspondingly, the level of analysis is *facility-chemical-year*.

This dataset has several features that suit our study. First, the setting is ideal to test hypotheses about learning because managers make choices about how to reduce waste by choosing different levels of complexity in waste management solutions. Thereafter, they document changes in waste levels, getting feedback on their choices, and decide whether or not to change their actions in the next period. Because we can observe each part of the process with respect to each chemical within each facility, we get very close to organizational learning. Second, these data describe an operational problem (waste reduction), along with resulting waste levels and information about manufacturing establishments' waste management activities concerning toxic chemical waste generation and reduction. Third, the TRI is different from other federal environmental programs in that it is an information disclosure, rather than environmental performance program. Thus, although TRI data are self-reported, because it is a disclosure program, and because the EPA can impose a fine of up to $25,000 per violation or misreporting, 95% of facilities reported information accurately (de Marchi and Hamilton, 2006).

After eliminating data prior to 1991, eliminating extreme values and logging the main variables, we are left with 58% of the original database. We lose 14% of the original data because they represent facilities' activities before 1991; we lose an additional 19% when we eliminate extreme (above 6) and incorrect (equal to or less than 0) values of the production index. Last, we lose 9% of the data as some facility-chemical-years report no toxic waste, or no use of waste disposal methods. This yields a dataset of 1.4 million observations.

We use a 25% subset of this dataset, creating an unbalanced panel of 10,436 firms with 47,186 facility-chemical pairs and 339,754 total observations. We chose to conduct the analysis on a subset of the data for two reasons: first, we maintain good data hygiene by developing our hypotheses on one subset of the data, then testing for robustness on multiple independent subsets.

Second, because the full dataset includes 2.4 million observations, we reduce the risk of user errors by working with a smaller subset.

Dependent variable

Operational performance: Our dependent variable—*operational performance*—is a measure of the change in total waste generated for each chemical within the facility year-over-year. This is a commonly used measure of performance by studies using these data and/or examining questions about environmental and operational performance (Berchicci, King, and Tucci, 2011; King and Lenox, 2002). *Operational Performance* is measured as the log of the total pounds of waste generated this year divided by the total pounds of waste generated last year.

$$Operational\ Performance_{fct} = ln\left(\frac{waste\ generation_{fct}}{waste\ generation_{fct-1}}\right) \quad (1)$$

Taking the log of this ratio has the twofold benefit of 1) reducing the effect of extreme changes in waste generated and 2) approximating percentage changes for moderate changes in waste generated (e.g., ln(1.1/1.0) = 0.95 ~ 10%) (Dutt and King, 2014).

Independent variables

Complexity: A facility can treat its toxic waste using five different treatments: 1) Recycling, 2) Energy Recovery, 3) Treatment, 4) Land Disposal, 5) Other. Furthermore, these can be done *onsite*, i.e., within the facility, or *offsite,* i.e., by a third party. Finally, facilities can mix and match across these modes. Thus, there exist up to 10 different modes of waste treatment prior to discarding the waste. We assume that the more modes a facility uses to treat waste, the greater the complexity of the waste management solution. Further, we acknowledge that there may be relevant differences across chemicals. Different chemicals may have chemical-specific features that may determine the ways in which they can be treated. For instance, some chemicals may be too toxic to dispose by landfill disposal; hence the number of available options will be fewer than 10.

Correspondingly, we measure *relative complexity* by accounting for such differences between the number of waste treatment methods a focal facility uses to treat a specific chemical in a given year and the number of waste treatment methods used on average across the population of manufacturing facilities for that chemical in that year. Results are consistent if we use a simplified *complexity* measure that merely counts the number of distinct ways a facility treats its toxic chemical waste.

Direct Experience: We maintain consistency with the learning literature (Argote, 2013) and examine the direct effect of learning at the chemical level by using the cumulative prior experience with the focal chemical. We measure *direct experience* as the log of cumulative waste emitted for the focal chemical up until the year t (ln(cumulative waste)). We expect learning that is a result of *direct experience* to be captured as negative and significant coefficient—which indicates relatively better performance—on this variable in our specifications.

