OPERATIONALIZING ENVIRONMENTAL SUSTAINABILITY THROUGH POLICY-BASED AND MARKET-BASED APPROACHES

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DEDICATION

To My Parents,

Savita and Saurabh Dhanorkar…

…without whom I would never have started this journey

&

To My Wife,

Shipi…

…without whom I would never have completed it!

ABSTRACT

Today, investors have become increasingly interested in corporate environmental practices and federal agencies have become actively involved with monitoring the environmental impact of corporations. As a result, organizations are increasingly recognizing environmental sustainability as an important driver of customer satisfaction and loyalty, quality, operational and financial performance. Such changes highlight the importance of environmental issues in today's business environment.

To actually bring about positive environmental change in firms, 'Source Reduction and Reuse' strategies are often considered "the most preferred" form of corporate environmental management compared to other initiatives such as Recycling, Energy Recovery and Disposal. It is widely acknowledged that Source Reduction and Reuse strategies can conserve energy and resources, curb pollution and maximize resource utilization. Yet, as companies face increasing competition, economic crises and customer expectations, Source Reduction and Reuse strategies are often sidelined in favor of other potentially easier-to-implement but environmentally-degrading options. To this end, my dissertation explores the feasibility of *policy-based* and *market-based* approaches, for promoting Source Reduction and Reuse within and across firms.

The *policy-based* approach provides insights into developing policies for externally promoting *source reduction* practices within firms. Using the context of government agencies promoting environmental change in firms, Essay 1 shows how *supportive* (e.g. environmental assistance, improvement recommendations) and *punitive* (e.g. regulatory inspections, sanctions) policies can be implemented in a complementary manner to promote *source reduction* initiatives.

The *market-based* approach develops insights for developing and operating online channels to promote material *reuse* across firms. Using transaction-level data, Essay 2 lays the foundation for understanding buyer and seller behaviors on online industrial reuse marketplace. Essay 3 explores the role of online intermediation and market design in reuse marketplaces. Together, these studies have important implications for developing policies to increase *reuse* of by-products, materials and wastes.

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Chapter 1

Introduction

Increasingly, organizations are recognizing environmental sustainability as an important driver of customer satisfaction and loyalty (Kassinis & Soteriou 2009), quality (Noori & Chen 2003), operational performance (Klassen & Whybark 1999; Sroufe 2003) and financial performance (Klassen & McLaughlin 1996; Jacobs et al. 2010). Investors have also become increasingly interested in corporate environmental activities. As of 2010, more than $3 trillion in professionally managed financial asset investments were made based on corporate environmental performance (2010). To put this in perspective, nearly one out of every eight dollars was invested based on a firm's record of environmental practices. In response to claims from investor advocacy groups and shareholder resolutions over the past decade (CERES 2014), federal agencies such as the Securities Exchange Commission (SEC) and the Environmental Protection Agency (EPA) have become actively involved with monitoring the environmental impact of corporations. Such changes highlight the importance of environmental issues to corporations and its stakeholders. As a result, corporations have started undertaking various environmental initiatives as they relate to their operations and supply chains.

According to the EPA's Waste Management Hierarchy[1] (see **Figure 1-1**), 'Source Reduction and Reuse' strategies are "the most preferred" form of corporate environmental management compared to other initiatives such as Recycling, Energy Recovery and Disposal. Source Reduction and Reuse strategies can conserve energy and resources, curb pollution and maximize resource utilization. Yet, as companies face increasing competition, economic crises and burgeoning customer expectations, Source Reduction and Reuse strategies can easily be sidelined. I take the perspective that we need innovative approaches for promoting adoption of Source Reduction and Reuse strategies. While corporations, today, are engaged in a wide gamut of environmental initiatives, I primarily focus on 'Source Reduction and Reuse' strategies since they are especially important to operations and supply chain management. To this end, my dissertation explores the feasibility of two such approaches, one *policy-based* and the other *market-based*, for promoting Source Reduction and Reuse within and across firms. The *policy-based* approach provides insights into externally promoting *source reduction* within firms. The *market-based* approach develops insights for the design of online markets to promote material *reuse* across firms. In my dissertation, I identify and examine ways to effectively implement these approaches in practice. Table 1-1 provides a scope of this dissertation.

[1] http://www.epa.gov/waste/nonhaz/municipal/hierarchy.htm

Figure 1-1. EPA's Waste Management Hierarchy

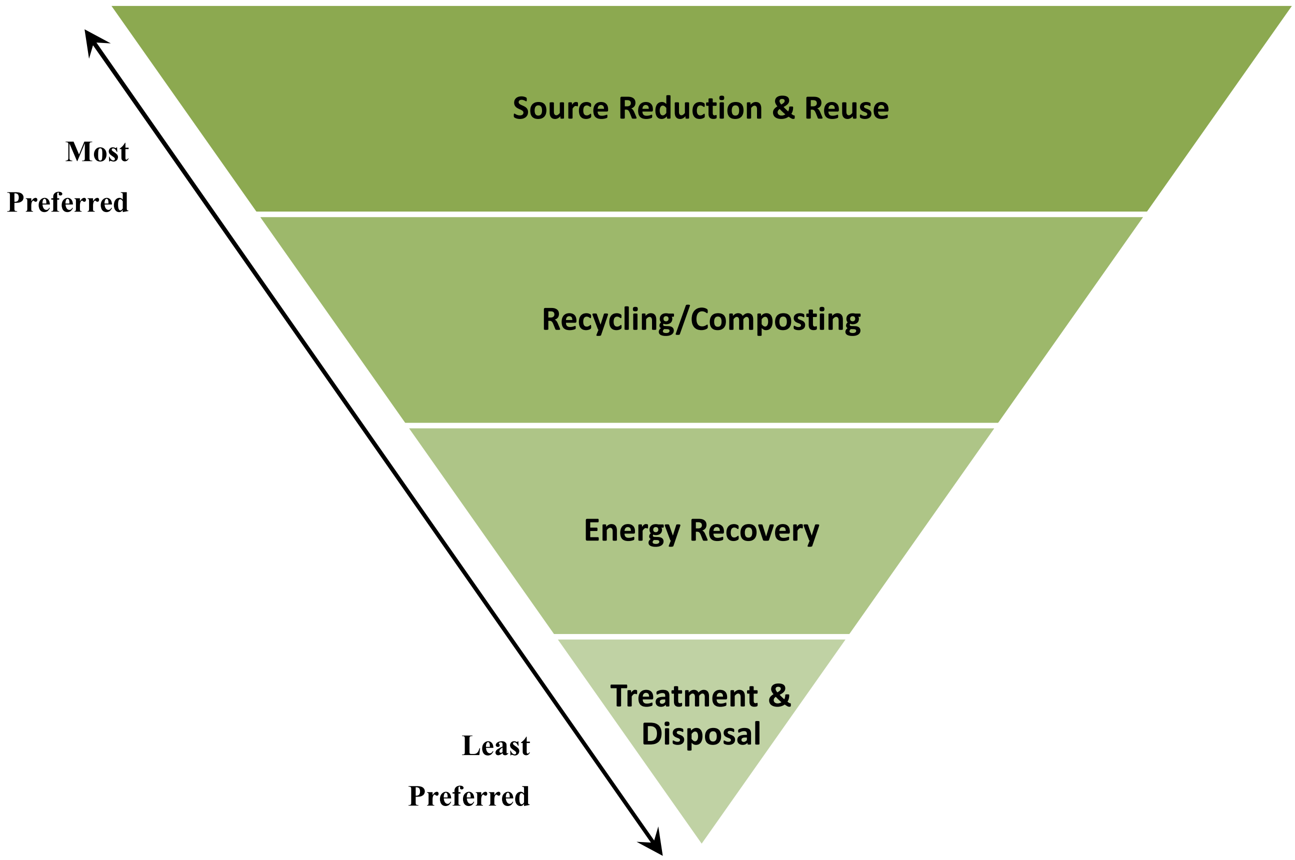

Table 1-1. Scope of the Dissertation

Strategies	**Source Reduction**	**Material Reuse**
Approach	Policy-based	Market-based
Primary Challenge	Externally driving Source Reduction through coordination	Driving Material Reuse efforts through Online Markets
Focus Area	Environmental Operations	Environmental Supply Chains

1.1 Policy-based Approach: Externally driving Source Reduction through Coordination

The Pollution Prevention Act of 1990 established source reduction as a United States national policy. Source reduction strategies typically imply changes in the design, manufacturing, purchase, or use of materials or products (including packaging) to reduce their amount or toxicity before they enter waste streams. Manufacturing companies in the U.S. spent close to $30 billion in 2013 on capital expenses and operating costs related to source reduction initiatives[2]. Yet, despite many of these initiatives being located on the "locus of profitable pollution reduction", companies often fail to successfully adopt ongoing source reduction initiatives. Why is this so? We posit that one of the major reasons is the policy approach being taken to externally promote source reduction efforts. The challenge of externally promoting change is ubiquitous in environmental operations, supply chain and policy settings. For example, downstream buyers, regulatory institutions, private auditing firms, as well as environmental assistance programs are involved in externally promoting source reduction efforts industrial facilities, with significant economic and environmental implications. Despite the diversity of institutions involved in externally influencing environmental changes, one of the fundamental ways to do so is through improvement recommendations. In this study, we decompose the typical external influence process into (i) managing the nature of influence (ii) managing recommendation-making and (iii) managing the implementation. Essay 1 – "Promoting Change from the Outside: Channeling Managerial Attention in Environmental Improvements" delves deeper to examine this approach.

We develop a research design based on our work with Minnesota Technical Assistance Program (MnTAP). Using longitudinal archival data on 650+ environmental improvement (EI) projects in industrial facilities located in Minnesota, we examine how various external influence tactics spur as well as disrupt implementation. Specifically, we highlight the effect of the variation in managing the above processes on an operational metric of project performance – implementation duration. We examine the implications of our findings under operations, supply chain and policy settings. These findings have implications for structuring policies for maximizing adoption rates of source reduction efforts in firms.

1.2 Market-based Approach: Material Reuse through Online Material & Waste Exchanges

Four of the world's leading industrialized countries (United States, Germany, France and United Kingdom) produce more than a billion tons of material waste annually[3]. Although repurposing (through various reuse programs) rates have increased over the years, most waste still gets disposed. According to 2010 estimates, the United States generated 250 million tons of solid waste, but repurposed only 87 million tons[4]. Furthermore, many corporate repurposing programs

[2] US Census Bureau 2008. Pollution Abatement Costs and Expenditures
[3] OECD. (2011). Environmental country reviews.
[4] EPA. (2011). Municipal Solid Waste Generation, Recycling, and Disposal in the United States: Facts and Figures for 2011.

focus mostly on high residual value products such as computers, copiers, auto batteries etc. Unfortunately, low-valued products (chemicals, paints, textiles, leather etc.) account for more than 70% of the total solid waste, but have historically suffered from low repurposing rates due to lack of markets for matching buyers and sellers.

Recently, Online Material and Waste Exchanges (OMWEs) have provided an innovative approach to match producers and consumers of low valued waste. In this dissertation, I examine a *market-based* approach which utilizes the power of online markets to effectively increase repurposing of industrial and commercial materials. My research investigates ways to maximize the number of successful matches and transactions on OMWEs. As a step forward, we ask the following questions: (1) *what are the buyer and seller-side factors that influence transactions in OMWEs?* (2) *what is the appropriate design for OMWEs?* Essay 2 – "Repurposing Materials & Waste through Online Exchanges: Overcoming the Last Hurdle" tackles the first question, while Essay 3 – "The Role of Online Intermediaries in Coordinating Industrial Surplus Chains: Operational Policy Change and Adverse Outcomes" examines the second question.

To address the questions, we analyze a dataset consisting of more than 4000 waste listings and 100,000 buyer-seller interactions from the Material Exchange Program (www.mnexchange.org) hosted by MnTAP. Our primary outcome of interest is an 'exchange' i.e. a successful transfer of waste between producer and consumer. Our analysis gives interesting insights into the exchange activity. On the seller-side, (i) poor regional repurposing norms and (ii) access to alternate disposal options are significantly associated with failed exchanges. Hence sellers are influenced by county-level policies on waste management, which has strong implications for policy-making. On the buyer-side, (i) product information and (ii) transaction information richness are significantly associated with successful exchanges. Hence, buyers are influenced by online information content, which has implications for designing online interfaces for waste markets. Further, our results also show that the more experience users gain on these exchanges, the more likely they are of engaging in successful exchanges. Finally, we also show that OMWE design requires the presence of physical (human) intermediaries or match-makers to alleviate uncertainty about the product quality, transaction outcomes and regulatory policies. This is especially true for certain categories of products and materials, as we highlight in Essay 3.

1.3 Practice-Focused Research: Minnesota Technical Assistance Program

In order to ground this research in practice, I have partnered with Minnesota Technical Assistance Program (MnTAP). MnTAP has implemented innovative *policy-* and *market-based* approaches in Minnesota with varying degrees of success. With these approaches as the research backdrop, I have strived to ask questions that have a direct impact on corporate environmental sustainability and policy development. My collaboration with MnTAP has allowed me to integrate academic insights with practical knowledge. Recommendations generated from our research findings are being applied on the field – in Minnesota and elsewhere in US and Canada. Some of the findings have been used by MnTAP to develop a new recommendation and follow-up system for Minnesota businesses. I hope these changes will improve the state of corporate environmental management and spur adoption of source reduction initiatives. Findings from to the *market-based* approach have been shared with state-level environmental agencies, the Materials Exchange Managers' Network and other exchanges in US and Canada. Over time, these findings will likely transform material and product reuse through online marketplaces.

The next three chapters delve deeper into specific research questions. Essay 1 examines the *policy-based* approach and provides solutions to achieve higher implementation rates. Essays 2 and 3 examine the *market-based* approach and provide ways to improve the efficiency of OMWEs. Finally, chapter 5 presents conclusions and general prescriptions for sustainable development.

Chapter 2

ESSAY 1 - Promoting Change from the Outside: Channeling Managerial Attention in the Implementation of Environmental Improvements[5]

Summary

Government agencies, supply chain partners and non-governmental organizations externally promote improvements in firms. In such setting, effectively channeling managerial attention to improvement efforts is the key to externally promoting change. Yet, the two most commonly used external influence approaches represent fundamentally opposite philosophies. While one approach uses *punitive tactics* to coerce companies, the other approach uses *supportive tactics* to encourage them instead. Using the context of government agencies promoting environmental change in firms, we examine whether such *supportive* (e.g. environmental assistance, improvement recommendations) and *punitive* (e.g. regulatory inspections, sanctions) tactics can be implemented in a complementary manner. Using a unique longitudinal dataset collected from two state-level environmental agencies in Minnesota, we analyze over 1100 *supportive* environmental improvement (EI) projects in combination with intermittent (but currently uncoordinated) *punitive* tactics. One key finding of our research is that the timing and nature of *punitive tactics* is critical for the efficacy of *supportive tactics*. Classifying *punitive* events as (1) either inspections or sanctions and (2) either related or unrelated allows us to further specify the type of punitive tactics that influence EI implementation the most. Further, our models explain the moderating role of managerial involvement and technological complexity.

Keywords: *sustainable operations, environmental policy, managerial attention, inspections, hazard modeling*

2.1. Introduction

Externally promoting change in firms is pivotal to managerial practice and public policy (Pfeffer & Salancik 2003). Federal regulatory agencies spend millions of dollars on programs intended to set firms onto a path of sustained quality and environmental performance (EPA 2011a; FDA 2013). In private sector supply chains, "gatekeeper" organizations (Short et al. 2010) and management consultants (Menon & Pfeffer 2003) influence industrial facilities through audits, inspections and recommendations. Similarly, downstream buyers increasingly face the challenge of influencing process (Plambeck & Taylor 2012) and environmental improvements (Klassen & Vachon 2009; Jira & Toffel 2013) at their supplier facilities. The implications of externally promoting change are also significant. For example, shortcomings in the federal regulatory

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approach can have severe implications for human lives[6], and failure of corporations to manage supplier quality can have significant monetary repercussions[7]. In the environmental domain, external influence efforts of environmental agencies collectively help prevent billions of pounds of pollution annually[8].

Despite its widespread importance, externally promoting improvements in firms is challenging. For instance, consider the case of externally promoting environmental initiatives. Government agencies have used a variety of punitive and supportive tactics to promote positive environmental change in firms (Spence 2001), with limited success. In response, manufacturing companies in the U.S. have also spent approximately $30 billion in 2013 on various environmental improvement initiatives. Yet, many of these initiatives never reach completion despite being located on the "locus of profitable pollution reduction" (King & Lenox 2002). In other words, non-implementation and abandonment of perfectly viable environmental opportunities is surprisingly commonplace (Charles 2009). The resulting environmental non-compliance can have severe economic implications. In 2013 alone, the Environmental Protection Agency (EPA) handed out $4.5 billion in fines and $1 billion in civil penalties. Such non-implementation of even profit-making improvement initiatives has been a long-standing problem (Beer & Walton 1987; Armenakis & Burdg 1988), since improvement projects are prone to various managerial biases and behavioral effects. Additionally, implementation of improvement initiatives is an inherently temporal phenomenon (Tyre & Orlikowski 1994), which presents challenges in sustaining managerial attention (Ocasio 1997). Hence, effectively channeling managerial attention to improvement efforts is the key to externally promoting change. What external influence tactics are most effective in channeling managerial attention and driving environmental change in firms? In this study, we show how *supportive* (e.g. environmental assistance, improvement recommendations) and *punitive* (e.g. regulatory inspections, sanctions) tactics can be used in a complementary fashion to drive positive environmental change.