Related Experience: Facilities may also learn by accumulating *related experience* by engaging in voluntary activities designed to reduce the use of toxic chemicals at the source, i.e., the input to the production system. These activities fall into 49 categories specified by the EPA. Examples of activities include: 1) improved maintenance scheduling, record keeping, or procedures and 2) optimized reaction conditions. Of facilities choosing to undertake source reduction activities, we observe that 58 percent choose to only pursue one source reduction activity per year per chemical. Accordingly, we measure *related experience* by coding a dummy variable equal to 1 if a facility undergoes any directed source reduction activity for the focal chemical in the focal year and 0 otherwise. Similar to *direct experience*, we expect learning that is a result of *related experience* to be captured as a negative and significant coefficient on this variable in our specifications.

Controls

Because a reduction or increase in waste in a given year may be attributed to facility- and chemical-level factors, we include a series of controls. We account for three facility-level factors and one chemical-level factor that are likely to influence *operational performance,* beginning with facility-level factors. First, we account for the *production index*, defined as the proportional increase or decrease in manufacturing volume relative to the prior year. Facilities are required to report the expansion, contraction, or stability of their manufacturing. This value takes a value of 1 if the manufacturing stayed the same year-over-year, values less than 1 to indicate the proportion by which the manufacturing shrank, and values greater than 1 to indicate expansion. We use a log of this value and only include observations for which the raw value reported by the facility is between 0 and 6. This restriction omits 19% percent of our observations, omitting what we consider to be unreasonable values, likely reflecting human errors in reporting of this variable that would bias the results. Second, we include a measure of *facility experience* which accounts for facility-level experience with waste treatment. We count the total number of years for which a focal facility has reported waste treatment activities for any chemical. Third, *total chemicals reported* is also likely to influence the complexity of waste treatment and learning. Thus, we include a count of the total number of chemicals being treated at each facility in each year.

Next, we account for a factor at the chemical level that is likely to influence *operational performance.* A facility’s yearly waste is affected by non-production waste that may arise from non-production sources, including waste emissions that result from accidents and/or are otherwise unplanned. We include *non-production waste* which is the log of the total waste connected to the focal chemical in a focal year that arises from non-production sources.

In addition to these four control variables, we include two fixed effects. First, we include *facility-chemical fixed effects* such that the results of our analysis capture changes within a specific facility-chemical over time. Second, we include *year fixed effects* to account for changes to the TRI reporting and macroeconomic factors that may shift all facilities reporting in given years.

Methodology

The aim of this paper is to understand the individual and joint effects of complexity and learning on facilities' abilities to reduce waste in production processes. In order to do so, we create a model that examines the effect of complexity and learning as well as their joint effect on waste reduction. We reduce the bias associated with facility- and chemical-level attributes through the use of fixed effects at the facility-chemical level as well as controls at the facility and chemical levels. Our base level model for individual learning and complexity is as follows:

$$Operational\ Performance_{fct} = \beta_1 Complexity_{fct} + \beta_2 Direct\ experience_{fct} + \beta_3 Related\ experience_{fct} + \sum_{j=1}^{m} \delta_j controls_{jfct} + \delta_{fc} + \theta_t + \varepsilon_{fct} \qquad (2)$$

We test for the joint effect of learning under complexity by interacting *complexity* with *direct experience* and *related experience*. Our decision to use a fixed effect at the facility-chemical level is quite restrictive, yet we believe it is necessary for this analysis where firm choices about how to process chemicals are endogenous. The fixed effect limits the analysis to within-chemical/within-firm effects to capture any effect of complexity. A less restrictive assumption would have compared variation in complexity across firms for chemicals of the same toxicity. However, this alternative, less restrictive assumption would be biased if firms of different capabilities make different selections with regard to managing chemical complexity.

RESULTS

After limiting our sample to those observations with reasonable production index values, we start our analysis with 339,754 observations. The facility and chemical characteristics vary dramatically across the sample. As expected and summarized in Table 1, the total waste emitted across chemicals varies substantially. We note that the average chemical emittance in a year is 424,423 pounds, though it varies from 0 to 910,000,000 pounds. The difference in these levels is partially explained by chemical toxicity, which restricts the amount of chemical generation by class. This variation is one reason for our inclusion of fixed effects at the facility-chemical level in all specifications.