Traditionally, regulatory agencies at the national- and state-level have heavily relied on *punitive tactics* such as environmental inspections, sanctions and penalties (Spence 2001). Punitive tactics are expected to deter firms from polluting in the future. Such tactics have, in the past, had some success in curbing pollution. According to the EPA, such policy efforts prevented approximately 1.8 billion pounds of pollution in 2011 (EPA 2011a). However, critics of punitive tactics have claimed that this regulatory approach is excessively castigatory. Most firms try to be

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6 http://www.nbcnews.com/id/9443039/ns/health-heart_health/t/guidant-recalls-thousands-pacemakers/#.VBcI2vldV8F

7 http://money.cnn.com/2014/05/27/autos/biggest-auto-recalls/

8 http://www2.epa.gov/enforcement/enforcement-annual-results-fiscal-year-fy-2013

in compliance with environmental regulations and any non-compliance is unintentional (Spence 2001). As a result, the past few decades have experienced a growth in the number of agencies and programs employing *supportive tactics*. Examples include Technical Assistance Programs (TAPs), Industrial Assessment Centers (IACs) in the United States and the recently initiated Environmental Compliance Assistance Program (ECAP) in Europe. The means used by these programs include expert assistance, environmental improvement (EI) recommendations, and follow-ups to promote EI implementation. Yet, given their voluntary nature and varying firm motivations, most *supportive* programs have failed to deliver significant environmental benefits (Koehler 2007). Although the effectiveness of *punitive* and *supportive* tactics has been individually examined by scholars (Spence 2001; Koehler 2007), these approaches continue to be viewed as fundamentally opposite. As a result, their complementarity with each other is unclear (Rothenberg & Becker 2004; Parker et al. 2009). Our paper fills this gap in our understanding of the complementary usage of *punitive* and *supportive* tactics to effectively promote environmental change in firms.

To ground this study in a real context, we develop a research design based on our interactions with two state-level environmental agencies - Minnesota Technical Assistance Program (MTAP) and the Minnesota Pollution Control Agency (MPCA). Borrowing ideas from the literature on managerial attention and environmental policy, we develop empirically testable hypotheses to generate broader insights for externally influencing improvements within firms. We build a longitudinal dataset of more than 1000 environmental improvement projects tracked over several months (sometimes years). Using various econometric modeling techniques, we estimate the success of *supportive tactics* (i.e. EI implementation probabilities and hazards) attributable to the 'timing' and 'nature' of *punitive tactics*. Broadly, our results indicate that the timing of *punitive tactics* (e.g. regulatory inspections, sanctions) is critical for the efficacy of *supportive tactics*. Greater coordination between punitive and supportive tactics can increase the EI implementation rates by a factor of 1.2 to 1.7. Conversely, a lack of coordination reduces EI implementation rates by a factor of 0.5 to 0.3. We further show how this effect varies depending on the nature of punitive tactics – inspections vs. sanctions and related vs. unrelated. Finally, we show that coordination between punitive and supportive tactics is even more critical in projects with higher managerial involvement and technological complexity. Our study has broader implications for using the *punitive* and *supportive* tactics in a complementary manner.

The rest of the paper is presented as follows. Section 2 describes the empirical setting. Section 3 presents the related literature and contributions made by this study. Section 4 develops hypotheses and Section 5 presents the data, modeling approaches and results. Section 6 discusses broader implications.

2.2. Empirical Context

2.2.1 Background on Punitive & Supportive Influence Tactics

In the U.S., the Environmental Protection Agency (EPA) regulates environmental activity. The EPA works in partnership with state-level environmental agencies (e.g. Minnesota Pollution Control Agency, New York Department of Environmental Conservation etc.), which are charged with the task of monitoring and enforcing environmental laws and regulations (EPA 2013b). Although EPA and state-level regulatory agencies have, in the past, explored supportive environmental initiatives (e.g. Environmental Leadership Program, Star Track Program etc.), the bulk of policy initiatives have been punitive in nature. In general, the punitive approach is based on the fundamental assumption that firms are "rational polluters" who pollute to the maximum possible extent given the threat of being sanctioned (Spence 2001). As a result of this ideology, the traditional *punitive tactics* have used the coercive threat of inspections, sanctions and penalties for ensuring environmental compliance. However, given the widespread criticism for punitive tactics (Spence 2001) and limited empirical support for the long-term effectiveness of regulatory approaches (Toffel & Short 2011), supportive programs have now emerged at the regional- and state-level. Today, hundreds of such federal and state-funded environmental agencies use *supportive tactics* to influence firms across the U.S. For example, Technical Assistance Programs (TAPs) are typically grant-funded intervention programs which provide pollution prevention assistance. According to the Environmental Protection Agency (EPA), *"Technical Assistance Programs provide businesses with cutting edge environmental management assistance and help identify and implement measures that reduce or eliminate pollution at its source"* (EPA 2011c). The EPA lists more than 100 such TAPs across different regions in the United States[9]. Other programs such as the Department of Energy's Industrial Assessment Centers (IACs) provide similar services. Industrial Assessment Centers *"…conduct the energy audits to identify opportunities to improve productivity, reduce waste, and save energy"* (DOE 2013). Previous studies have used IACs as a research context for examining the adoption of energy efficiency projects (Anderson & Newell 2004; Muthulingam et al. 2013). The supportive programs primarily rely on providing expert assistance through environmental improvement recommendations. Such environmental improvements (EIs) consist of *operational*

[9] http://www.epa.gov/opptintr/p2home/pubs/assist/index.htm

changes to technology, materials or procedures that aim to reduce the negative impact on the environment (adapted from Simpson *et al.*(2004)).

2.2.2 Research Setting

To examine the complementarity of *punitive* and *supportive* tactics, we develop a research design based on our discussions with two state-level agencies in Minnesota--MTAP and MPCA. MTAP is a state-level organization that uses *supportive* tactics in the form of EI recommendations and reminders to encourage pollution prevention. MTAP specialists make site visits to manufacturing or service facilities, typically by invitation. Each site-visit consists of a detailed assessment of the facility and results in one or more EI recommendations (see Appendix for examples). This EI initiation is followed by a time period during which the facility engages in the adoption of EIs led by the EI "owner" (i.e. the person responsible for the improvement). It is important to emphasize that the adoption of these EIs is not mandated but strongly encouraged. After each site-visit, MTAP specialists make reminders to the EI owner to influence implementation and to record the implementation status. In summary, MTAP's approach, based on EI recommendations and reminders, is representative of *supportive* tactics. However, facilities receiving assistance from MTAP are also under the constant surveillance of environmental regulatory agencies, irrespective of their initiation or implementation of the *supportive* EIs. In Minnesota, the MPCA monitors and regulates facility-level compliance to environmental regulations. MPCA conducts regular facility inspections to identify environmental problems and sanctions facilities if found out of compliance. As such, MPCA's approach, based on inspections and sanctions, is representative of the traditional *punitive* tactics.

Although MTAP and MPCA communicate regarding policy matters, facility-level tactics are not coordinated. As a result, a facility undertaking EIs outlined by MTAP may be inspected and potentially sanctioned by MPCA. In other words, the same facility could be simultaneously facing both – *punitive* and *supportive* tactics. Since these tactics are not endogenous or coordinated, an interesting empirical question is what sequence of *punitive* and *supportive* tactics leads to complementary (or counterproductive) results, and under what circumstances? Hence, the aim of this study is to reconcile the *supportive tactics* (EI recommendations) with the *punitive tactics* (inspections and sanctions) by showing that the complementary and/or counterproductive influence of these tactics depends on their timing and nature. Based on discussions with MTAP and MPCA, we distinguish between the 12-month periods before and after EI initiation, and then estimate the impact of *punitive tactics* occurring before (i.e. 12-month "pre-improvement phase") and after (i.e. 12-month "improvement phase") initiation of *supportive* EIs on the EI implementation probabilities and hazards. We further decompose the punitive tactics into (1) inspections vs. sanctions and (2) related vs. unrelated to gain more nuanced insights about the interplay between punitive and supportive tactics. Finally, we examine the contingent effect of managerial involvement and technological complexity.

2.3. Literature Review and Contributions

Earlier studies have examined various economic (Anderson & Newell 2004), behavioral (Charles 2009; Muthulingam et al. 2013), technological (Sroufe 2003; Klassen & Whybark 1999), organizational (DeCanio 1998), supply chain (Klassen & Vachon 2009), institutional (Bansal & Clelland 2004) and stakeholder related (Sarkis et al. 2010) factors that promote EIs in firms. More broadly, previous research has also examined the role of knowledge capital (Dewar & Dutton 1986), quality-based learning (Fine 1986), trade-offs (Ferdows & De Meyer 1990), behavioral factors (Repenning & Sterman 2002) and work systems (Tucker 2007) in driving improvement efforts in general. Our study departs from these earlier studies in three major ways. First, we examine how two fundamentally opposite intervention approaches can be reconciled to externally influence environmental improvements. Second, we highlight behavioral factors that moderate the degree of managerial attention given to EIs. Third, we apply various modeling approaches to longitudinal project-level data to confirm findings.

2.3.1 Intervention Approaches & Externally Promoting Change in Firms

Externally influencing firms in policy implementation and supply chain management can be difficult. Recent research has questioned the effectiveness of regulatory (Spence 2001; Ball et al. 2013) and command-and-control (Short et al. 2010; Plambeck & Taylor 2012) tactics for ensuring process and environmental compliance. Researchers have also examined the challenges faced by policy-makers (Short & Toffel 2010) and NGOs (Kraft et al. 2013) in externally influencing environmental activities in firms. Past research in environmental policy has examined complementarities between policy instruments (Foulon et al. 2002; Rousseau 2007; Short & Toffel 2010), revealing several contingencies. For example, Short and Toffel (2010) found that voluntary self-regulation can work, albeit for already environmentally-proactive firms. Kraft et al. (2013) analytically examine whether NGOs should target industry or regulatory bodies to influence firms to replace hazardous substances. Our research contributes to this literature by showing how government agencies can externally influence improvements in firms by using punitive and supportive approaches in a complementary fashion.

While our study is grounded in the context of government agencies externally influencing private firms, similar questions exist in the context of private sector supply chains. Researchers (Krause et al. 1998; Modi & Mabert 2007; Klassen & Vachon 2009; Muthulingam & Agarwal

2013) have examined how downstream firms in a supply chain can influence the improvement initiatives of their upstream partners. The root cause of quality problems often lies with suppliers, and thus managing quality requires a broad supply chain perspective. The field of supplier development differentiates between various approaches, which include, 'basic' and more punitive tactics such as evaluating their performance and inspecting/certifying their plants, as well as more 'advanced' and supportive forms, such as joint process improvement initiatives (Sánchez-Rodríguez et al. 2005; Klassen & Vachon 2009). Notions of a hierarchy of supplier development approaches (basic vs. advanced and evaluative vs. supportive) indicate a progression, where one form of supplier development succeeds another as firms progress in their relationships. Similar questions are also being examined in the context of third-party auditors influencing industrial facilities (Bartley 2007; Short et al. 2010). Yet little research exists in this area to study whether these approaches are substitutes, such that more advanced techniques can replace simpler ones, or that these approaches are complementary, where one approach requires the other. We discuss our findings more broadly to show how external influence can be productively used under different settings. Finally, our study also contributes to the scant research on using externally-sourced knowledge (Menon & Pfeffer 2003).

2.3.2 Managerial Attention & Behavioral Issues in Improvement Projects

Gutierrez and Kouvelis (1991) were one of the first to recognize behavioral effects in improvement projects. In their paper, Gutierrez and Kouvelis (1991) applied the widely accepted Parkinson's law (1957) to show how the deadlines affect the actual amount of work done or as the law states "work expands so as to fill the time available for its completion." A recent study (Deo et al. 2014) empirically examines this behavioral phenomenon in a healthcare setting, to show the effect of operational goals and deadlines on worker pace. Muthulingam et al. (2013) highlight how "order effects" (i.e. effect of presentation order of recommendations) and "choice overload" (i.e. effect of too many options) can influence the implementation outcomes in the case of energy efficiency recommendations made by the Industrial Assessment Centers (IACs). Related research on energy efficiency (Blass et al. 2014) and IT projects (Tyre & Orlikowski 1994) is also very relevant to our context. For example, Tyre and Orlikowski (1994) highlight how improvement projects (especially timelines and outcomes) are influenced by various managerial biases and pressures.

Previous seminal research on attention-based view (ABV) (Ocasio 1997; Ocasio 2011) also highlights the behavioral issues (Simon 1979) in implementing improvements. A central premise of this view is that organizational structures, problem domains and external influences can divert managerial attention towards and away from improvements. For operations managers, this implies a rethinking of ways in which improvement projects are structured and executed over time. Understanding the temporal aspect of improvements is immensely important, yet it is rarely addressed in research. *"It is ironic that time may be the most important and most overlooked variable in our management discipline"* (Van de Ven 2013). Although scholars in OM have alluded to the dynamic nature of change (Sterman et al. 1997), few studies, to our knowledge, have tried to empirically examine the temporal nature of improvement projects. Past studies (Sroufe 2003; Sarkis et al. 2010; Muthulingam et al. 2013) examining EI adoption have also primarily taken a static perspective on improvement initiatives. Yet, discussions we conducted with MTAP experts and facility managers provided strong evidence in favor of temporal effects. For example, our discussants expressed that the managerial attention and resource allocation decisions were dynamic and influenced by external events. To accurately capture these nuances, our research accounts for behavioral explanations and temporal effects.

2.4. Hypotheses Development

It is not merely the internal resources, participants and processes that drive organizational change, but external influences also play a crucial role (Weick & Quinn 1999). External influences, in the form of *punitive* and *supportive* interventions, can affect internal processes (Anand et al. 2012) by providing critical feedback and (re)directing managerial attention. We develop hypotheses to identify situations when the feedback received through *punitive* tactics is complementary vs. counterproductive to *supportive* tactics. Our discussions with facility managers revealed that *punitive* tactics can trigger entirely different managerial responses, resource allocation and employee behaviors depending on the timing and nature of their occurrence. How managers attend (Ocasio 2011) to punitive tactics in relation to the supportive interventions is therefore a relevant question.

2.4.1 Timing of Punitive Tactics in Relation to Supportive Tactics

The timing of events can generate varying cognitive and behavioral reactions from managers (Ocasio 1997). In our context, we therefore argue that the timing of punitive tactics in relation to the supportive tactics will play a significant role in driving EI implementation. Improvements are often a reaction to episodic events such as punitive regulatory events (Weick & Quinn 1999). Punitive tactics stimulate environmental improvement initiatives by endangering corporate legitimacy. Prior research has examined the impact of regulatory events on product recalls (Haunschild & Rhee 2004), quality compliance (Anand et al. 2012) and firm performance (Haveman et al. 2001). These studies have argued that regulatory actions (e.g. audits, sanctions) act as "renewals" to stem the degradation of internal processes (Anand et al. 2012), and thus have a lasting effect on organizational systems (Shimshack & Ward 2005). By acting as "jolts" or "shocks" (Romanelli & Tushman 1994), regulatory actions can focus managerial attention (Ocasio 1997) to specific systems (e.g. environmental) or issues (Cho & Hambrick 2006) and spur improvements. We therefore expect that the lingering effect (Tushman & Anderson 1986) of *punitive tactics* occurring in the pre-improvement phase (i.e. 12-month period before initiation of supportive EIs) can positively affect EI implementation.

How do *punitive tactics* occurring *during* the improvement phase (i.e. 12-month period after initiation of supportive EIs) affect EI implementation? By causing perturbations in the resource allocation mechanisms (Haveman et al. 2001), badly timed regulatory events could impede ongoing improvement efforts. The intention behind regulatory actions is to bring to surface environmental issues that may be hidden or neglected by facilities. Our discussions with MPCA suggested that regulatory events occurring during the improvement phase brought to light new environmental concerns. In such cases, a natural response of facility managers is reallocation of existing resources to tackle the more recent (and conceivably more urgent) environmental compliance issues. Naturally, attending to the issues brought to light by the regulatory inspections/sanctions creates an appearance of legitimacy. *Punitive* tactics can therefore spur new activities, which often come at the cost of "replacement" of ongoing initiatives (Ford & Ford 1994). And so, we expect that *punitive tactics* occurring during the improvement phase could have a detrimental impact, leading to delays and abandonment of ongoing EIs.

H1a: *Punitive Tactics in the form of inspections/sanctions that occur in the pre-improvement phase will promote EI implementation*

H1b: *Punitive Tactics in the form of inspections/sanctions that occur in the improvement phase will disrupt EI implementation*

2.4.2 Nature and Relatedness of Punitive Tactics

Not all *punitive* tactics are alike. Some inspections lead to sanctions, whereas others simply provide informational feedback. In our empirical setting, MPCA conducts facility inspections to identify environmental non-compliance and sanctions facilities only if found out of compliance. While sanctions certainly illustrate the use of punitive tactics against the facility, inspections per se are not punitive in nature. As a result, we believe that inspections and sanction will differ in their effects on EI implementation. While inspections (which do not result in sanctions) may simply provide informational feedback to organizations (Anand et al. 2012; Ball et al. 2013), sanctions are intended to bring urgent attention to compliance problems. Therefore, sanctions represent a significantly higher threat to the facility's environmental legitimacy. As a result, we expect sanctions will have a significantly stronger (promotive and disruptive) effect on EI implementation.

H2a: *Punitive Tactics in the form of sanctions that occur in the pre-improvement phase will have a stronger promotive influence on EI implementation compared to inspections*

H2b: *Punitive Tactics in the form of sanctions that occur in the improvement phase will have a stronger disruptive influence on EI implementation compared to inspections*

The fact that a facility is engaged in "…[air] emissions improvements does not guarantee that it will not face regulatory actions for other [compliance] issues…say solid waste disposal (MPCA Officer 2014)." In the pre-improvement and improvement phases, a facility may experience punitive events which might or might not be directly related to the supportive EI being undertaken. It is important to understand the effect of these related and unrelated punitive tactics on attentional processes (Simon 1979; Ocasio 2011) within the facility, to accurately identify complementarities between punitive and supportive tactics. In general, related punitive tactics (compared to unrelated punitive tactics) that occur in the pre-improvement phase will focus greater attention to environmental issues that are closely related to the EIs and should hence have a greater promotive effect. On the other hand, unrelated punitive tactics (compared to related punitive tactics) that occur in the improvement phase should focus attention away from ongoing EIs and towards the new compliance issues, thus having a greater disruptive effect. This explanation suggests a more nuanced effect that what was hypothesized in H1.

H3a: *Related Punitive Tactics that occur in the pre-improvement phase will have a stronger promotive influence on EI implementation compared to Unrelated Punitive Tactics*

H3b: *Unrelated Punitive Tactics that occur in the improvement phase will have a stronger disruptive influence on EI implementation compared to Related Punitive Tactics*

2.4.3 Managerial Involvement & Technological Complexity

The above hypotheses highlight the importance of timing and nature of *punitive* tactics in relation to the *supportive* EIs. Yet, it is important to emphasize that not all EIs are alike. We expect that the coordination (or lack thereof) between punitive and supportive tactics may be more (or less) important for certain types of EIs. Hence, we develop moderating hypotheses based on two characteristics of EIs – Senior Manager Involvement and Technological Complexity.

Attention is differentially distributed across the chain of command (Rerup 2009; Ocasio 2011). In other words, issues that hold high relevance for senior managers might not necessarily take precedence for all other employees. Given the nature of punitive events, senior managers are often held liable for any compliance failures. Naturally, punitive tactics hold a position of prominence for senior managers which, we expect, should result in amplified responses (both promotive and disruptive) to punitive tactics.

H4: *The influence (both promotive and disruptive) of Punitive Tactics on EI implementation is amplified under Senior Manager Involvement in EIs.*

Technologically complex improvement projects require greater coordination from organizational sub-units. Successful coordination in technologically complex projects may hence require external triggers (Hoffman & Ocasio 2001), in the form of events that signal crisis (e.g. punitive tactics). As a result, pre-improvement punitive tactics will likely have a greater promotive influence on technologically complex EIs. Given the need for greater coordination, ongoing technologically complex projects are also more prone to abandonment resulting due to attentional shifts (Ocasio 2011) and dissolution of improvement teams (Tyre & Orlikowski 1994) over time. As a result, ill-timed punitive tactics occurring in the improvement phase are also likely to be more disruptive in the case of technologically complex improvement projects.

H5: *The influence (both promotive and disruptive) of Punitive Tactics on EI implementation is amplified under Technological Complexity of EIs.*

2.5. Methods

2.5.1 Data

We take advantage of an empirical setting where facilities were being influenced by two different types of governmental agencies practicing *punitive* and *supportive* tactics respectively. Our primary dataset was obtained from a supportive environmental intervention program in Minnesota – Minnesota Technical Assistance Program (MTAP). We had initial access to data consisting of approximately 1200 EI recommendations, characteristics and implementation timelines from MTAP. An additional dataset used in our analysis comes from the Minnesota Pollution Control Agency (MPCA), through a request for information made to their Data Service Center. The compliance dataset consisted of facility-level information regarding all environmental inspections and sanctions since 1999. This dataset provided information about each facility's compliance history in addition to a record of *punitive tactics* that were used in the pre-improvement and improvement phases of EI initiatives. Previous studies have used similar data to assess the effectiveness of punitive shocks under different contexts (Karpoff et al. 2005; Darnall et al. 2009). In order to compile complete information about each EI and the associated context, it was essential to accurately match the MTAP and MPCA datasets. Matching the two datasets was a non-trivial task, especially since we required accurate information on regulatory events in the improvement and pre-improvement phases. The matching was done manually by one of the co-authors. Following initial coding, we had multiple interactions with officials at MPCA and MTAP, as and when additional clarification was required. Additional compliance level information related to type and relatedness of inspections/sanctions was obtained through an online tool[10] recently made publicly available by MPCA. This resulted in additional verification and elimination of cases, which indicated data recording errors (e.g. missing EI-initiation date, reminder date, implementation date, implementation status).

Table 2-1. Descriptive Statistics and Correlations

Variables	Mean	S.D.	1	2	3	4	5	6	7	8
Implementation Status	0.40	0.49	1							
Implementation Time (Days)	370.75	362.64	-0.0509*	1						
Ln(Savings)	6.27	3.90	0.1890*	0.1815*	1					
Ln(Hours)	2.27	1.46	-0.1234*	-0.1711*	0.0249	1				
Ln(Employees)	2.65	2.73	0.0051	0.1795*	0.1867*	0.0898*	1			
Senior Manager	1.59	0.49	-0.0759*	-0.0744*	-0.0186	0.0945*	0.0091	1		
Ln(Recommendation Number)	1.10	0.85	-0.1775*	0.1255*	-0.0990*	0.2153*	0.0639*	0.0717*	1	
Ln(Total Recommendations)	1.78	0.84	-0.1870*	0.1179*	-0.0763*	0.3171*	0.0910*	0.0819*	0.6876*	1
Ln(Time between follow-ups)	4.37	1.02	0.1370*	0.5175*	0.1424*	-0.2666*	0.0906*	-0.1489*	-0.0423	-0.0219
Punitive Tactics (Pre-Improvement)	0.37	0.73	0.0429	0.1315*	0.0592*	-0.0061	0.1761*	-0.1073*	0.0059	0.0453*
Punitive Tactics (Improvement)	0.26	0.64	-0.0312	0.2814*	0.1513*	-0.0566*	0.2622*	-0.0626*	-0.0147	-0.0062
Inspections (Pre-Improvement)	0.15	0.36	0.028	0.1104*	0.0018	-0.0018	0.1793*	-0.1726*	0.0186	0.0592*
Sanctions (Pre-Improvement)	0.14	0.52	0.0796*	0.0518*	0.0548*	-0.0237	-0.0325	0.037	-0.0242	-0.011
Inspections (Improvement)	0.09	0.28	-0.032	0.2253*	0.1501*	-0.0672*	0.1840*	0.0476*	-0.0245	-0.0276
Sanctions (Improvement)	0.12	0.48	0.0212	0.1469*	0.0495*	-0.0151	0.1568*	-0.1410*	-0.0036	0.0064
Related Punitive Tactics (Pre-Improvement)	0.07	0.26	0.1154*	0.0381	-0.0529*	-0.0353	-0.0674*	-0.0994*	-0.0136	0.0133
Unrelated Punitive Tactics (Pre-Improvement)	0.30	0.71	0.0021	0.1201*	0.0796*	0.0066	0.2046*	-0.0738*	0.0109	0.0416
Related Punitive Tactics (Improvement)	0.04	0.19	0.0291	0.0995*	0.0716*	-0.0692*	0.0796*	-0.0467*	-0.0408	-0.0374
Unrelated Punitive Tactics (Improvement)	0.22	0.63	-0.0407	0.2573*	0.1335*	-0.0372	0.2446*	-0.0501*	-0.0028	0.0049

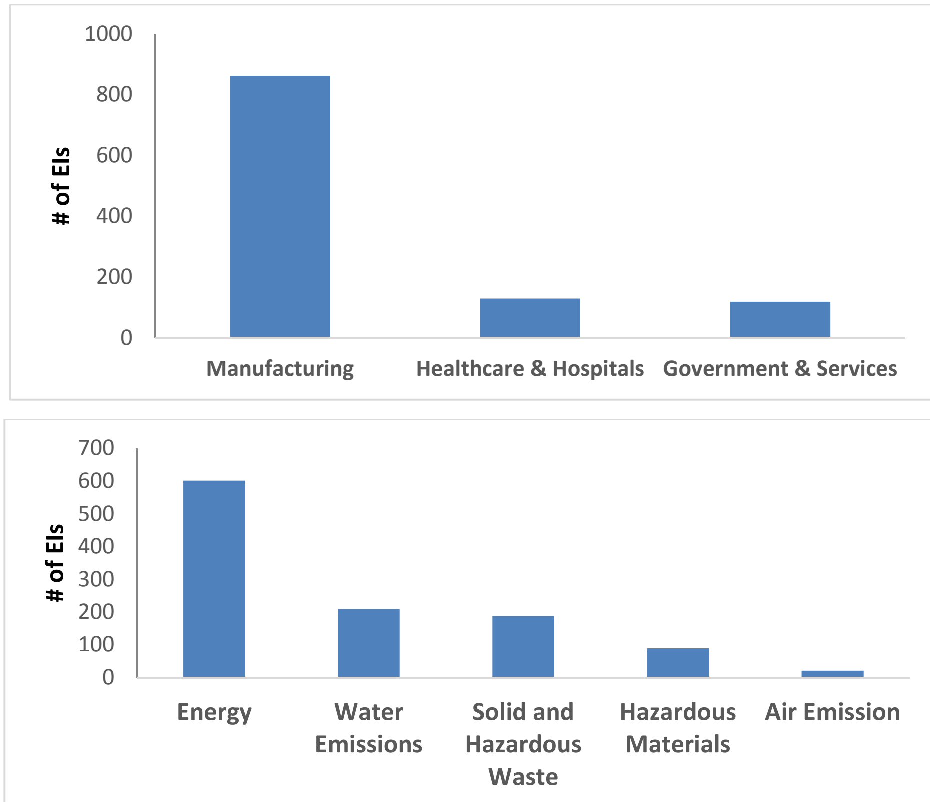
Variables	9	10	11	12	13	14	15	16	17	18
Implementation Status										
Implementation Time (Days)										
Ln(Savings)										
Ln(Hours)										
Ln(Employees)										
Senior Manager										
Ln(Recommendation Number)										
Ln(Total Recommendations)										
Ln(Time between follow-ups)	1									
Punitive Tactics (Pre-Improvement)	0.1158*	1								
Punitive Tactics (Improvement)	0.1839*	0.3332*	1							
Inspections (Pre-Improvement)	0.0657*	0.7536*	0.2069*	1						
Sanctions (Pre-Improvement)	0.0764*	0.4926*	0.1840*	-0.1161*	1					
Inspections (Improvement)	0.0710*	0.2342*	0.7216*	0.0922*	0.1877*	1				
Sanctions (Improvement)	0.1646*	0.2364*	0.5582*	0.2495*	0.028	-0.0772*	1			
Related Punitive Tactics (Pre-Improvement)	0.0081	0.2401*	-0.0024	0.4007*	0.2858*	-0.0322	0.0771*	1		
Unrelated Punitive Tactics (Pre-Improvement)	0.1150*	0.9363*	0.3418*	0.6261*	0.4007*	0.2513*	0.2140*	-0.1161*	1	
Related Punitive Tactics (Improvement)	0.0293	0.1310*	0.2260*	0.1648*	-0.0078	0.2983*	0.3534*	0.0697*	0.1088*	1
Unrelated Punitive Tactics (Improvement)	0.1791*	0.3019*	0.9562*	0.1624*	0.1908*	0.6494*	0.4655*	-0.0234	0.3173*	-0.0690*

Additional facility-level data for the control variables was obtained from other secondary sources - Hoover's and ORBIS. After matching several datasets, our final sample consisted of longitudinal data on 1110 EIs undertaken at 296 facilities across Minnesota. Descriptive statistics

[10] MPCA's What's in my Neighborhood Online Application: http://cf.pca.state.mn.us/wimn/search.cfm

and correlations for the measures are summarized in **Table 2-1**. **Figure 2-1** provides descriptive information about EI characteristics.

Figure 2-1. Descriptive Information on Industry and EI Characteristics (# of EIs)



2.5.2 Measures

Dependent Variables

Our interest lies in capturing the probabilities of EI implementation as well as the evolution of EIs over time. We therefore use two dependent variables – implementation status [dichotomous] and implementation hazard [longitudinal]. Implementation status has been the preferred outcome variable in similar studies (Anderson & Newell 2004; Muthulingam et al. 2013), but can suffer from measurement errors. The recorded EI implementation status is dependent on the last interaction between the environmental agency (MTAP in our case) and the facility. Using either a logit or probit model here can bias the findings since the recorded status from the last interaction might differ from the final (i.e. actual) implementation status. By estimating instantaneous implementation rates, hazard models (e.g. Cox model) significantly overcome this limitation by using the best available information about implementation status at recorded times. Therefore, we use hazard models in addition to logit models. Hazard/duration modeling requires specification of beginning and ending times for each unit (EI). In our case, the time (t_0) begins with MTAP's site-visit and ends (t_{end}) either with implementation or with "censoring," i.e. the last interaction between the facility and MTAP. For our logit models, we assume information on the EI implementation status as being accurate. Together, these modeling approaches provide substantial robustness to our findings.

Independent Variables

We capture *punitive tactics* using regulatory inspections and sanctions data from MPCA. As is evident from the research design, our study differentiates between punitive tactics that occur in the pre-improvement and improvement phases. For *Punitive Tactics (Pre-Improvement Phase)* occurring before initiation of EIs, we used MPCA data to collect information on all regulatory actions taken during 365 days leading up to the EI initiation, since the coercive effect of regulatory actions is likely to last for at least a year (Shimshack & Ward 2005). The length of the improvement phase might differ based on the time to EI adoption, with the maximum being 365 days where the time to EI implementation either equaled or exceeded 365 days. For EIs that were implemented within 365 days after their initiation, the improvement phase is taken as the time period between EI-initiation and implementation (or censoring i.e. last follow-up made by MTAP). For *Punitive Tactics (Improvement Phase),* we used MPCA data to collect information on all regulatory actions taken during the improvement phase. We created additional variables to test hypothesis 2 based on whether the punitive tactics involved an inspection with or without a sanction. These variables are *Inspection (Pre-Improvement), Inspection (Improvement), Sanction (Pre-Improvement)* and *Sanction (Improvement)*. Next, we created variables to test hypothesis 3 based on whether the punitive tactics were related/unrelated to the supportive EIs. These variables are *Related Punitive Tactics (Pre-Improvement), Unrelated Punitive Tactics (Pre-Improvement), Related Punitive Tactics (Improvement)* and *Unrelated Punitive Tactics (Improvement)*. *Senior Manager Involvement* in EIs was coded as a dummy variable [1 = Senior Manager (plant manager, vice president, director, facility manager etc.) is identified as the "owner" of the EI being undertaken; 0=Otherwise]. See Appendix for examples. Further, we categorized *Material/Equipment* EIs modifications as *High Technological Complexity,* and *Procedural* EIs as *Low Technological Complexity*. See Appendix for examples of EIs in each category.

Control Variables

We controlled for various industry-, year-, firm- and EI-specific effects using data obtained from MTAP, MPCA and other public data sources – ORBIS and Hoover's. In line with Anderson and Newell's (2004) study, we controlled for log of expected net savings [*Ln (Net Savings)*] and squared log of net expected savings [*Ln (Net Savings)*^{2}]. Our discussions with MTAP revealed that there was significant uniformity across their staff regarding the protocol followed for conducting site-visits and estimating net savings. Hence, we safely assume accuracy of expected net savings. We controlled for the type of EI being undertaken [*Procedural/ Material/ Equipment*]. Recent research (Muthulingam et al. 2013) found that the number of simultaneous improvements and the sequence of presenting these improvements to the management can affect adoption. Hence, two additional variables were included to control for the number of EIs being undertaken at the facility [*Ln (Total Recommendations)*] and the serial position of the EI [*Ln (Recommendation Number)*]. We controlled for number of hours spent by MTAP staff on the site visit [*Ln (Hours)* and *Ln (Hours)*^{2}] to account for any differences in effort exerted on the EI initiatives. Additionally, 4 material type dummies were included to control for the type of pollution prevention [*Solid Waste/Water Emissions/Air Emissions/Energy Efficiency*] effort being undertaken. MTAP conducts follow-ups (via email or phone) with the EI owner during the improvement phase. Frequent follow-ups are likely to influence implementation. We therefore control for the *Ln (Time between Follow-ups)* which occurred between the date of site-visit and EI implementation (or censoring i.e. last reminder made by MTAP). Number of Employees at the facility was controlled for in all models [*Ln (Employees)*]. Industry dummies were included to account for industry level differences in regulatory activity and EI implementation. We also included year dummies for 1999-2012 to account for any differences in economic conditions and other time-varying exogenous factors.

2.5.3 Estimating EI Implementation Probabilities

We used two modeling techniques to ensure robustness of results. First, we used panel probit models with robust standard errors. Facility-level unobservable effects (managerial commitment, resources, facility structure etc.), which might not have been accounted for through control variables, were captured through a panel random effects specification. Previous studies in environmental operations have used similar models to estimate implementation likelihood of environmental initiatives such as ISO 14001 (King et al. 2005) and energy efficiency recommendations (Muthulingam et al. 2013).

The results are shown in **Table 2-2**. *Punitive Tactics (Pre-Improvement)* have significant promotive influence on EI implementation probability (Table 2, Column 1, $\beta = 0.58$, $p<0.01$; Odds Ratio=1.78). We find that *Punitive Tactics (Improvement)* have a significant disruptive effect on EI implementation probability (Table 2, Column 1, $\beta = -1.15$, $p<0.01$; Odds Ratio=0.31) of EIs. Hence, H1a and H1b are supported. This further stresses the importance of timing of punitive tactics.

H2 examines the effect of inspections vs. sanctions. We find that both, *Inspections* (Table 2, Column 2, $\beta = 0.41$, $p<0.05$; Odds Ratio=1.50) and *Sanctions* (Table 2, Column 2, $\beta = 0.87$, $p<0.01$; Odds Ratio=2.39) occurring in the pre-improvement phase, have a positive influence on

EI implementation. A Wald's test ($F=3.28$, $p<0.05$) suggested that, in the pre-improvement phase, sanctions have a significantly stronger promotive effect compared to inspections, thus providing support for H2a. In the improvement phase, we find that both, *Inspections* (Table 2, Column 3, $\beta = -1.25$, $p<0.05$; Odds Ratio=0.28) and *Sanctions* (Table 2, Column 3, $\beta = -1.01$, $p<0.01$; Odds Ratio=0.36) have a disruptive influence on EI implementation. A Wald's test ($F=0.20$, $p>0.10$) suggested that, in the improvement phase, sanctions did not have a significantly stronger disruptive effect compared to inspections. Hence, H2b is not supported in the case of punitive tactics occurring in the improvement phase.