[INSERT TABLE 1 ABOUT HERE]

The average facility has 9.4 years of experience with the focal chemical, 12 years of experience with general waste management, and reports on 12 chemicals. These chemicals are, on average, treated in two ways, which represents slightly more complexity (0.15) than the average facility-chemical across the United States each year. Finally, about 15 percent of facility-chemicals are undergoing related source reduction activities in any given year in addition to whatever waste management methods are used.

Table 2: H0, H1, H2—Experience, Complexity & Operational Performance

In Table 2, we analyze the effect of *direct experience* and *relative complexity* on firm performance. First, in Specification (1), we find that the coefficient on *production index* is greater than 1: increases in production are positively and significantly associated with greater waste generated in the focal year. These results are expected. Similarly, in Specification (2), we find that *non-production waste*, which includes accidents, is also associated with more waste being generated. Next, in Specification (3), we include *facility experience* and observe a significant reduction in waste. This coefficient supports the idea that facilities are learning to reduce waste over time. In Specification (4), we include *total chemicals reported* by the facility and find that increases in chemicals reported are also associated with a slightly larger waste production. Here, we might imagine that an increase in the number of chemicals by a facility may require some additional effort and attention, which reduces the amount of targeted attention on any given chemical's management.

In Specifications (5)–(7), we move to assessing the effect of *direct experience*, *related experience*, and *relative complexity* on *operational performance*. We examine *direct experience* first, which we capture as the logged cumulative waste for the focal chemical. We find that greater *direct experience* is associated with proportionately more waste reduction, as indicated by the negative coefficient (-0.072). This coefficient can be interpreted to mean that an additional log-unit of cumulative waste is associated with a 7 percent reduction in waste year-over-year. Therefore, *direct experience* is associated with more improvement in performance, which supports our first hypothesis (H1). Importantly, the introduction of *direct experience* overrides the practical significance of the *facility experience* measure, both giving us assurances that *direct experience* is likely to be correlated with learning and is the more relevant learning measure in this setting. In Specification (6), we also include our measure of complexity, *relative complexity*. We find that facilities undergoing more complex management of their focal chemical achieve relatively lesser improvement in waste reduction year over year. This detrimental effect of *relative complexity* on *operational performance* supports Hypothesis 0 (H0). Last, in Specification (7), we examine the directed efforts by facilities to improve performance via source reduction activities. We find that waste reduction activities do improve performance, resulting in about 11 percent extra in operational performance improvements. This finding supports Hypothesis 2 (H2).

Beyond the statistically meaningful support for H0, H1 and H2, these results highlight the large economic impact of facilities' choices about learning and complexity. First, based on an average facility size of 400,000 pounds, the economic impact of an additional level of complexity relative to the average for a focal chemical is a 13 percent increase in waste, which translates to 52,000 pounds of waste for the focal chemical. Conversely, learning benefits from one additional logged unit of waste treated in a prior year is associated with a 7 percent reduction, and any source reduction activity with an 11 percent reduction which translates to 28,000 pounds and 44,000 pounds of waste reduction for a focal chemical in a given year.

[INSERT TABLE 2 ABOUT HERE]

Table 3: H3a & H3b—Experience-Complexity Interactions & Operational Performance

In Table 3, we examine the effect of *direct experience* and *related experience* when interacted with *relative complexity*. First, Specification (1) replicates Specification (7) from Table 2 to illustrate the main effects without any interactions. We examine the interaction between *direct experience* and *relative complexity* in Specification (2). The negative coefficient on the interaction between cumulative waste and complexity suggests that those facilities with greater *direct experience* managing the focal chemical have relatively better *operational performance* while managing complexity in waste treatment. In other words, the negative effect of *relative complexity* is reduced with more experience; facilities seem to learn, mitigating at least some of the negative effects of complexity. The coefficients on *direct experience*, *relative complexity*, and their interaction have p-values equal to 0.00, which provides evidence in support of Hypothesis 3a.