H3 examines the effect of related vs. unrelated punitive tactics. We find that *Related Punitive Tactics* (Table 2, Column 3, $\beta = 0.96$, $p<0.01$; Odds Ratio=2.60) had a marginally stronger (Wald's F-test=1.56, $p=0.105$) promotive effect compared to *Unrelated Punitive Tactics* (Table 2, Column 3, $\beta = 0.42$, $p>0.01$; Odds Ratio=1.50) occurring in the pre-improvement phase. In the improvement phase, we find that *Unrelated Punitive Tactics* (Table 2, Column 3, $\beta = -1.43$, $p<0.01$; Odds Ratio=0.23) had a significantly stronger (Wald's F-test=5.23, $p<0.05$) disruptive influence compared to *Related Punitive Tactics* (Table 2, Column 3, $\beta = -0.32$, $p>0.01$; Odds Ratio=0.72). Overall, H3a is not well-supported in the case of pre-improvement punitive tactics, but H3b is strongly supported for punitive tactics occurring in the improvement phase.

H4 and H5 predict the amplified promotive and disruptive influence in the case of *Senior Manager Involvement* and *Technological Complexity* respectively. We find that the promotive influence of *Punitive Tactics (Pre-Improvement)* is significantly stronger under *Senior Manager Involvement* (Table 2, Column 4, $\beta = 0.68$, $p<0.10$; Odds Ratio=1.96); the disruptive influence of *Punitive Tactics (Improvement)* is significantly stronger under *Senior Manager Involvement* (Table 2, Column 4, $\beta = -1.26$, $p<0.05$; Odds Ratio=0.28). Hence H4 is supported. Next, we find that the promotive influence of *Punitive Tactics (Pre-Improvement)* is not significantly stronger under *Technological Complexity* (Table 2, Column 5, $\beta = -0.15$, $p>0.10$; Odds Ratio=0.86); but the disruptive influence of *Punitive Tactics (Improvement)* is significantly stronger under *Technological Complexity* (Table 2, Column 5, $\beta = -0.97$, $p<0.05$; Odds Ratio=0.38). H5 is partially supported.

Table 2-2. Random Effects Logit Models for EI Implementation Probabilities

	Punitive Tactics Characteristics			Moderating Effects	
Variables	**Timing (1)**	**Type (2)**	**Relatedness (3)**	**Manager (4)**	**Complexity (5)**
Ln(Savings)	0.40***	0.40***	0.40***	0.42***	0.40***
	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)
Ln(Savings)^2	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Ln(Hours)	-0.73***	-0.73***	-0.80***	-0.83***	-0.71***
	(0.25)	(0.26)	(0.26)	(0.27)	(0.25)
Ln(Hours)^2	0.18***	0.18***	0.19***	0.19***	0.17***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Ln(Employees)	0.13***	0.13***	0.12***	0.04	0.14***
	(0.04)	(0.03)	(0.04)	(0.05)	(0.04)
Senior Manager	0.07	0.05	0.05	-0.03	0.06
	(0.38)	(0.35)	(0.37)	(0.41)	(0.42)
Ln(Recommendation Number)	-0.31**	-0.31**	-0.31**	-0.31***	-0.36***
	(0.13)	(0.13)	(0.13)	(0.12)	(0.13)
Ln(Total Recommendations)	-0.35*	-0.35*	-0.35*	-0.42*	-0.33
	(0.20)	(0.20)	(0.19)	(0.23)	(0.20)
Time between follow-ups	0.35**	0.33**	0.36**	0.34**	0.36**
	(0.16)	(0.15)	(0.16)	(0.15)	(0.16)
Punitive Tactics (Pre-Improvement)	0.58***			0.29	0.72**
	(0.20)			(0.22)	(0.36)
Punitive Tactics (Improvement)	-1.15***			-0.52	-0.59
	(0.39)			(0.34)	(0.38)
Inspection (Pre-Improvement)		0.41**			
		(0.20)			
Sanction (Pre-Improvement)		0.87***			
		(0.31)			
Inspection (Improvement)		-1.25**			
		(0.60)			
Sanction (Improvement)		-1.01***			
		(0.27)			
Related Punitive Tactics (Pre-Improvement)			0.96***		
			(0.31)		
Unrelated Punitive Tactics (Pre-Improvement)			0.42		
			(0.26)		
Related Punitive Tactics (Improvement)			-0.32		
			(0.49)		
Unrelated Punitive Tactics (Improvement)			-1.43***		
			(0.45)		
Punitive Tactics (Pre-Improvement)				0.68*	
× Senior Manager				(0.41)	
Punitive Tactics (Pre-Improvement)				-1.26**	
× Senior Manager				(0.53)	
Punitive Tactics (Improvement)					-0.15
× Technological Complexity					(0.47)
Punitive Tactics (Improvement)					-0.97**
× Technological Complexity					(0.40)
F-Tests (Pre-Improvement)		3.28**	1.56		
F-Tests (Improvement)		0.20	5.23**		
Constant	-0.07	0.15	-0.20	-0.29	-0.34
	(1.78)	(1.77)	(1.77)	(1.84)	(1.65)
Observations	1110	1110	1110	1110	1110
Wald's chi2	83.61	84.17	86.11	78.43	78.38
Log Likelihood	-602.61	-602.20	-599.93	-606.30	-607.43

Robust Standard Errors in parantheses; *** p<0.01, ** p<0.05 *p<0.1

2.5.4 Estimating EI Implementation Hazards

Next, we also use a hazard modeling approach to overcome limitations of the logit models and to explore longitudinal effects. Past research in management (Hom & Kinicki 2001) and medical sciences (Stukel et al. 2007) has extensively used these methods to examine questions which involve temporal elements. Hazard models are commonly used where the interest is in understanding the relationship between the risk of an event (implementation) occurring at time *t* and the values of explanatory variables of interest to the problem. We model the EI implementation *hazard* (where higher hazard is good) using Cox Proportional Hazard (PH) Models. The baseline hazard function in a Cox PH model is estimated non-parametrically, which provides additional flexibility (Bradburn et al. 2003a). Recent studies in operations management have also used Cox models (Ramdas & Randall 2008; Levine & Toffel 2010).

The results are shown in Table 2-3. *Punitive Tactics (Pre-Improvement)* have significant promotive influence on EI implementation hazard (Table 3, Column 1, $\beta = 0.19$, $p<0.10$; Hazard Ratio=1.21). We find that *Punitive Tactics (Improvement)* have a significant disruptive effect on EI implementation hazard (Table 3, Column 1, $\beta = -0.77$, $p<0.01$; Hazard Ratio=0.46) of EIs. Hence H1a and H1b are supported, which provides further support for the importance of timing of punitive tactics.

H2 examines the effect of inspections vs. sanctions. We find that *Sanctions* (Table 3, Column 2, $\beta = 0.49$, $p<0.01$; Hazard Ratio=2.39) occurring in the pre-improvement phase, have a significantly stronger (Wald's F-test=12.37, $p<0.01$) promotive influence on EI implementation hazard compared to *Inspections* (Table 3, Column 2, $\beta = 0.02$, $p>0.10$; Hazard Ratio=0.98). This provides support for H2. In the improvement phase, we find that both, *Inspections* (Table 3, Column 3, $\beta = -0.79$, $p<0.01$; Hazard Ratio=0.45) and *Sanctions* (Table 3, Column 3, $\beta = -0.77$, $p<0.05$; Hazard Ratio=0.49) have a disruptive influence on EI implementation hazards. A Wald's test (F=0.03, $p>0.10$) suggested that, in the improvement phase, sanctions did not have a significantly stronger promotive effect compared to inspections. Hence, H2a is supported in the case of pre-improvement punitive tactics, but H2b is not supported for punitive tactics occurring in the improvement phase.

H3 examines the effect of related vs. unrelated punitive tactics. We find that *Related Punitive Tactics* (Table 3, Column 3, $\beta = 0.32$, $p<0.01$; Hazard Ratio=1.37) do not have a significantly stronger (Wald's F-test=0.57, $p>0.10$) promotive effect compared to *Unrelated Punitive Tactics* (Table 3, Column 3, $\beta = 0.17$, $p>0.01$; Hazard Ratio=1.18) occurring in the pre-improvement phase. In the improvement phase, we find that *Unrelated Punitive Tactics* (Table 3, Column 3, $\beta = -0.91$, $p<0.01$; Hazard Ratio=0.40) had a significantly stronger (Wald's F-test=3.64, $p<0.05$) disruptive influence compared to *Related Punitive Tactics* (Table 3, Column 3, $\beta = -0.43$, $p>0.10$; Hazard Ratio=0.64). Overall, H3a is not supported in the case of pre-improvement punitive tactics, but H3b is strongly supported in the case of punitive tactics occurring in the improvement phase.

H4 and H5 predict the amplified promotive and disruptive influence in the case of *Senior Manager Involvement* and *Technological Complexity* respectively. We find that the promotive influence of *Punitive Tactics (Pre-Improvement)* is not significantly stronger under *Senior Manager Involvement* (Table 3, Column 4, $\beta = 0.07$, $p>0.10$; Hazard Ratio=1.02); but the disruptive influence of *Punitive Tactics (Improvement)* is significantly stronger under *Senior Manager Involvement* (Table 2, Column 4, $\beta = -1.13$, $p<0.05$; Hazard Ratio=0.31). Hence H4 is partially supported. Next, we find that the promotive influence of *Punitive Tactics (Pre-Improvement)* is not significantly stronger under *Technological Complexity* (Table 2, Column 5, $\beta = -0.15$, $p>0.10$; Hazard Ratio=0.86); but the disruptive influence of *Punitive Tactics (Improvement)* is significantly stronger under *Technological Complexity* (Table 2, Column 5, $\beta = -0.75$, $p<0.05$; Hazard Ratio=0.47). H5 is partially supported. Overall, the moderating effects of *Senior Manager Involvement* and *Technological Complexity* are much stronger during the improvement phase.

2.5.5 Robustness Checks

Alternate Modeling Approach for EI Implementation: The Cox model assumes that survival curves for the different strata (determined by different levels of covariates) have hazard functions that are proportional over time. However, this proportional hazards assumption is likely to fail when implementation times are excessively long. Hence, we use accelerated failure time (AFT) analysis to provide robustness to our results. In longitudinal survival analysis, the length of time (i.e. duration) is typically modeled for examining whether an explanatory covariate either stretches or shrinks the duration to the event (i.e. EI implementation) (Kiefer 1988; Bradburn et al. 2003b). AFT models require distributional assumptions but do not require the proportional hazard assumption which makes these models more flexible to handle changes over time. Overall, the results from the AFT models (**Table 2-4**) are very consistent with the results from the logit (**Table 2-2**) and Cox models (**Table 2-3**), implying robustness across modeling techniques and distributional assumptions.

Follow-up Frequency and Intrinsic Motivations: Based on our discussions with MTAP, we wanted to examine whether follow-ups can be used as a policy lever to influence firm behaviors. To address this issue, we created two subsamples based on the median *Time between follow-ups* (90 days).

Table 2-3. Cox Models for EI Implementation Hazards

	Punitive Tactics Characteristics			Moderating Effects	
	Timing	**Type**	**Relatedness**	**Manager**	**Complexity**
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Ln(Savings)	0.22***	0.22***	0.23***	0.20***	0.22***
	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)
Ln(Savings)^2	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Ln(Hours)	0.06	0.07	0.03	-0.02	0.07
	(0.16)	(0.17)	(0.16)	(0.16)	(0.16)
Ln(Hours)^2	-0.01	-0.02	-0.01	0.00	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Ln(Employees)	0.02	0.03*	0.02	-0.01	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Senior Manager	-0.01	-0.07	-0.04	0.08	-0.02
	(0.20)	(0.18)	(0.20)	(0.21)	(0.22)
Ln(Recommendation Number)	-0.32***	-0.31***	-0.32***	-0.31***	-0.34***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Ln(Total Recommendations)	-0.19*	-0.19*	-0.19*	-0.24***	-0.17
	(0.11)	(0.10)	(0.10)	(0.07)	(0.11)
Time between follow-ups	-0.57***	-0.61***	-0.56***	-0.59***	-0.57***
	(0.15)	(0.15)	(0.16)	(0.11)	(0.15)
Punitive Tactics (Pre-Improvement)	0.19*			0.20	0.33*
	(0.11)			(0.17)	(0.17)
Punitive Tactics (Improvement)	-0.77***			-0.29	-0.31*
	(0.20)			(0.27)	(0.18)
Inspection (Pre-Improvement)		-0.02			
		(0.13)			
Sanction (Pre-Improvement)		0.49***			
		(0.12)			
Inspection (Improvement)		-0.79***			
		(0.29)			
Sanction (Improvement)		-0.71**			
		(0.29)			
Related Punitive Tactics (Pre-Improvement)			0.32***		
			(0.11)		
Unrelated Punitive Tactics (Pre-Improvement)			0.17		
			(0.16)		
Related Punitive Tactics (Improvement)			-0.43		
			(0.30)		
Unrelated Punitive Tactics (Improvement)			-0.91***		
			(0.22)		
Punitive Tactics (Pre-Improvement)				0.07	
× Senior Manager				(0.26)	
Punitive Tactics (Pre-Improvement)				-1.13**	
× Senior Manager				(0.45)	
Punitive Tactics (Improvement)					-0.15
× Technological Complexity					(0.18)
Punitive Tactics (Improvement)					-0.75***
× Technological Complexity					(0.19)
F-Tests (Pre-Improvement)		12.37***	0.57		
F-Tests (Improvement)		0.03	3.64**		
Observations	1089	1089	1089	1089	1089
Wald's chi2	825.25	1579.92	6571.93	748.05	2226.25
Log Likelihood	-2271.59	-2269.03	-2269.38	-2272.09	-2281.95

Robust Standard Errors in parantheses; *** p<0.01, ** p<0.05 *p<0.1

The results based on a subsample analysis are shown in **Table 2-5**. The results indicate that the promotive influence of *Punitive Tactics (Pre-Improvement)* is much stronger for EIs with low follow-up frequency; disruptive influence of *Punitive Tactics (Improvement)* is much stronger for

EIs with low follow-up frequency. These promotive and disruptive effects are almost negligible for EIs with high follow-up frequency. These results can have two possible explanations. First, projects with high follow-up frequency are simply more resistant to both, promotive and disruptive effects of *Punitive Tactics*. This implies that MTAP could successfully use this policy lever to encourage implementation. Such steps are being taken, based on our findings, by MTAP through an initiative called 'Follow-up Tuesdays'. Second, we cannot ignore the possibility that the frequency of follow-ups is likely to be influenced by the MTAP staff's expectations and beliefs about EI implementation probabilities and hazards. Discussions with MTAP revealed that all of their officials followed a standard protocol for conducting site-visits. Although the officials rejected the notion that their expectations might influence their timing of follow-ups, they admitted that they were often able to identify signs during site-visits indicating whether or not a recommendation was likely to be implemented. Hence, follow-up frequency is likely to be correlated with MTAP staff's expectations of EI implementation, which, on the other hand are likely to be correlated with the unobservable level of 'intrinsic' commitment that facilities may have at EI initiation. This explanation might imply that facilities, potentially exhibiting low intrinsic commitment to EIs, are more likely to be influenced by external influences through *Punitive Tactics*.

Additional Sensitivity Checks: We identified the pre-improvement and improvement phases as a 12-month periods before and after the EI-initiation respectively. However, one might argue that the results might be affected by the time period selected. In order to alleviate this concern, we extended (14 months) and reduced (10 months) the time window. This approach did not have any significant impact on the findings (detailed results from this analysis available upon request). One could argue that any Punitive Tactics could impact operational activity, irrespective of their strength. Next, we suspected that certain EIs (*Material Type = Water*) in our sample might have been influenced by another regional regulatory authority (Metropolitan Council Environmental Services), which manages wastewater permits and monitors industrial sewage discharge. We therefore reanalyzed all our models by excluding these potentially biased EIs from our sample. Doing so did not change our results (available upon request) qualitatively, thereby alleviating concerns of other exogenous effects driving our findings. During the process of matching our two datasets, we were not able to identify the exact identities of seven facilities. These facilities were among the many facilities owned by a single firm in the same city. Although we matched datasets based on interviews and information from the public data sources, errors were likely to have occurred in these seven cases. As a final sensitivity test, we dropped these cases (seven facilities; 24 EIs) from our models to avoid biases. This procedure did not have any impact on our findings.