In Specification (3), we interact *related experience* with *relative complexity* to find that facilities seem to achieve smaller improvements in performance for relatively more complex chemicals than they achieve for chemicals managed with lower complexity. This result suggests that while source reduction activities may have first-order benefits for *operational performance*, they result in penalties when organizations employ them in combination with a larger number of waste treatment methods. This result supports Hypothesis 3b where we predicted that pursuit of *related experience* would result in diminished performance improvements for those relatively more complex chemicals.

[INSERT TABLE 3 ABOUT HERE]

Overall, we find that experience and complexity have significant effects on facilities' abilities to improve performance over time.[2] *Direct experience* and *related experience* have benefits for improvement whereas complexity hinders performance improvement. Most interestingly, the detrimental effect of complexity is reduced over time for facilities that have more experience managing complexity. However, this ability to overcome the detrimental effects of complexity does not extend to experience with related experience.

Table 4: Mechanism Tests

The results in Tables 2 and 3 provide support for the hypothesized effects of experience and complexity on waste reduction, while including very fine levels of controls. In particular, the results suggest that facilities likely benefit by learning from experience and face costs from complexity. Nevertheless, we recognize that there may be alternative ways to measure complexity that may not align with our hypothesis, and therefore test the mechanisms underlying our initial results. We exploit information about where waste treatment is being done—onsite or offsite—to

[2] We repeat Specification (3) of Table 3, which includes all of our main findings for alternative random samples from the TRI data in Appendix Table 1. Specifically, we draw 10 additional random samples from the 75 percent of the data that was not used in this main analysis and re-run the analysis on these samples. We find consistent results across each additional sample.

examine how the location of experience and complexity is associated with changes in *operational performance*. We would expect that, in terms of complexity, facilities that are doing waste management both onsite and offsite should face greater coordination costs. For instance, facilities using both a treatment pool and an incinerator to treat their waste should incur lower costs if both modes of treatment are onsite vs. if one mode is onsite and the other is offsite.

We code three dummy variables to capture different waste management combinations. *Dual Waste Mgmt* is 1 for facilities managing a focal chemical both onsite and offsite; *All Offsite Waste Mgmt* is 1 for facilities managing a focal chemical offsite only; and *All Onsite Waste Mgmt* is 1 for facilities managing a focal chemical onsite only. Overall, 41.7 percent of firms manage chemicals both on and offsite, 30.6 percent manage all onsite, and the remainder choose management all offsite. Specification (1) in Table 4 includes all the results testing the hypotheses. Starting in Specification (2), we include dummy variables for *Dual Waste Mgmt* and *All Offsite Waste Mgmt* which allows us to examine the penalty (or benefit) associated with these locational waste management choices as compared to the omitted location of management, *All Onsite Waste Mgmt*. We find that there are significantly larger penalties for managing waste at least partially offsite. The largest penalty (0.272) is associated with managing waste both on and offsite. This penalty is significantly different from and larger than the penalty associated with only offsite waste management (p-value = 0.00). We consider the management of waste both onsite and offsite to be the most complex way to manage waste, as facilities taking this approach are disposing of waste in 2.9 different ways, on average, as compared to an average 1.3 ways for either management all onsite or all offsite. These results support the mechanisms highlighted in the paper and provide additional support to the idea that complexity is costly for performance.

In Specification (3), we examine the impact of *direct experience* on the effect of these choices about where to manage waste. We find that the penalty of waste management at least partially offsite is lowered for those facilities with more *direct experience*. There is no difference in improvement associated with prior experience between facilities managing partially versus totally offsite. Facilities which are employing at least some offsite management seem to improve more quickly with more prior experience as compared to those facilities managing chemicals only onsite. This result may suggest that facilities are somehow able to reap the benefits of learning from external knowledge sources. There may be many ways to learn, and facilities that lack capabilities to treat waste themselves can potentially benefit from collaborators in their ecosystem. Overall, these results provide additional and alternative support to the claim that management of chemicals in more complex ways leads to a greater initial penalty but that facilities seem to be able to learn from prior experience with complexity such that the penalty is lowered over time.