Table 2-4. AFT Models for Robustness Checks

	Punitive Tactics Characteristics			Moderating Effects	
	Timing	Type	Relatedness	Manager	Complexity
Variables	(1)	(2)	(3)	(4)	(5)
Ln(Savings)	0.22***	0.22***	0.22***	0.20***	0.22***
	(0.07)	(0.07)	(0.07)	(0.05)	(0.06)
Ln(Savings)^2	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Ln(Hours)	0.05	0.04	0.00	-0.04	0.05
	(0.18)	(0.19)	(0.18)	(0.16)	(0.17)
Ln(Hours)^2	-0.01	-0.01	0.00	0.01	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Ln(Employees)	0.03*	0.04**	0.03	-0.01	0.04**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Senior Manager	-0.04	-0.04	-0.02	0.03	-0.05
	(0.19)	(0.17)	(0.19)	(0.20)	(0.20)
Ln(Recommendation Number)	-0.29***	-0.28***	-0.29***	-0.29***	-0.31***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Ln(Total Recommendations)	-0.16	-0.17*	-0.17*	-0.22***	-0.14
	(0.10)	(0.10)	(0.10)	(0.08)	(0.10)
Time between follow-ups	-0.48***	-0.49***	-0.45***	-0.50***	-0.48***
	(0.11)	(0.11)	(0.12)	(0.08)	(0.11)
Punitive Tactics (Pre-Improvement)	0.17**			0.16**	0.24***
	(0.07)			(0.08)	(0.09)
Punitive Tactics (Improvement)	-0.46***			-0.23	-0.23***
	(0.10)			(0.16)	(0.08)
Inspection (Pre-Improvement)		0.03			
		(0.12)			
Sanction (Pre-Improvement)		0.44***			
		(0.12)			
Inspection (Improvement)		-0.74***			
		(0.28)			
Sanction (Improvement)		-0.70***			
		(0.26)			
Related Punitive Tactics (Pre-Improvement)			0.31***		
			(0.11)		
Unrelated Punitive Tactics (Pre-Improvement)			0.18		
			(0.15)		
Related Punitive Tactics (Improvement)			-0.42		
			(0.30)		
Unrelated Punitive Tactics (Improvement)			-0.86***		
			(0.20)		
Punitive Tactics (Pre-Improvement)				0.01	
× Senior Manager				(0.10)	
Punitive Tactics (Pre-Improvement)				-0.71*	
× Senior Manager				(0.39)	
Punitive Tactics (Improvement)					-0.12
× Technological Complexity					(0.14)
Punitive Tactics (Improvement)					-0.36**
× Technological Complexity					(0.14)
F-Tests (Pre-Improvement)		10.50***	0.51		
F-Tests (Improvement)		0.01	3.34**		
Constant	-3.74***	-3.16***	-4.04***	-3.49***	-3.49***
	(0.83)	(1.05)	(1.08)	(0.82)	(0.74)
Observations	1089	1089	1089	1089	1089
Log Likelihood	-939.22	-937.18	-936.93	-941.77	-945.38

Robust Standard Errors in parantheses; *** p<0.01, ** p<0.05 *p<0.1

Table 2-5. Robustness Models for Follow-up Frequency and Intrinsic Motivations:

	Logit Models		Hazard Models	
	Follow-ups High	Follow-ups Low	Follow-ups High	Follow-ups Low
Variables	(1)	(2)	(3)	(4)
Ln(Savings)	0.43***	0.36***	0.29***	0.16**
	(0.12)	(0.11)	(0.09)	(0.08)
Ln(Savings)^2	-0.03***	-0.02**	-0.03***	-0.01**
	(0.01)	(0.01)	(0.01)	(0.01)
Ln(Hours)	-1.18***	-0.13	-0.02	0.40
	(0.43)	(0.52)	(0.21)	(0.25)
Ln(Hours)^2	0.23***	0.06	0.00	-0.07
	(0.08)	(0.17)	(0.04)	(0.08)
Ln(Employees)	0.15	-0.00	0.01	-0.02
	(0.09)	(0.05)	(0.04)	(0.03)
Senior Manager	-0.16	0.43	-0.16	0.08
	(0.74)	(0.40)	(0.20)	(0.19)
Ln(Recommendation Number)	-0.31	-0.20	-0.26**	-0.40**
	(0.24)	(0.13)	(0.12)	(0.17)
Ln(Total Recommendations)	-0.02	-0.51**	-0.30*	-0.21
	(0.33)	(0.25)	(0.17)	(0.17)
Punitive Tactics (Pre-Improvement)	0.16	1.14**	-0.01	0.30***
	(0.51)	(0.50)	(0.14)	(0.11)
Punitive Tactics (Improvement)	1.11	-1.74***	-0.01	-0.65**
	(0.79)	(0.44)	(0.19)	(0.27)
Constant	3.59	1.31*		
	(4.21)	(0.68)		
Observations	596	514	587	502
Wald's chi2	41.66	73.66	94.02	235.82
Log Likelihood	-291.67	-406.87	-912.64	-1260.61

Robust Standard Errors in parantheses; *** p<0.01, ** p<0.05 *p<0.1

Table 2-6. Effects of Implementation on Long-Term Compliance

	Logit Model	Negative Binomial Model
Variables	DV=Penalty Received	DV=Days to Closure
Facility Fixed Effects (258 facilities)	Yes	Yes
Year Fixed Effects (1999-2013)	Yes	Yes
Compliance Issue Dummies (15 Issues)	Yes	Yes
Compliance Action Dummies (14 Action Types)	Yes	Yes
Facility Implemented At Least One EI	-3.01***	-0.18**
	-0.66	-0.09
Constant	3.53***	8.00***
	-0.87	-1.03
Observations	878	758
Log Likelihood	-40.56	-4677.16

Robust Standard Errors in parantheses; *** p<0.01, ** p<0.05 *p<0.1

2.5.6 Economic and Environmental Implications of Well-timed and Ill-timed Punitive Tactics

In this section, we present the estimated economic and environmental implications of well-timed (pre-improvement phase) and ill-timed (improvement phase) *Punitive Tactics*. Although we make necessary assumptions to arrive at these numbers, the idea is to provide baseline estimates in order to inform policy decisions. We present estimates for two types of EIs – those related to *Energy* (601 EIs) and to *Solid & Hazardous Waste* (188 EIs). It might be useful to reiterate that the Odds Ratio (OR) represents the odds that EI implementation will occur given a particular event, compared to the odds of the outcome occurring in the absence of that event. Hazard Ratios (HR) can be interpreted as the exponent of coefficients, such that ratios below 1 indicate reduced hazard (of implementation) and ratios above 1 represent an increased hazard. As shown below, HRs provide more conservative estimates of energy-efficiency savings and waste elimination compared to ORs. Together, they can be viewed as providing a range of expected benefits (or lost opportunities) related to the use of well-timed and ill-timed *Punitive Tactics*.

The average savings for energy-related EIs in our sample were 83,000 KWh and $8600. Considering the total energy related [*Material Type=Energy*] improvements in our data set, the "potential" annual energy savings (from 601 EIs) accumulate to 50 million KWh and $5.1 million. Factoring in the current average implementation rate (50%), this would lead to potential "base-level" energy savings of 25 million KWh resulting in approximately 2.5 million dollars' worth opportunities. The OR for *Punitive Tactics (Pre-Improvement)* was 1.78 which implies that the odds of implementation are 1.78 times higher for EIs when facilities face punitive tactics during the 12-month pre-improvement phase. This would, ideally, provide estimated savings of 44 million KWh and $4.6 million, which is a significant improvement over base-level implementation savings. With similar calculation using Hazard Ratio (HR) of 1.21 for *Punitive Tactics (Pre-Improvement)*, we can arrive at more conservative savings of 30 million KWh and $3.1 million, which still indicates a 20% rise over base-levels. The OR for *Punitive Tactics (Improvement)* was 0.31 which implies that the odds of implementation are 0.31 times lower for EIs when facilities face punitive tactics during the improvement phase. This suggests estimated savings of 7.7 million KWh and $ 0.8 million, which is a drastic reduction over base-level implementation benefits. With similar calculation using Hazard Ratio (HR) of 0.46 for *Punitive Tactics (Improvement)*, we arrive at estimated savings of 11.0 million KWh and $1.2 million, which is a conservative, yet significant reduction over base-levels.

The average waste eliminated from *Waste*-related EIs in our sample was 373,000 lbs. Considering the total *Waste*-related improvements in our data set, the "potential" annual waste eliminated (from 188 EIs) was approximately 70 million lbs. Factoring in the current average implementation rate (50%), this would lead to potential "base-level" waste elimination of approximately 35 million lbs. The OR for *Punitive Tactics (Pre-Improvement)* was 1.78 which would, ideally, eliminate an estimated 62 million lbs. of waste, representing a significant improvement over base-level estimates. With similar calculation using Hazard Ratio (HR) of 1.21 for *Punitive Tactics (Pre-Improvement)*, we can arrive at more conservative number of 42.5 million lbs., which still indicates a 20% rise over base-level waste elimination. The OR for *Punitive Tactics (Improvement)* was 0.31 which implies that the odds of implementation are 0.31 times lower for EIs when facilities face punitive tactics during the improvement phase. This suggests estimated waste elimination of 10.8 million lbs., which is a drastic reduction over base-level estimates. With similar calculation using Hazard Ratio (HR) of 0.46 for *Punitive Tactics (Improvement)*, we arrive at estimated waste reduction of 16.1 million lbs., which indicates a conservative, yet significant reduction over base-levels.

Although we might need to be cautious in extrapolating our results to other similar settings, the cumulative benefits (and lost opportunities) from assistance programs across United States (at least 100 programs currently exist) would be substantial. Our study suggests re-thinking the timing of *punitive tactics*, especially during the facility's improvement phase, would be a crucial next step for policy. For ease of understanding, we do not provide estimates of energy savings and waste reduction based on inspections vs. sanctions and related vs. unrelated punitive tactics. Yet, our analysis suggests a need to carefully consider not only the 'timing', but also the 'nature' of *punitive* tactics in relation to *supportive* tactics.

2.5.7 Effect of EI Implementation on Long-Term Compliance Outcomes

Our hypotheses hinge on the assumption that EI implementation is beneficial for facilities. Above, we illustrated the potential economic and environmental benefits from ensuring EIs implementation. Yet, from a policy standpoint, one might question whether EI implementation provides any long-term environmental benefits. In the absence of significant long-term environmental benefits, any policy efforts to coordinate *supportive* and *punitive* tactics may be futile. On the other hand, as expected by proponents of voluntary environmental programs (Koehler 2007), EI implementation could really be an important starting point in a facility's trajectory toward improved environmental compliance. If that is truly the case (i.e. EI implementation matters in the long-run), our findings should inform environmental policy and attempts at coordinating supportive and punitive tactics are justified. To answer this question, we compiled data on all compliance records of facilities participating in MTAP's assistance programs. The compliance records spread across 1999-2013 consisted of facility-level compliance events, compliance issue type (water, air, solid waste etc.), compliance action type (e.g. Notice of Violation, Administrative Penalty Order, Warning), dollar penalties and days to compliance case closure.

We used this data to test for within-facility changes in (i) likelihood of receiving a dollar penalty and (ii) days to case closure after (vs. before) implementing at least a single EI. The two outcome metrics capture overall compliance and ability to address compliance issues respectively. One might question the validity of using ‘implementation of at least a single EI’ as a dichotomous measure. However, we believe this measure should adequately capture a facility’s transition to improved environmental standards. Similar modeling strategies have been used earlier to capture intent to adhere to improved environmental standards (Reid & Toffel 2009). A fixed-effects logit model (Table 2-6) shows that odds of a facility receiving a dollar penalty for a compliance issue went down more than 90% when a facility implemented at least a single EI. Similarly, facilities that implemented at least a single EI significantly improved their ability to resolve compliance issue faster. On average, case closure durations for facilities implementing at least one EI are 0.83 times lower. Overall, these results show that EI implementation can have significant implications for long-term compliance outcomes. As a result, the issue of coordinating punitive and supportive tactics is relevant from both short-term (EI implementation) and long-term (reduced penalties, faster case closures) perspectives.

2.6. Discussion

Our findings have important policy implications for the timing of *punitive* and *supportive* tactics. Past research has highlighted the advantages (Haveman et al. 2001; Christmann 2004) and disadvantages (King & Lenox 2000) of regulatory institutions. Although regulatory actions might be necessary for long-term improvements (Anand et al. 2012), our results show that they may also hold implications for operational activity (EIs in this context) in the short-term. Our findings suggest that existing regulatory approaches can be complementary and/or counterproductive, depending on the timing of their usage. Policy-makers need to be wary of the disruptive impact of their punitive tactics occurring in the improvement phase. On the other hand, assistance programs can generate more effective outcomes by aligning their EI initiatives with existing punitive tactics. Information on environmental inspections and sanctions is widely available, which should allow greater cooperation between regulatory agencies and assistance programs in the coming years. Such targeting policy (Short & Toffel 2007; Rousseau 2007) has been shown to have increased environmental compliance. As noted earlier, currently there is limited communication between many regulatory agencies and intervention programs, especially when it comes to specific facilities. A more coordinated effort could lead to more favorable environmental outcomes.

We examine whether punitive and supportive tactics can be implemented in a complementary manner in the context of government agencies influencing environmental improvement (EI) projects in firms. However, improvement projects can be related to various other corporate functions such as quality management and human resources. While we believe that our findings are generalizable to other contexts where firms are externally influenced, it will be interesting to examine complementarity between the two tactics under different contexts. Using archival data collected from two state-level environmental agencies in Minnesota, we conduct a longitudinal analysis of over 1000 EI projects tracked over several months. Yet these projects were undertaken in a single state – Minnesota. Although this approach minimizes the spurious effect of other factors, such as state level policies, it also limits generalizability to some extent. Future research could examine whether differences in organizational contexts (e.g. regulation, competition) moderate the effect of punitive and supportive tactics. Furthermore, organization-specific (e.g. location, parent influence) and firm-specific (e.g. centralization, supply chain structure) factors could also have a moderating influence. Our study uses archival data from state level agencies, which is prone to recording and measurement errors. Hence, a potential extension of this study is to experimentally examine complementary effects between punitive and supportive tactics. While quasi-experiments or field studies will help ground this phenomenon empirically, laboratory experiments will give additional insights into behavioral responses to the timing of polar tactics. We examine two policy approaches in this study. Yet, other policy approaches, such as voluntary environmental programs (VEPs), might also offer interesting empirical settings for future research on coordinated policy-making. Finally, future research could also examine the role of internal influence tactics, incentives and managerial control.

Chapter 3

ESSAY 2 - Repurposing Materials & Waste through Online Exchanges: Overcoming the Last Hurdle[11]

Summary

Online Material & Waste Exchanges (OMWEs) face several challenges in providing online channels to repurpose by-products, unused materials and waste from industrial and commercial facilities. First, sellers may have access to other disposal options, which limits their commit to the exchange. Second, buyers can face high uncertainty about the product and transaction. Overcoming these challenges is the 'last hurdle' to make OMWEs successful. This study investigates factors that increase the *sellers' commitment* to the OMWE and reduce the *buyers' uncertainty* by analyzing novel transaction-level data from an online exchange (MNExchange.org) combined with other archival public records on county-level repurposing and disposal statistics. We find that regional *repurposing* policies and alternatives have a complementary effect on sellers' commitment towards OMWEs, resulting in increased OMWE exchanges. However, regional *disposal* policies and alternatives have a substitution effect on sellers' *commitment*, resulting in reduced exchange success. Further, greater product and transaction information reduces the buyer's uncertainty and increases exchange success. Our analysis also shows that higher familiarity between the buyer-seller pair and familiarity with the OMWE system increases the likelihood of exchange success. This study lays the foundation for understanding OMWEs and has important implications for developing policies and operations to increase online transactions of by-products, materials and wastes.

Keywords: socially responsible operations, materials and waste exchange, sustainability, online markets, closed loop supply chains

3.1 Introduction

"One man's trash is another man's treasure" –

McGraw-Hill Dictionary of American Idioms and Phrasal Verbs

Increasingly companies search for ways to become more environmentally sustainable. As a first step towards this goal, many companies develop channels for repurposing their industrial waste. Repurposing (i.e. reuse/recycling) industrial waste helps mitigate its potential negative impact to the environment by avoiding disposal via landfill or incineration. In 2010, repurposing programs in the U.S. helped divert more than 183 million metric tons of CO_2, which is equivalent to eliminating emissions from 34 million passenger vehicles (EPA 2011b). While

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repurposing rates have increased in recent years, most waste still gets disposed in landfills and incinerators. According to 2010 estimates, the United States repurposed less than 50% of its waste (EPA 2011b). Most companies accumulate a large amount of waste and surplus materials, such as industrial packaging (e.g. boxes, containers), mixed electronics (e.g. lamps, tapes), unused raw materials (e.g. wood, rubber) and by-products (e.g. chemicals, leather). Such items account for approximately 70% of total solid waste in the U.S. (EPA 2011). Unfortunately, these items suffer from low repurposing rates due, in part, to a failure to match the generators of the waste (sellers) with potential users (buyers).

Online Material & Waste Exchanges (OMWEs) offer one possible remedy to this problem (EPA 2013a). An OMWE provides an online platform for matching sellers of surplus materials with buyers. In these exchanges, the sellers post items for "sale" and buyers contact sellers directly to obtain additional information before making a possible exchange (i.e. transaction). While this process appears straightforward, many OMWEs including MNExchange.Org (Minnesota), ReuseMarketplace.Org (Northeast U.S.), and BCImex.CA (Canada) among others[12], continue to experience low exchange rates (EPA 1994; MPCA 2011). This study seeks to understand the factors that influence exchanges in these unique markets. Understanding the factors that influence exchanges can help inform policies to better design and manage OMWEs. To understand what influences exchanges, we focus on the dilemmas that buyers and sellers face when deciding to exchange surplus material. First the sellers face a *commitment* dilemma to the exchange. Sellers often have access to more convenient disposal options, such as landfills and incineration plants. Consequently, even after they have listed an item on the exchange, they still face a dilemma of spending the effort to pursue a successful exchange, or just dispose the item through landfill or incineration. On the other hand, buyers face an *uncertainty* dilemma about the product and its transaction. From the buyer's perspective, they may find it difficult to assess the quality or usability of the product. Furthermore, in these markets, buyers and sellers have fewer, infrequent interactions which make it difficult for buyers to judge sellers based on their reputation. While customer ratings and pricing mechanisms (e.g., auctions) can reduce uncertainties in some online markets (Pavlou & Gefen 2004), OMWEs typically do not have such mechanisms (e.g., our survey of 25 large scale OMWEs revealed that only 2 offered these mechanisms or associated services).

[12] We surveyed existing OMWEs in various parts of United States (California, Texas, Minnesota, New York, Maine, Pennsylvania, Washington etc.) as well as in Canada (Alberta, British Columbia, Ontario, Quebec etc.) Specifically, we examined the online platforms carefully to collect qualitative information on various characteristics such as listing, display, pricing, reputation mechanisms etc. In addition, we also had telephonic conversations with five other OMWEs (four in the U.S. and one in Canada), which were a part of the Materials Exchange Managers Network, an informal network of administrators and policy-makers engaged in OMWE development. A detailed list of OMWEs in U.S. is available with EPA: http://www.epa.gov/osw/conserve/tools/exchange.htm.

The challenge of overcoming the sellers' *commitment* dilemma and buyers' *uncertainty* dilemma represents the 'last hurdle' problem in successfully matching sellers and buyers on OMWEs. Our research draws from prior theory, and knowledge gained from interactions with our industry partners, to identify specific factors that influence exchanges. We hypothesize that the sellers' *commitment* dilemma is influenced by the level of disposal and repurposing alternatives within the seller's vicinity. Furthermore, we hypothesize that the buyers' *uncertainty* dilemma is influenced by the type of information provided on the listing, the seller's size, and the geographic proximity between the buyer and seller. Finally, we hypothesize that users' prior experience with the OMWE positively influences exchange outcomes. We test the impact of these factors on the likelihood of a successful exchange using a novel data set from MNExchange.Org consisting of 4300+ material/waste listings and 100,000+ buyer-seller interactions. The analysis shows that product and transaction information richness reduces the buyer's *uncertainty* and increases likelihood of a successful exchange. In addition, regional repurposing practices and alternative disposal options impacts the sellers' *commitment* which affect the likelihood of an exchanges. Finally, the analysis shows that users' (buyers and sellers) familiarity with the OMWE influences the likelihood of an exchange. Specifically, the more a buyer and seller interact with one another and the more role-based experience (i.e. familiarity with the OMWE system) they have, the higher the likelihood of an exchange.

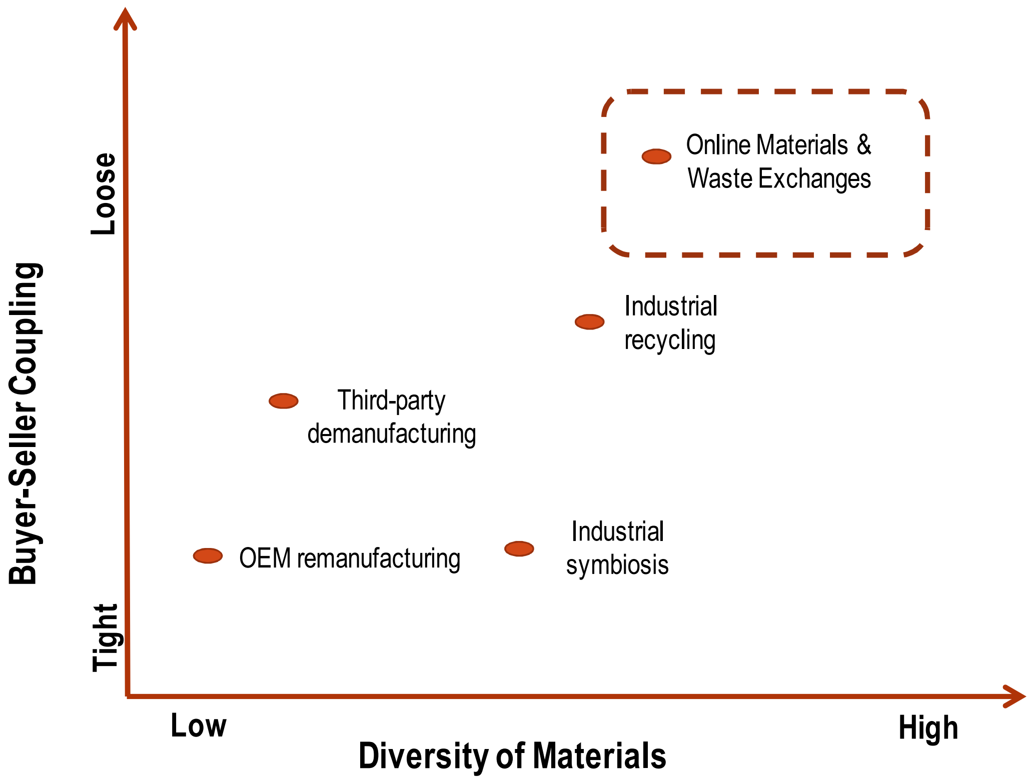
The next section of the paper provides a conceptual overview, positions the study in the extant literature and develops hypotheses. Section 3 introduces the research context and variables. Section 4 reports the empirical results. Section 5 discusses managerial and policy implications and section 6 presents future research directions.

3.2 Conceptual Overview and Theory Development

3.2.1 OMWEs within Repurposing Supply Chains

OM scholars increasingly recognize the importance of repurposing supply chains (Linton et al. 2007; Atasu, Guide, et al. 2008). To compare OMWEs with other types of repurposing supply chains, we develop a taxonomy based on two dimensions - *Diversity of Materials* and *Buyer-Seller Coupling*. *Diversity of Materials* refers to the range of materials in the repurposing supply chain, while *Buyer-Seller Coupling* refers to the degree of coordination between buyers (waste consumers) and sellers (waste producers). **Figure 3-1** positions the following repurposing supply chains based on this framework: OMWEs, OEM remanufacturing, third-party demanufacturing, industrial recycling, and industrial symbiosis. Some of these repurposing supply chains (e.g. OEM remanufacturing, third-party demanufacturing) have been examined under the broader umbrella of closed loop supply chains (Guide & Van Wassenhove 2009), while others have received little attention from OM scholars.

Figure 3-1. Repurposing Operations & Supply Chains



OEM remanufacturing deals with the disassembly and recovery of valuable components from a product, which are later reused or recycled. Scholars have generated important insights for inventory management (Toktay et al. 2000), product design (Guide & Wassenhove 2001), and strategic marketing (Atasu et al. 2008) of remanufactured products. Most research in this domain focuses on managing durable products (Thierry et al. 1995; Toktay et al. 2000; Guide et al. 2006) with relatively high value. OEM remanufacturing is a low diversity-tight coupling repurposing supply chain since it applies to specific product types with pre-determined contractual arrangements between supply chain members. Examples of OEM remanufacturers include Xerox, HP, Dell and Kodak. In third-party demanufacturing, third-party providers handle the logistics, sorting and demanufacturing processes (Spicer & Johnson 2004). Here, secondary market brokers manage product returns across multiple supply chains through centralized returns centers (Savaskan et al. 2004; Tibben-Lembke 2004). As a result, this setting comprises more material diversity and moderate coupling compared to OEM remanufacturing. Examples of third-party demanufacturers include Total Reclaim and Dataserv USA.

Other repurposing supply chains, such as industrial recycling and industrial symbiosis, have received more attention from scholars in industrial ecology (Linton et al. 2007). Although similar to third-party demanufacturers, industrial recyclers often handle more diversity of materials such as assorted metals, plastics, wood and paper. They also have looser buyer-seller coupling since materials come from a wider variety of sources. Covanta Energy is an example of an industrial recycler that has more than 40 mixed materials recycling facilities across United States and abroad. The industrial symbiosis perspective views industrial processes as a biological ecosystem, which can potentially be designed to thrive on its own by-products (Desrochers 2004; Chertow 2007). Industrial symbiosis typically focuses on redirecting multiple waste streams in highly coordinated supply chains. The Kalundborg eco-industrial park in Denmark is an example of industrial symbiosis. It has co-located facilities that create an industrial symbiosis among waste streams consisting of sulfur, sludge, waste water and gas (Chertow 2007). Despite its benefits (Linton et al. 2007), this approach requires substantial investment, planning, foresight and a tight buyer-seller coupling.

In contrast to these other approaches, OMWEs connect multiple products and waste streams across multiple buyers and sellers. Buyers and sellers are loosely coupled due to relatively low volume and infrequent transactions. Online Materials & Waste Exchanges (OMWEs) have received limited attention in the literature. While a few case studies (Tsai & Chou 2004; Wei & Huang 2001) provide a description of physical waste exchange programs in Asian countries, they do not examine 'online' exchanges or study operational factors of such exchanges. To the best of our knowledge, this is the first empirical study on OMWEs.

According to the EPA (2013a), Material & Waste Exchanges *"are markets for buying and selling reusable and recyclable commodities. Some are physical warehouses that advertise available commodities through printed catalogs, while others are simply Web sites that connect buyers and sellers."* Such exchanges vary in their geographic reach as well as the diversity of materials being exchanged. In light of the recent technologies advances, most exchanges in the U.S. and Europe now have a major online component. Often, OMWEs handle specific types of products such as plastics or wood. For example, the California Plastics Exchange (CAplasticsmarket.com) acts as an online intermediary to match sellers, buyers and recyclers of industrial plastics. CRUMB Rubber (Crumb.rubber.com) located in Ontario, Canada offers another example of an exchange for granulated rubber products. Mixed materials and waste exchanges such as MNexchange.org (Minnesota), ReuseMarketplace.Org (Northeast U.S.), and

BCImex.CA (Canada) can host hundreds of listings for industrial materials, by-products and wastes.

OMWEs share some similarities with B2B online markets (for detailed discussions on B2B markets, see Pavlou (2002) and Koch & Schultze (2011)). Typically, online markets aggregate buyer demand or seller offerings, build trust, facilitate transactions, and match supply with demand (Bailey & Bakos 1997). Online markets lower the buyer's search costs in obtaining product and seller information (Bakos 1991). A recent stream of research studies the online exchange of used goods (Ghose 2009; Subramanian & Subramanyam 2012; Dimoka et al. 2012), which has similarities with OMWE transactions. These papers highlight the problem of buyer uncertainty in the used goods online market. Recent research on e-commerce in supply chains (Balakrishnan & Geunes 2004; Johnson & Whang 2002) also relates to OMWEs. This research shows the importance of accurate information (Lee & Whang 2001) and user interface (Boyer & Olson 2002) to facilitate transactions.

In comparison to conventional online markets (Overby & Jap 2009), buyers in OMWEs face higher uncertainty due to limited information about product characteristics and transaction outcomes. Uncertainty creates agency problems (Dimoka et al. 2012) and increases transaction costs (Teo & Yu 2005). Consequently, reducing uncertainty has been the focus of many studies on online markets (Pavlou & Gefen 2004; Pavlou et al. 2007). Studies have also considered how transactional characteristics (Jarvenpaa et al. 1999) influence online exchanges. Research also shows how prior experience between buyers and sellers influences exchanges (Gefen 2000). These literature streams help inform our theoretical arguments about OMWEs.

3.2.2 Theory & Hypotheses Development

This study investigates the factors that lead to successful exchanges (i.e. transactions between buyers and sellers) in OMWEs. On the seller side, the 'last hurdle' problem arises when sellers choose other disposal options over OMWEs. This relates to the seller's lack of *commitment* to the exchange. On the buyer side, the 'last hurdle' problem arises when buyers do not make the purchase through the exchange despite their interest in the item listed. This relates to the buyer's *uncertainty* about the product and transaction attributes. Finally, the buyers' and sellers' prior *experience* with the online exchange may also affect transactions. Drawing on Transaction Cost Economics (TCE) and other literature streams, we develop hypotheses that relate the sellers' uncertainty, buyers' commitment and user experience with OMWEs to a transaction success. We also draw on discussions (see Appendix) with MNExchange.org staff and OMWE users to further inform the hypotheses.

The Seller's 'Commitment' Dilemma

The sellers transaction decision in OMWE is influenced by multiple factors other than price and product attributes (Schmidt et al. 2007). For example, sellers face the transaction costs of searching for buyers and engaging in contractual negotiations (Dahlman 1979). Sellers also bear the economic cost of carrying materials/wastes until they are exchanged with potential buyers. As a result, sellers may avoid engaging in an online exchange when the transaction costs (e.g. searching, contracting) and carrying costs outweigh the economic, reputational and environmental benefits (Coase 1937). Here, we argue that sellers' transaction costs (and commitment to OMWEs) may be influenced by (i) access to other alternatives and (ii) regional repurposing and disposal policies.

Access to Other Alternatives

Previous studies have argued that transaction costs depend on relative access to different alternatives (Bajari & Tadelis 2001; Hennart 1988). Research in logistics shows that a user's decision to adopt a green option depends on their geographic location, access to other alternatives and the transaction costs incurred (Burns & Golob 1976). Geographic and location factors affect the economic, social and environmental benefits of adopting environmental practices (Schmidt et al. 2007; Barrett & Lawlor 1997). In a related vein, the literature on supply chain management suggests that the seller's commitment to a contract depends on their relative access to other supply channels (Klein et al. 1990; Tsay & Agrawal 2000; 2004). Applying this logic, increased access to alternatives (i.e. substitutes) can reduce the transaction costs of using these alternatives. For example, increased access to rubber disposal facilities in the region may reduce a tire manufacturing facility's inclination to use OMWEs. This logic suggests that increased access to other *disposal alternatives* may reduce the seller's commitment to OMWEs, decreasing the likelihood of an exchange.

While *disposal alternatives* act as clear substitutes for OMWEs, *repurposing alternatives* could conceivably act as either substitutes or complements. Viewing them as substitutes, more repurposing alternatives could increase competition for the seller's "goods" and hence reduce seller commitment to OMWEs. In other words, increasing the number of alternatives within the vicinity may reduce the seller's commitment to OMWE exchanges. On the other hand, a TCE-based analysis (Madhok 2002) suggests that positive spillover effects of other repurposing alternatives could generate complementary benefits (Porter 2000) for sellers on OMWEs. In line with the concept of industry clusters (Porter 2000), an "informally linked geographic concentration of organizations" can provide efficiency and coordination benefits. Applying this logic to our context, more repurposing facilities in the sellers' region may give rise to a "repurposing cluster", which could reduce the overall transaction and coordination costs for sellers in OMWEs. In addition, many buyers in OMWEs are repurposing facilities (e.g. industrial recyclers and refurbishing centers) "who use the OMWE as a platform to source their operations" (MPCA Officer 2014). As a result, more repurposing facilities in the sellers' region could help sellers on OMWEs to more efficiently identify buyers for their materials and wastes. In summary, while both complementary and substitutive effects of repurposing alternative may be at play, we expect the complementary effect (as predicted by TCE and the concept of clusters) will be stronger. Therefore we predict that sellers' increased access to other *repurposing alternatives* (excluding OMWEs) has a positive spillover effect on OMWEs and increases the likelihood of exchanges. Hence, we hypothesize:

Hypothesis 1 (H1): *The Sellers' Access to other (a) disposal alternatives is negatively associated with the likelihood of a successful exchange while (b) repurposing alternatives is positively associated with the likelihood of a successful exchange.*

Regional Repurposing and Disposal Policies

While H1 considers access to disposal and repurposing alternatives, the next hypothesis examines the relative effect of disposal versus repurposing policies within a seller's region (i.e. county). Counties within each state have the authority to develop policies and infrastructure to promote repurposing alternatives over disposal alternatives. Repurposing policies "…reflect the significant [state- and county-level] investment in the recycling system, as well as strong material markets…" (MPCA 2010). A Minnesota Pollution Control Agency (MPCA) employee confirmed that "county-level initiatives are important, … which is why we [MPCA] work on developing *regional* recycling markets…" (MPCA Officer 2014).

Discussions with the exchange staff revealed that local (i.e. county-level) repurposing and disposal policies influence the seller's commitment to the exchange. Regional policies can alter the institutional environments in which seller organizations operate (Sharma 1995), which can make the repurposing alternatives more (or less) favorable. For example, favorable policies can reduce the transaction costs (Tadelis & Williamson 2010) of repurposing by creating an environment for peripheral repurposing business (e.g. material & waste transportation) to develop (Porter 2000). Furthermore, supportive repurposing policies in a region can foster pro-environmental beliefs and attitudes which affects the sellers' use of the OMWE (Henriques & Sadorsky 1996; Schwab et al. 2012). Research shows that companies undertake pro-environmental actions when embedded in regions that expect higher environmental compliance (Christmann 2004). According to TCE, such adherence to regional policies lowers the sellers' overall transaction costs (Nee 1998; Roberts & Greenwood 1997) of conducting business. The positive spillover effect can lead to an increase in sellers' commitment to repurposing alternatives like the OMWE. As a result, sellers in regions with supportive repurposing (relative to disposal) policies may show more commitment to OMWE transactions, leading to higher likelihood of OMWE exchanges. Hence:

Hypothesis 2 (H2): *The Repurposing to Disposal Ratio in the Seller's County is positively associated with the likelihood of a successful exchange.*

The Buyer's 'Uncertainty' Dilemma

The literature on online markets recognizes the problems that arise from *product uncertainty* and *transaction uncertainty* (Pavlou et al. 2007; Dimoka et al. 2012; Pavlou & Gefen 2004). In online markets, product uncertainty comes from hidden or asymmetric information, which prevents the buyer from accurately evaluating product characteristics; transaction uncertainty comes from concerns about hidden actions and contractual shirking by the seller (Arrow 1984). These problems become further amplified in online markets for secondary/used materials (Ghose 2009) such as OMWEs. As a result, reducing product and transaction uncertainty may improve exchange success (Pavlou et al. 2007).