[INSERT TABLE 4 ABOUT HERE]

Robustness Test: 2SLS Analysis

Because firms are choosing the level of complexity—i.e.., the number of ways to treat waste prior to disposal—an unobserved factor may be driving the choice of complexity as well as the potential benefits gleaned from complexity. For instance, better quality facilities may choose lower values of *complexity*, which are correlated with greater improvements in *operational performance;* thus, it could be the quality of the facility that is driving the results. We address this challenge in two ways. First, the primary analyses are designed to limit concerns about omitted variables by both including multiple measures of experience (which are likely to be correlated with underlying quality) and by conducting the analysis at the facility-chemical level. In particular, we track how changes in complexity within a specific facility treating a specific chemical over time influence changes in waste output of that particular chemical. For instance, facility A may be producing both dioxin waste and nitrous oxide waste; we are able to track how changes in the process of treating dioxin waste influence change in the output of dioxin annually. Thus, the level of analysis is granular and we are able to compare each facility-chemical pair to itself over time.

Second, we conduct a two-stage analysis using *district complexity* as an instrument for *relative complexity*. A district is a region within a state that elects a single member of congress and is decided by population. Drawing from prior studies that have used similar instruments (Forman, Goldfarb, and Greenstein, 2005; Nagle, 2016), we assume that facilities are likely to be influenced by the level of complexity used in their district of operation when choosing how many ways to treat waste. The waste management decisions of other facilities processing the chemical in the district are exogenous to the focal facility. However, these facilities likely face similar conditions to the focal facility regarding opportunities for offsite management, which would suggest that the district faces similar opportunities for choosing complex management options. We assume that within each district there is a local economy such that there are likely to be similarities in the cost of waste treatment options—such as the availability of offsite waste treatment operators—that should collectively influence the level of complexity. Thus, for any firm in a given year, the level of complexity in waste treatment should be correlated with the average complexity across all chemicals in that district. We construct *district complexity* as the relative complexity for the focal chemical in the congressional district in which the focal facility is located.

To conduct a complete two-stage analysis to replicate all the results in Tables 2 and 3, we would need multiple instrumental variables to account for each of the interactions with *relative complexity*. However, it is difficult to identify factors that influence *relative complexity* but not *operational performance*, are not highly correlated with each other, and for which we have reliable measures across such a large dataset. Thus, we conduct a two-stage analysis of our baseline model (Equation 2) to compare and contrast the magnitude of the effects of *relative complexity* on *operational performance* and assess the reliability of the baseline analysis.

Specification (4) of Table 4 uses the instrumental variable approach to interpret the effect of the *relative complexity* coefficient. The results of this specification are remarkably similar to the Specification (7) in Table 2: facilities still suffer a penalty for choosing relatively more complex management, though with a lower magnitude. The first stage F-statistic is large (36.76), suggesting that the instrument is valid. In sum, we provide additional evidence that this endogenous form of complexity chosen by the firm does result in worse initial performance which is lessened for those facilities with more experience managing these chemicals.

DISCUSSION AND CONCLUSIONS

Organizational research on learning and complexity has identified the benefits of learning and the costs of complexity with respect to organizational performance across numerous settings. While the accrual of costs from complexity typically arise from coordination and integration activities that are absent when organizations engage in simpler actions and organizational forms, the benefits from learning arise both from learning by doing and the accumulation of new knowledge. Learning processes are dynamic in that they modify both the level learned and the ability to learn over time. Therefore, the interaction between learning and complexity suggests important insights about how firms should manage complexity to improve their operational performance. We examine this interaction through multiple lenses—how much prior experience is needed, what types of prior experience are needed, and where the learning must occur—to better understand how organizations can best manage the costs of complexity.

These findings are especially relevant because as organizations grow and evolve they may be unable to reduce complexity through restructuring their activities or changing organizational design, but learning can offer an alternative to maintaining performance. For instance, if complexity arises as an outcome of organizational growth (Chen, Williams, and Agarwal, 2012; Holbrook *et al.*, 2000), environmental change (Csaszar and Siggelkow, 2010), or a strategic choice to constrain imitators (Pil and Cohen, 2006; Rivkin, 2000), organizations may have to persist with complexity. By learning from complexity, such organizations can improve their overall performance while still engaging in complex activities. Learning may also be particularly relevant for organizations solving operational problems that are recurrent and ongoing, as improvement can have an significant incremental impact on long-term profitability (Dosi, 1982; Pisano, 1996; Reichstein and Salter, 2006; Utterback and Abernathy, 1975; Vivero, 2002).