Product Uncertainty

Product uncertainty is defined as "the buyer's difficulty in evaluating the product and predicting how it will perform in the future" (Dimoka et al. 2012). Products listed on the online waste exchange tend to be non-standardized and non-branded, which increases product uncertainty. Also, used or secondary products such as those sold in OMWEs have higher product heterogeneity due to variations in quality (Ghose 2009). As a result, buyers have more difficulty assessing product quality in OWMEs. Some conventional online markets such as eBay and Amazon reduce uncertainty by providing reliable pricing signals either through buyer bids or seller-provided prices (Smith et al. 2001; Brynjolfsson 2002). However, waste exchanges typically do not provide this type of information. For example, in our study setting, less than 5% of sellers provided an initial "asking price". Given these factors, buyers in online waste exchanges have higher *product uncertainty.*

Product uncertainty increases the search costs (through higher evaluation challenges), which may also lead buyers to exit the market (Teo & Yu 2005). However, information can reduce product uncertainty by improving "product diagnosticity" (Dimoka et al. 2012). The director of a software provider for OMWEs noted that "the way [listing] information is presented and the [online] content influences users' decision….whether they should go ahead…is it worth the effort?..." (Director at iWasteNot Systems 2014). In OMWEs, textual description and visual content (e.g. picture) together provide buyers with a "first cut" of information about the item (MNExchange.Org Staff 2013). As a result, we expect that more product information will reduce buyer's uncertainty, and consequently increase the likelihood of exchange. Hence:

Hypothesis 3 (H3): *Reduced Product Uncertainty through higher (a) Textual information length and (b) Visual information content is positively associated with the likelihood of a successful exchange.*

Transaction Uncertainty

Transaction uncertainty reflects the buyer's difficulty in predicting the outcome of the transaction (Dimoka et al. 2012). High transaction uncertainty may limit the buyers' ability to predict seller behavior and the transaction outcome (Koopmans 1957; Sutcliffe & Zaheer 1998). For example, "…the buyer might think…Hey, I don't know this person [i.e. seller] well enough…will this work out?" (MNExchange.Org Staff 2013). Transaction uncertainty may be higher in OMWEs, compared with other conventional C2C or B2C markets like Amazon or eBay, due to the lower trade volumes and infrequent transactions in OMWEs. For example, in our study only 2% of the users on MNExchange.Org completed more than one successful exchange (either buying or selling) between 2000 and 2008. Consequently, even reputation mechanisms and seller ratings, which lower transaction uncertainty in conventional online markets (Subramanian & Subramanyam 2012), have less applicability in OMWEs due to smaller trade volumes and infrequent exchanges. Given the high uncertainty in OMWEs, the transaction costs might outweigh the benefits of making an online waste exchange (Teo & Yu 2005). Hence, reducing transaction uncertainty becomes critical.

In the OMWE context, the seller's size and geographical proximity to the buyer may influence the level of transaction uncertainty. For example, a larger seller may provide a buyer with lower transaction uncertainty due to their familiarity and reputation. This is consistent with Doney and Cannon (1997), who argue that buyers have more trust in larger sellers since they are less likely to renege on commitments due to the higher risks to their reputation. In addition, information accuracy increases with closer geographical proximity between transacting parties (Pavlou & Gefen 2004), which lowers transaction costs. Greater buyer-seller proximity also has a direct benefit of lower transportation costs and convenience. Economists have confirmed that geographical proximity between buyers and sellers not only decreases transportation costs and tariffs but also reduces "informational frictions" (i.e. transaction uncertainty) in search, negotiation and monitoring (Anderson & Van Wincoop 2004; Hortaçsu et al. 2009). Discussions with MNExchange.Org staff confirmed that buyers are reluctant to engage with "far-away sellers" due to their inability to assess material quality *a priori* and settle potential quality issues *post hoc*. Overall, we expect seller size and geographical proximity to have a positive impact on the likelihood of an exchange. Hence:

Hypothesis 4 (H4): *Reduced Transaction Uncertainty through greater (a) Seller size and (b) Geographical proximity between the buyer-seller pair is positively associated with likelihood of a successful exchange.*

Buyer & Seller Prior Experience

Reputation and pricing mechanisms play an important role in building efficient online markets (Bakos 1991; Gefen 2002; Gefen et al. 2003; Luo 2002). In the context of remanufactured products, Subramanian and Subramanyam (2012) show that reputation signals and warranties helped promote efficient markets. But, OMWEs have low transaction volumes and few repeat sales, consequently rating (i.e. feedback) mechanisms do not effectively provide aggregate seller reputation information (Dellarocas 2003). This may explain why only one OMWE out of the 25 we surveyed allowed buyers to rate their transaction experiences. Pricing mechanisms and warranties are also usually not available on OMWEs since the transacted items are low valued, non-standardized and non-branded. For example, less than 1% of items in MNExchange.Org have an asking price with the majority listed as either "negotiable" of "free". The quoted prices rarely reflect the final exchange amount since bargaining is common in these markets. As a result, in OMWEs, "…a lack of credible [seller and pricing related] information and problems with bargaining are often the reasons for failed matches…" (MNExchange.Org Staff 2013). Given this lack of reputation and pricing mechanisms, OMWE users may be forced to rely on their *past experiences* to overcome transactional challenges.

Past Buyer-Seller Familiarity

Research shows that prior experience influences actions (Ouellette & Wood 1998). When faced with uncertainty, decision makers often rely on experience to inform their decisions. For example, buyers may store relevant past experiences and evoke previously established decision routines to make decisions (Howard & Sheth 1969). In other words, decision-making tasks can be simplified when faced with familiar situations or when interacting with familiar buyers/sellers. Recently, Bolton et al. (2004) found that successful transactions often depend on the level of experience with the transacting "partner". Previous interactions with the same buyer/seller increases perceived trust which mitigates uncertainty, fears of opportunism and online information privacy concerns (Pavlou et al. 2007). Similarly, in the OMWE context, previous experience between two transacting parties (i.e. buyer-seller pairs) may engender trust and reduce transactional difficulties (Pavlou 2002), thus increasing the likelihood of an exchange. This suggests the following hypothesis.

Hypothesis 5 (H5): *Past familiarity between the buyer-seller pair is positively associated with the likelihood of a successful exchange.*

Past Role-based Experience

In OMWEs, buyers and sellers may not have clear information about the other party's intentions and behavior. Although each new transaction presents different challenges, users may benefit from their prior experience of having been "in the other's shoes". Early research in social psychology has documented the influence of role-playing on opinions and perceptions (Janis & King 1954). Decision-makers learn from experience gained through other roles, which can alter their beliefs and attitudes (Elms 1967). Experience gained through other roles (i.e. buyers having transacted as sellers and *vice versa*) may also increase familiarity with the online system, which can improve transaction decisions (Gefen et al. 2003). In OMWEs, being in the role of the opposite transacting party can improve the users' understanding of the OMWE system. This understanding may benefit buyers and sellers. Having previously been a buyer can improve sellers' understanding of factors that can alleviate buyer uncertainty, resulting in positive actions (e.g. improved information provision) that increase the likelihood of exchange. Similarly, having previously been a seller can reduce the buyers' search and negotiation costs in future exchanges. Hence:

Hypothesis 6 (H6): *Past role-based experience in the form of (a) Buyer's experience as Seller or (b) Seller's experience as Buyer is positively associated with the likelihood of a successful exchange*

3.3 Research Context & Data

The primary data for this study comes from transactions on the MNExchange.Org (henceforth also referred to as "the exchange"). Although OMWEs may differ in terms of their size, geographic reach and material diversity, the basic characteristics of most OMWEs in U.S. and Canada are fairly similar. MNExchange.Org provides a useful context for studying OMWEs in several respects. First, the exchange has been operational since 1999, making it relatively mature. By 2008, MNExchange.Org had facilitated transactions exceeding 25 million pounds of materials and wastes, saving more than $6 million for local businesses. As of 2008, the exchange had more than 10,000 registered members representing approximately 7000 industrial and commercial facilities. The scale and longevity of MNExchange.Org make it an appropriate empirical setting for our study. Second, its operations (e.g. functionality, web interface, policies for listings, registration) are similar to many other mixed exchanges across the United States and Europe, which improves applicability of our findings. Third, OMWEs of low valued products tends to be localized, hence studying regional exchanges similar to MNExchange.Org is critical to understanding how to increase repurposing.

MNExchange.Org hosts a web interface that allows registered companies to list and browse product listings. The Appendix provides recent snapshots of the web interface. At any given time, the online exchange may host hundreds of listings by different waste categories. First-time users setup individual accounts by providing information about their organization, size, activities, location, and contact details. When a user submits a listing, the exchange displays item-specific information such as the quoted price, product description, frequency (whether one-time or recurring) and location (by county and zip code). For example, a construction company (seller) might list its surplus storm water concrete pipes (Appendix) on MNExchange.Org with accompanying product and transaction information. Sellers are not allowed to list multiple items (pipes, equipment, windows etc.) together; each item (material, by-product or waste) is listed separately, although the quantities for each listing might vary (e.g. 10 concrete pipes). This information allows potential buyers to browse the listings and sort on specific criteria. Interested registered buyer(s) can then contact the seller directly (through seller-provided contact details) to get more information about the product, price, logistics etc. before negotiating an exchange. The terms of exchange are mutually decided offline by the transacting parties. Although MNExchange.Org provides an inexpensive channel for producers and consumers of industrial materials and waste, it does not offer any price or product guarantees. Also, repeat exchanges for the same buyer-seller pair are infrequent (merely 150 repeat exchanges between 2000 and 2008).

In traditional online markets, prices signal product value and allow comparisons with substitutes (Brynjolfsson & Smith 2000; Brynjolfsson 2002). OMWEs typically have non-standardized and non-branded products which make price comparisons difficult. In these markets, sellers often do not provide price quotes. Out of 4330 total listings in our data, only 20 items had an asking price; all others were either listed as “negotiable” or “free”. Approximately 45% of the listings are items being offered for free. In such cases, the incentive for the seller may come from enhanced environmental legitimacy or reduced disposal costs. Additional discussions with other OMWEs in U.S. and Canada (see Appendix) confirmed these trends observed in MNExchange.Org.

The available archival data spans 1999-2010 and consists of product listings, buyer requests for seller information, and if an exchange occurred between the buyer and seller. Our analysis is based on data between 2000 and 2008 since this period was deemed the most representative of normal exchange activity. The excluded years had little activity due to external factors. In particular, 1999 was the first operating year of the exchange and the 2009-2010 phase was influenced by effects of the economic crisis. This reduced data set represents approximately 4500 listings. To test our hypotheses, we matched other county-level data from Minnesota state public records and Minnesota Pollution Control Agency (MPCA) reports on county-level statistics. Since we rely on multiple secondary sources, missing data is a potential concern. Approximately 460 out of the 4500 listings had missing information for at least one measure, mostly due to recording errors (for user size, county, organization type etc.). We resolved 215 of these cases through discussions with MNExchange.Org and other secondary data sources (Hoover's and ORBIS), and dropped listings where information was missing on more than two control or independent variables. For the remaining cases, we used the mean imputation method for handling missing data. Using more advanced multiple imputation techniques (White et al. 2013) did not affect findings. The final sample resulted in 4330 listings and 100,625 buyer-seller interactions, with descriptive statistics provided in Table 3-1. Table 3-2 and Table 3-3 provide a description of variables and summary statistics.

Table 3-1. Descriptive Statistics by Material Types

Serial No.	TYPE OF LISTING (Item Classification)	# OF ITEMS (N)	EXCHANGED (Percent of Listed)		TOTAL_HITS (Average)		HAZARDOUS (Percent)		RECURRING (Percent)	
		ALL	**ALL**	**FREE**	**ALL**	**FREE**	**ALL**	**FREE**	**ALL**	**FREE**
1	Boxes & packaging	244	13.1%	17.2%	22.4	33.0	27.9%	17.2%	31.6%	38.8%
2	Chemicals & cleaners	190	14.7%	13.0%	15.0	16.1	38.9%	44.8%	25.8%	23.4%
3	Construction materials	191	8.9%	11.0%	41.3	56.2	0.5%	1.1%	45.0%	40.7%
4	Containers & pallets	170	18.8%	19.1%	44.2	42.3	0.6%	0.9%	64.1%	60.0%
5	Electronics	552	22.1%	25.8%	19.9	19.3	1.1%	1.2%	27.0%	22.0%
6	Equipment & machinery	166	22.3%	26.4%	23.1	24.3	1.2%	2.2%	30.7%	24.2%
7	Office Furniture	782	19.7%	22.2%	31.4	37.9	0.3%	0.0%	21.7%	24.3%
8	Office Supplies	405	26.9%	26.0%	20.6	25.6	1.2%	0.4%	11.1%	13.8%
9	Paints & stains	103	18.4%	10.5%	27.3	30.1	16.5%	19.3%	23.3%	14.0%
10	Paper products	31	9.7%	16.7%	22.8	27.5	0.0%	0.0%	38.7%	27.8%
11	Plastics & rubber	627	19.9%	26.3%	17.8	29.1	1.6%	1.1%	14.9%	14.2%
12	Textiles & leather	284	24.6%	25.5%	16.2	21.1	1.4%	1.9%	9.9%	9.8%
13	Wood Products	133	30.1%	34.2%	41.4	53.4	0.0%	0.0%	31.6%	32.9%
14	Other Miscellaneous	452	18.7%	20.6%	23.4	28.4	1.1%	2.2%	51.8%	36.5%
	Total/Average	**4330**	**20.3%**	**22.3%**	**26.2**	**31.7**	**6.6%**	**6.6%**	**30.5%**	**27.3%**

N(All)=4330; N(Free)=2334

Table 3-2. Descriptions and Summary Statistics (Primary Variables)

Variable	Level	Effect	Variable Description	Mean	S. D
Exchange Listing (DV)	Listing	==	Binary Variable indicating whether *at least one* successful exchange occurred for the listed item	0.202	0.401
Exchange Interaction (DV)	Interaction	==	Binary Variable indicating whether the buyer-seller interaction resulted in a successful exchange. Captures outcome of each interaction between each buyer-seller pair	0.010	0.090
Seller's Access to Disposal (H1a)	Listing	(-)	Count variable for disposal sites operating in the seller's county when item was listed. Obtained from Minnesota Pollution Control Agency (MPCA) for each county-year. Variable was not logged since permitted landfills are too few per county (Mean<1).	0.647	0.477
Seller's Access to Repurposing (H1b)	Listing	(-)	Logarithm of the number of other repurposing sites in the seller's county when item was listed. This data was obtained from the MPCA for the year 2009, which was then mapped on to years 2000-2008.Annual data was unavailable. This approach was considered appropriate since "…the number of permitted recyclers per county is quite stable across time" (MPCA Officer, 2014). This variable excludes other OMWEs	3.277	0.875
Repurposing/Disposal in Seller's County (H2)	Listing	(+)	The total tons of materials/waste collected for some form of Repurposing (either recycling or reuse through different channels) divided by the total tons of materials/waste Disposed (landfill, incineration or uncollected items). Includes all types of solid materials/waste. This rate captures overall repurposing versus disposal policies within counties since counties spend considerable resources on developing repurposing markets and infrastructure. Yearly data was obtained from MPCA	0.677	0.158
Textual Information Length (H3a)	Listing	(+)	Log of Number of Characters in textual information provided by sellers for the listed item.	3.921	0.942
Visual Information Content (H3b)	Listing	(+)	Binary variable indicating if the Seller provided visual information content (e.g. picture, user manual etc.) along with listing.	0.108	0.310
Seller Size (H4a)	Listing	(+)	Ordinal Variable for Size of the seller organization. Data available was Categorical based on # of employees: Small (<500); Medium (501 - 3000); Large (>3000) Companies.	0.298	0.620
Geographical Distance (H4b)	Interaction	(-)	Log of distance between each buyer-seller pair was taken as a proxy for geographical proximity. The distances between zip-codes of buyers and sellers were used. Exact addresses were not used due to confidentiality issues.	3.124	1.555
Past Buyer-Seller Familiarity (H5)	Interaction	(+)	Binary variable indicating whether the specific buyer-seller pair had a previous interaction (either successful or unsuccessful) on MNExchange.Org any time before the current interaction.	0.399	0.489
Buyer's Experience as Seller (H6a)	Interaction	(+)	Binary variable indicating whether the specific buyer had been a seller on MNExchange.Org at any given point in time before the current interaction.	0.133	0.340
Seller's Experience as Buyer (H6b)	Interaction	(+)	Binary variable indicating whether the specific seller had been a buyer on MNExchange.Org at any given point in time before the current interaction.	0.543	0.498

N (Listings) = 4330; N (Interactions) = 100625; Means and Standard Deviations are at analysis level as indicated. Effect gives the hypothesized direction

Table 3-3. Descriptions and Summary Statistics (Control Variables)

Variable Name	Variable Description	Mean	S. D
Buyer Size	Ordinal Variable for Size of the buyer organization. Data available was Categorical based on # of employees: Small (<500); Medium (501 - 3000); Large (>3000) Companies	0.12	0.41
Free Listing	Binary Variable representing whether item was offered for 'free' by the seller. Free items were more likely to be exchanged.	0.52	0.50
Hazardous	Binary variable indicating if the item posed any safety hazard. This was controlled for because such materials were less likely to get exchanged due to risks and higher transportation costs.	0.04	0.20
Recurring	Binary variable indicating if the item was being offered by the seller on a recurring basis (i.e. weekly/ monthly etc). Such materials might generate interest from specific buyers looking for long-term exchanges.	0.27	0.44
Total Hits on Listing	Log of total number of buyer web hits on the listed item. Controls for the overall interest in the listing i.e. potential demand. The variable was standardized to avoid multi-collinearity.	2.46	1.26
Total Hits on Listing^2	Squared logarithm of total buyer hits on the listed item. Interviews and exploratory analysis showed that successfully exchanged items tended to have either low hits (indicating fast exchange) or high hits (indicating high potential interest). This suggested a curvilinear relationship. Variable standardized to avoid multi-collinearity.	7.65	6.35
Time Listed	The time for which item was listed on the OMWE before being deleted by user or archived by MnExchange.Org. This controlled for the seller's inclination to wait for a buyer request and the availability of the item for purchase. Data available was Categorical (0-3, 3-6, 6-12, >12 months).	2.02	1.19
MNExchange.Org Users in Seller's County	Log of the number of registered MNExchange.Org users in seller's county. This accounts for diffusion of OMWEs, hence capturing seller's self-selection into OMWEs.	6.45	1.03
MNExchange.Org Users in Buyer's County	Log of the number of registered MNExchange.Org users in buyer's county. This accounts for diffusion of OMWEs, hence capturing buyer's self-selection into OMWEs.	5.79	1.57
Seller's Access to Other OMWEs	Binary Variable indicating whether other OMWEs were operating in the seller's county and immediate bordering counties when item was listed on MNExchange.Org. This data was obtained from MPCA & EPA.	0.43	0.50
Buyer's Access to Other OMWEs	Binary Variable indicating whether other OMWEs were operating in the buyer's county and immediate bordering counties when item was listed on MNExchange.Org. This data was obtained from MPCA & EPA.	0.40	0.49
Item Category Dummies	14 Material and Waste categories were controlled for using dummy variables. The detailed list and summary statistics are provided in Table 2. This classification is used by MnExchange.Org since it captures differences in repurposing policies and regulations.	NA	NA
Year Dummies	Year dummies were included to control for differences in yearly (2000-2008) economic conditions and other factors.	NA	NA