Our baseline results raise three implications relevant for scholars and practitioners of complexity and learning. First, we enrich the literature on complexity and diseconomies of scope by illustrating how learning from experience—both direct and related—can diminish the detrimental effect of complexity on operational performance. These findings contribute to a nascent area of research on the benefits of complexity for organizational performance by highlighting the contrasting effects of costs within any one period of complexity and accumulated learning benefits over time. Particularly for organizations that cannot eliminate complexity, our findings suggest that actively documenting and learning from complexity can improve long-term performance.

Second, by theorizing, measuring, and testing the learning benefits that arise from complexity, we also enrich our knowledge of how learning occurs. Because prior research has highlighted contingencies to learning from experience, we consider whether experience is beneficial in learning from complexity, and what types of experience is most helpful. Our analyses, by examining the effect of two distinct learning mechanisms—learning by doing and learning from related efforts—show that while both types of experience are independently helpful, in conjunction with a high level of complexity only direct experience has a beneficial effect on operational performance. Furthermore, the mechanism tests highlight that while the independent influence of learning is highest when it occurs onsite, the joint effect of learning from complexity is better in conjunction with external knowledge. These findings highlight the fact that directly learning from complexity is possible and should be encouraged, while, in the long-term, external knowledge can also be a complement to learning from one's own experience.

Third, although common to many settings, research on operational problems is limited, and the empirical context offers its own contributions. We examine ongoing operational performance in a manufacturing setting at the facility-chemical level—essentially inputs and outputs on the production line—such that the measures and concepts are closely tied together. We retest ideas proposed in prior research—such as the negative influence of complexity and the positive influence of learning—and find support that can quantify their impact on operational performance improvements. Because our study examines establishment-level data in manufacturing settings across many different industries, we believe our fine-grained analysis provides robust and reliable results.

Our argumentation and results build upon prior research on learning by doing and clarify the mechanisms through which learning is helpful for complexity. Because ongoing enhancements in operational activities can have ripple effects on improving overall performance, highlighting the benefits from learning and how they accrue is relevant for both scholars and practitioners. Because a substantial proportion of organizational activity occurs in the form of operational changes within firms, which are often overlooked by researchers—in part because of measurement difficulties and in part because of their ubiquitous nature (Cohen and Klepper, 1996; Cohen, Nelson, and Walsh, 2000; McElheran, 2015; Reichstein and Salter, 2006; Rosenberg, 1982)—these results are highly relevant.

Limitations

The study has three limitations that provide opportunities for future research. First, we assume a problem-solving model in which employees are making decisions about how many disposal methods to use in each period. It is possible that different decision models are at work across different facilities; for instance, some decisions might be made centrally rather than at the level of the chemical or facilities. Not accounting for these different decision models may be adding noise to our estimates. Second, we are unable to fully identify the causal link between complexity, learning, and operational performance. Although the additional analyses with district complexity as an instrument for complexity suggest a consistent pattern in the results, to robustly tease out causality we would need additional instruments and/or a natural experiment. Third, we are unable to consider whether different problems—namely, radical one-time problems—would elicit the same learning from complexity and/or the same types of experience benefits. Research on learning from rare events and failures suggests mixed responses by organization: this limits the generalizability of this research.

Overall, we extend research on learning and complexity by testing how these two factors interact to influence problem-solving in the context of an important class of problems: operational problems. We are able to show that while the direct effect of complexity is to diminish performance, there are dynamic learning benefits over time. Specifically, the findings highlight the long-term benefits of complexity but only when an organization is able to accumulate experience. The results bring to light important implications in terms of how managers of experienced and inexperienced organizations should select the complexity of their operational processes in order to best improve operational performance.

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TABLE 1: Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Total Waste Emitted	1									
Operational Performance	0.02	1								
Total Chemicals Reported	0.017	-0.0021	1							
Facility Experience	0.000	-0.048	0.0177	1						
Chemical Experience	0.025	-0.021	0.033	0.7321	1					
ln(Production Index)	0.002	0.180	0.021	-0.059	-0.0654	1				
ln (Non-production Waste)	0.055	0.048	0.054	-0.003	0.031	-0.0061	1			
Direct Experience	0.089	-0.086	0.108	0.172	0.347	-0.060	0.0704	1		
Relative Complexity	0.055	0.038	0.139	0.015	0.068	-0.003	0.085	0.2242	1	
Related Experience	-0.001	-0.002	-0.013	-0.107	-0.052	0.002	0.022	0.030	0.0831	1
Observations	339754	321941	339754	339754	339754	339754	339754	339754	339754	339754
Mean	424423.1	-0.0288134	12.10357	12.64775	9.405658	0.7063333	0.1458367	10.35155	0.1477198	0.1563072
Standard Deviation	5498427	1.207134	21.64199	7.191812	6.753078	0.1728519	0.9845349	4.872186	0.9802941	0.3631469
Min	0.0000001	-15.41562	1	0	0	0.0099503	-16.12159	-16.1181	-2.8	0
Max	910000000	15.34865	253	27	27	1.944481	16.30042	22.18065	6.368962	1

TABLE 2: Effect of Direct Experience, Related Experience, and Complexity on Operational Performance

DV: Op. Performance	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(Production Index)	0.522	0.522	0.522	0.522	0.503	0.501	0.501
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
ln (Non-production Waste)		0.048	0.048	0.048	0.049	0.048	0.048
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Facility Experience			-0.016	-0.016	-0.001	-0.001	-0.001
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total Chemicals Reported				0.002	0.002	0.002	0.002
				(0.000)	(0.000)	(0.000)	(0.000)
Direct Experience					-0.073	-0.074	-0.074
					(0.002)	(0.002)	(0.002)
Relative Complexity						0.125	0.126
						(0.004)	(0.004)
Related Experience							-0.108
							(0.007)
Fixed Effect:							
Facility-Chemical	X	X	X	X	X	X	X
Year	X	X	X	X	X	X	X
Observations	314,865	314,865	314,865	314,865	314,865	314,865	314,865
R-squared	0.373	0.374	0.374	0.374	0.387	0.389	0.390

Notes: Dependent variable is the log change in waste between last year and this year. All columns estimated using a fixed effect model at the facility-chemical and year levels. Errors clustered at the facility-chemical level. Standard Errors indicated in parentheses. Asterisks for significance levels omitted per the policy of the *Strategic Management Journal.*

TABLE 3: Dynamic Effects of Learning and Complexity on Operational Performance

DV: Op. Performance	(1)	(2)	(3)
ln(Production Index)	0.501	0.501	0.501
	(0.008)	(0.008)	(0.008)
ln (Non-production Waste)	0.048	0.049	0.049
	(0.003)	(0.003)	(0.003)
Facility Experience	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Total Chemicals Reported	0.002	0.002	0.002
	(0.000)	(0.000)	(0.000)
Direct Experience	-0.074	-0.071	-0.071
	(0.002)	(0.002)	(0.002)
Relative Complexity	0.126	0.282	0.279
	(0.004)	(0.017)	(0.017)
Related Experience	-0.108	-0.109	-0.116
	(0.007)	(0.007)	(0.008)
Direct Experience * Relative Complexity		-0.013	-0.013
		(0.001)	(0.001)
Related Experience * Relative Complexity			0.015
			(0.006)
Fixed Effect:			
Facility-Chemical	X	X	X
Year	X	X	X
Observations	314,865	314,865	314,865
R-squared	0.390	0.391	0.391

Notes: Dependent variable is the log change in waste between last year and this year. All columns estimated using a fixed effect model at the facility-chemical and year levels. Errors clustered at the facility-chemical level. Standard Errors indicated in parentheses. Asterisks for significance levels omitted per the policy of the *Strategic Management Journal*.

TABLE 4: Mechanism and Robustness Checks

DV: Op. Performance	(1)	Onsite vs Offsite vs Both (2)	(3)	2SLS (4)
ln(Production Index)	0.501	0.502	0.502	0.497
	(0.008)	(0.008)	(0.008)	(0.009)
ln (Non-production Waste)	0.049	0.049	0.049	0.046
	(0.003)	(0.003)	(0.003)	(0.003)
Facility Experience	-0.001	-0.004	-0.004	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Total Chemicals Reported	0.002	0.002	0.002	0.002
	(0.000)	(0.000)	(0.000)	(0.001)
Direct Experience	-0.071	-0.073	-0.055	-0.073
	(0.002)	(0.002)	(0.003)	(0.002)
Relative Complexity	0.279			0.108
	(0.017)			(0.033)
Related Experience	-0.116	-0.107	-0.106	-0.105
	(0.008)	(0.007)	(0.007)	(0.008)
Direct Experience * Relative Complexity	-0.013			
	(0.001)			
Related Experience * Relative Complexity	0.015			
	(0.006)			
Dual Waste Mgmt		0.282	0.551	
		(0.014)	(0.038)	
All Offsite Waste Mgmt		0.186	0.433	
		(0.016)	(0.040)	
Direct Experience * Dual Waste Mgmt			-0.024	
			(0.003)	
Direct Experience * All Offsite Waste Mgmt			-0.023	
			(0.003)	
Constant				0.801
				(0.022)
Fixed Effect:				
Facility-Chemical	X	X	X	X
Year	X	X	X	X
First Stage F-Statistic				37.04
Observations	314,865	314,865	314,865	281,814
R-squared	0.391	0.389	0.390	

Notes: Dependent variable is the log change in waste between last year and this year. All columns estimated using a fixed effect model at the facility-chemical and year levels. Errors clustered at the facility-chemical level. Standard Errors indicated in parentheses. Asterisks for significance levels omitted per the policy of the *Strategic Management Journal*.

APPENDIX TABLE 1: Robustness to Alternative Samples of the Data

DV: Op. Performance	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ln(Production Index)	0.528	0.483	0.535	0.489	0.481	0.477	0.511	0.471	0.480	0.506
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.008)
ln (Non-production Waste)	0.058	0.062	0.063	0.053	0.056	0.058	0.063	0.064	0.057	0.065
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Facility Experience	-0.002	-0.001	-0.001	-0.000	-0.001	-0.002	-0.001	-0.001	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total Chemicals Reported	0.000	0.002	0.000	0.003	-0.001	0.003	0.002	0.002	0.000	-0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Direct Experience	-0.068	-0.073	-0.073	-0.074	-0.076	-0.073	-0.071	-0.073	-0.069	-0.073
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Relative Complexity	0.259	0.304	0.262	0.315	0.262	0.255	0.280	0.263	0.298	0.280
	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)	(0.016)
Related Experience	-0.116	-0.116	-0.119	-0.105	-0.122	-0.124	-0.119	-0.119	-0.119	-0.120
	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)
Direct Experience * Relative Complexity	-0.012	-0.015	-0.011	-0.016	-0.011	-0.011	-0.012	-0.011	-0.014	-0.013
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Related Experience * Relative Complexity	0.002	0.002	0.015	-0.016	0.010	-0.012	0.003	-0.003	0.005	-0.004
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
Facility-Chemical Fixed Effect	X	X	X	X	X	X	X	X	X	X
Year Fixed Effect	X	X	X	X	X	X	X	X	X	X
Observations	308,383	311,745	304,613	302,430	319,551	310,048	302,691	304,432	312,818	313,016
R-squared	0.393	0.390	0.399	0.385	0.380	0.408	0.396	0.385	0.387	0.390

Notes: Specifications (1)-(10) repeat Table 3 Specification (3) for each of the 10 alternative samples of the TRI data. The alternative samples are sampled randomly, with replacement, from the 75% of the TRI data not used in the main analysis (randomly drawing 1/3 of the sample to match the 25% sample in the main analysis). Dependent variable is the log change in waste between last year and this year. All columns estimated using a fixed effect model at the facility-chemical and year levels. Errors clustered at the facility-chemical level. Standard Errors indicated in parentheses. Asterisks for significance levels omitted per the policy of the Strategic Management Journal.