N (Listings) = 4330; N (Interactions) = 100625

3.4 Analysis & Results

3.4.1 Listing & Interaction Level Analysis

The analysis takes place at two levels – *listing level* and *interaction level*. The analysis at the *listing level* tests the seller dilemmas and the buyer dilemmas (H1a, H1b, H2, H3a, H3b and H4a). The analysis at this level uses a binary dependent variable (*Exchange_Listing*) indicating whether each listed item was exchanged. The unit of analysis here is each listed item. Each listing can have multiple interested buyers (up to 500 in our dataset) who access the listing and seller information, thereby indicating an interest in the product. Analysis on buyer-seller pairs is therefore conducted at this *interaction level*, where we use information related to the buyer-seller dyads. We use this dyadic data to test the effects of experience (H5, H6a and H6b) since past experience is likely to have an effect on the way users interact with the opposite transacting party. Additionally, we use the interaction level of analysis to test the effect of geographic distance between buyer-seller pairs (H4b). At the *interaction level,* the binary dependent variable (*Exchange_Interaction*) indicates whether the buyer-seller interaction resulted in a successful exchange. This study views an exchange (either as listing of interaction level) as the occurrence of a physical transaction between buyers and sellers (irrespective of the quantity). We do not consider the actual quantity exchanged since this data is not always available or accurate. The two levels of analysis allow us to conduct tests of item-specific, seller-specific and interaction-specific attributes. The hypotheses related to sellers (H1, H2 and H4a) and product (H3) requires testing at the *listing level*, while the hypotheses which rely on dyadic attributes (H4b, H5 and H6) require testing at the *interaction level*. The analysis uses logistic regression models with clustered standard errors. At the interaction level, we also present results using panel logistic regression models with fixed effects (Greene 2003), and bias corrected models (Firth 1993). Table 2 provides detailed explanations of all dependent and independent variables. We included controls in our logistic regression models to account for a variety of buyer, seller, product and regional characteristics. Table 3 provides a description of all the control variables. The analysis uses the following econometric models at listing (Equation 1) and interaction level (Equation 2):

$$P(\textit{Exchange Listing}_{it} = 1|X_{it}) = \beta_0 + \beta_{CL}X_{CL} + \beta_1\textit{Seller's Access to Disposal}_t + \beta_2\textit{Seller's Access to Repurposing}_t + \beta_3\textit{Repurposing/Disposal in Seller's County}_t + \beta_4\textit{Textual Information Length}_i + \beta_5\textit{Visual Information Content}_i + \beta_6\textit{Seller Size}_i \quad \ldots(1)$$

$$P(\textit{Exchange Interaction}_{ijt} = 1|X_{ijt}) = \gamma_0 + \gamma_{CI}X_{CI} + \gamma_1\textit{Geographical Distance}_j + \gamma_2\textit{Past Buyer-Seller Familiarity}_{jt} + \gamma_3\textit{Buyer's Experience as Seller}_{jt} + \gamma_4\textit{Seller's Experience as Buyer}_{jt} \quad \ldots(2)$$

The indices represent each listing *i,* interaction *j* and year *t.* X_{CL} and X_{CI} are vectors of controls at the listing and interaction levels respectively, while β and γ are respective coefficients at the listing and interaction levels. For the independent variables, subscripts (*i, j* and *t*) indicate the dimensions across which these variables vary i.e. whether the variance is listing- (*i*), interaction- (*j*) or time- (*t*) specific.

Table 3-4. Listing Level Analysis

Variables (Hypotheses Tested)	Base Model (1)	Seller's Commitment (2)	Buyer's Uncertainty (3)	Pooled Logit (4)	Heckman Model (5)	Odds Ratios
Total Hits on Listing	-0.73**	-0.75**	-0.73*	-0.75**	-0.75**	0.47
	(0.37)	(0.37)	(0.38)	(0.37)	(0.37)	
Total Hits on Listing^2	0.12**	0.12**	0.12**	0.12**	0.12**	1.13
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	
Time Listed	0.25***	0.28***	0.26***	0.28***	0.28***	1.32
	(0.08)	(0.07)	(0.08)	(0.07)	(0.07)	
Hazardous	-0.33	-0.36	-0.38*	-0.40*	-0.41**	0.76
	(0.25)	(0.23)	(0.22)	(0.20)	(0.20)	
Recurring	-0.43***	-0.43***	-0.42***	-0.42***	-0.42***	0.65
	(0.12)	(0.12)	(0.12)	(0.11)	(0.12)	
Free Listing	0.71***	0.71***	0.69***	0.70***	0.69***	1.99
	(0.25)	(0.26)	(0.25)	(0.26)	(0.26)	
MNExchange.Org Users in Seller's County		0.05		0.04	0.05	1.04
		(0.05)		(0.05)	(0.05)	
Seller's Access to other OMWEs		-0.01		0.02	0.04	1.02
		(0.16)		(0.13)	(0.12)	
Seller's Access to Disposal (H1a)		-0.31***		-0.33***	-0.34***	0.72
		(0.12)		(0.11)	(0.11)	
Seller's Access to Repurposing (H1b)		0.26***		0.23***	0.23***	1.25
		(0.06)		(0.07)	(0.07)	
Repurposing/Disposal in Seller's County(H2)		0.45*		0.49**	0.48**	1.63
		(0.25)		(0.22)	(0.22)	
Textual Information Length (H3a)			0.04*	0.05**	0.05***	1.04
			(0.02)	(0.02)	(0.02)	
Visual Information Content (H3b)			0.12*	0.13*	0.14**	1.13
			(0.07)	(0.07)	(0.06)	
Seller Size (H4a)			0.32**	0.27**	0.20	1.31
			(0.14)	(0.13)	(0.12)	
Observations	4330	4330	4330	4330	4330	
Log Likelihood	-1947.56	-1928.82	-1937.79	-1921.36	-1916.73	
Akaike Information Criterion	3905.12	3867.14	3885.51	3852.72	3843.46	
Bayesian Information Criterion	3936.98	3899.51	3917.44	3884.59	3875.33	

*Dependent Variable=Exchange Listing; Cluster Robust Standard Errors; *p<.10, **p<0.05, ***p<0.01; Material Codes included for 14 Categories; Year dummies for years 2000-2008; Controls for 6 Seller Types (Commercial, Education, Manufacturing, Government, Non-Profit and Other); Coefficient on inverse Mills ratio for the Heckman models was 1.81 [SE=0.80]; Odds Ratios given for full model*

Table 3-5. Interaction Level Analysis

Variables (Hypotheses Tested)	Base Model (1)	Pooled Logit (2)	Fixed Effects (3)	Bias Corrected (4)	Heckman Model (5)	Odds Ratios
Total Hits on Listing	-1.87***	-1.83***	0.00	-1.82***	-1.85***	0.16
	(0.24)	(0.22)	(.)	(0.07)	(0.22)	
Total Hits on Listing²	0.16***	0.16***	0.00	0.16***	0.16***	1.17
	(0.03)	(0.03)	(.)	(0.01)	(0.03)	
Time Listed	0.22***	0.22***	0.00	0.22***	0.22***	1.24
	(0.08)	(0.08)	(.)	(0.04)	(0.08)	
Hazardous	-0.29	-0.30	0.00	-0.29	-0.30	0.73
	(0.27)	(0.28)	(.)	(0.22)	(0.27)	
Recurring	-0.21*	-0.22	0.00	-0.22**	-0.20	0.84
	(0.12)	(0.14)	(.)	(0.09)	(0.13)	
Free Listing	0.65***	0.66***	0.00	0.66***	0.65***	1.93
	(0.18)	(0.18)	(.)	(0.09)	(0.18)	
OMWE Users in Seller's County	0.04	0.02	-0.10	0.04	0.02	1.02
	(0.07)	(0.08)	(0.11)	(0.05)	(0.08)	
OMWE Users in Buyer's County	0.04**	0.03*	-0.02	0.04	0.03*	1.03
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	
Seller's Access to Disposal	-0.33***	-0.32***	-0.53	-0.31***	-0.33***	0.72
	(0.10)	(0.09)	(0.52)	(0.12)	(0.10)	
Seller's Access to Repurposing	0.22***	0.19**	0.00	0.19***	0.17**	1.20
	(0.08)	(0.08)	(.)	(0.07)	(0.07)	
Seller's Access to other OMWEs	0.02	0.01	0.00	0.00	0.03	1.00
	(0.18)	(0.18)	(.)	(0.12)	(0.16)	
Buyer's Access to other OMWEs	0.22*	0.16	0.14*	0.16**	0.17	1.07
	(0.13)	(0.12)	(0.08)	(0.07)	(0.13)	
Repurposing/Disposal in Seller's County	0.40***	0.43***	-0.91	0.49**	0.43***	1.49
	(0.09)	(0.09)	(3.52)	(0.22)	(0.09)	
Textual Information Length	0.11**	0.12***	0.00	0.12***	0.12***	1.11
	(0.05)	(0.04)	(.)	(0.04)	(0.04)	
Visual Information Content	0.13*	0.13*	0.12	0.13	0.14*	1.13
	(0.07)	(0.07)	(0.23)	(0.11)	(0.08)	
Seller Size	0.29**	0.27**	0.00	0.27***	0.27**	1.33
	(0.12)	(0.12)	(.)	(0.06)	(0.12)	
Buyer Size	-0.34***	-0.38***	-0.26**	-0.37***	-0.37***	0.71
	(0.10)	(0.10)	(0.11)	(0.10)	(0.10)	
Geographical Distance (H4b)		-0.06***	-0.06**	-0.05***	-0.07***	1.94
		(0.02)	(0.02)	(0.02)	(0.02)	
Past Buyer-Seller Familiarity (H5)		0.36***	0.48***	0.36***	0.37***	1.43
		(0.13)	(0.09)	(0.07)	(0.14)	
Buyer's Experience as Seller (H6a)		0.48***	0.18	0.49***	0.28***	1.62
		(0.08)	(0.12)	(0.08)	(0.08)	
Seller's Experience as Buyer (H6b)		-0.01	-0.13	-0.00	-0.19*	0.99
		(0.14)	(0.33)	(0.08)	(0.11)	
Observations	100625	100625	21758	100625	100625	
Log Likelihood	-4911.33	-4871.74	-2442.21	-4751.11	-4882.72	
Akaike Information Criterion	9834.66	9755.47	4930.12	9628.01	9777.44	
Bayesian Information Criterion	9891.77	9812.58	5114.14	10112.73	9834.55	

*Dependent Variable=Exchange Interaction; Cluster Robust Standard Errors; *p<.10, **p<0.05, ***p<0.01; Material Codes included for 14 Categories; Year dummies for years 2000-2008; Controls for 6 Buyer and Seller Types included (Commercial, Education, Manufacturing, Government, Non-Profit and Other); Seller- and Item- specific coefficients not estimated (as expected) from Fixed Effects model due to lack of within variance; Bias Corrected model is based on Firth (1993); Coefficient on inverse Mills ratio for the Heckman model was 0.06 [SE=0.44]; Odds Ratios given for Pooled model*

3.4.2 Listing Level Results [H1a, H1b, H2, H3a, H3b and H4a]

Table 3-4 summarizes the results for the *listing level* of analysis for seller's dilemma. As predicted, *Seller's Access to Disposal* is negatively associated (β=-0.33, $p<0.01$, Odds Ratio=0.72) with the likelihood of exchange. This translates into an approximately 0.72 times reduction in the odds of exchange when there is at least one disposal alternative in the seller's county. Also, *Seller's Access to Repurposing* is positively associated (β=0.23, $p<0.01$, Odds Ratio=1.25) with the likelihood of exchange. This translates into an approximately 1.25 times rise in the odds of exchange for one standard deviation (S.D) change in *Seller's Access to Repurposing* i.e. when three additional repurposing alternatives were located in the seller's county. Overall, the analysis supports H1a and H1b. Further, *Repurposing/Disposal in Seller's County* is positively associated (β=0.49, $p<0.05$, Odds Ratio=1.63) with likelihood of exchange, which supports H2. This translates into an approximately 1.63 times rise in the odds of exchange for a one S.D. change in the ratio i.e. approximately 15% rise in the *Repurposing/Disposal in Seller's County*. Table 4 also provides results at the listing level for the buyer's dilemma. *Textual Information Length* (β=0.05, $p<0.05$, Odds Ratio=1.04) and *Visual Information Content* (β=0.13, $p<0.10$, Odds Ratio=1.13) significantly relate to the likelihood of exchange, which supports H3a and H3b. Translating this effect, an increase in the length of description by one S.D. (3-4 characters) leads to 1.04 times higher odds of exchange. Similarly, providing a visual illustration leads to 1.13 times higher the odds of exchange. Therefore, accounting for other factors, product information does influence buyer's decision. Finally, *Seller Size* significantly increases the likelihood of an exchange (β = 0.27, $p<0.05$, Average Odds Ratio=1.31), supporting H4a. Thus, increase in seller size (small to medium; medium to large) leads to 1.31 times higher odds of exchange.

3.4.3 Interaction Level Results [H4b, H5, H6a and H6b]

Table 3-5 summarizes the results for the *interaction level* of analysis. *Geographical Distance* decreases the likelihood of exchange (β = -0.06, $p<0.01$, Odds Ratio=0.91). This translates into a 0.91 times drop in the odds of exchange for a one S.D. (5-mile) increase in geographic distance between buyer and seller. The effect of *Geographical Distance* also holds across alternative models at the interaction level, which we discuss later. This result indicates that greater geographic separation between buyers and sellers leads to higher transaction uncertainty, higher transportation costs and lower exchange likelihood. Overall, the analysis supports H4b.

Next, we interpret the effect of user prior experience with the exchange. *Past Buyer-Seller Familiarity* has a positive effect on the likelihood of an exchange (β = 0.36, $p<0.01$; Odds Ratio=1.43). Hence, buyers and sellers with more familiarity with the each other have higher likelihood of successful exchanges; having interacted earlier leads to 1.43 times higher odds of exchange. Overall, the analysis supports H5. Further, *Buyer's Experience as Seller* has a positive association with the likelihood of exchange ($\beta = 0.48$, $p<0.01$, Odds Ratio=1.62). Thus, buyer's previous experience as a seller results in 1.62 times higher odds of exchange. This result does not hold for sellers i.e. *Seller's Experience as Buyer* does not have a significant association with exchange likelihood. H6a is supported but H6b is not. In our discussions, the exchange staff also noted that a buyer who has previously been a seller is better able to distinguish between the quality and fit of products. The mixed results for H6 suggest that sellers might not derive a similar benefit from having previously been a buyer.

3.4.4 Robustness Analyses

Panel Models at the Interaction Level: The interaction level data consists of multiple buyer-seller interactions nested under each listed item, which results in an unbalanced panel. We therefore ran additional panel models (Greene 2003) at the interaction level. Table 5 (Column 3) reports the results from these models. The results from panel random effects model (not shown) were almost identical to the pooled logit model with robust standard errors (Column 2). This provides additional support for H4b, H5 and H6a. However, a Hausman test (χ^2=165.16, $p<0.001$) indicated that the estimates obtained from random effects may be inconsistent, thus a fixed effects model might be more appropriate (Greene 2003; Andress et al. 2012). The results from panel fixed effects model (Table 5, Column 3) do not support H6, but H4b and H5 are supported. Since fixed effects modeling is a within-group estimation technique which uses mean differencing, time-invariant item- and seller-specific coefficients are automatically dropped during the estimation process (Cameron & Trivedi 2009), leading to multiple lost observations. This could have affected our results.

Accounting for User Self-Selection: In our study, we focus only on actual users (i.e. sellers that list and buyers that interact with sellers) and exclude dormant registrants. However, this approach could introduce self-selection bias since certain types of registrants may be more/less likely to "use" MNExchange.Org. To account for this potential problem, we conduct the Heckman (1979) correction approach. This approach consists of first calculating the inverse Mills ratio from a probit model using "Usage of MNExchange.Org" as the binary dependent variable (N=All registered organizations). The inverse Mills ratio is then used as a control variable in the final second-stage models (equations 1 and 2) to provide consistent and unbiased estimates (Greene 2003) for the hypothesized effects. This approach (Table 4, Column 5; Table 5, Column 5) did not affect our results, suggesting that self-selection does not introduce significant bias. Although we account for selection based on "usage" with the above approach, our data does not allow us to control for the potential self-selection based on "registration" with MNExchange.Org. In other words, we lack information on companies that never registered with MNExchange.Org. Hence, our conclusions are limited to registered companies, which is in line with the approach followed by most studies on online markets (Brynjolfsson & Smith 2000; Overby & Jap 2009).

Accounting for Rare Outcomes at Interaction Level: Estimation of exchange likelihoods at the interaction level could lead to potential problems since the number of positive outcomes (*Exchange_Interaction*=1) is very rare (see Table 2). In our setting, merely 1% of buyer-seller interactions lead to successful exchanges. This rare event problem can be handled by the general estimation bias correction method proposed by Firth (1993), which uses a penalized maximum likelihood approach in logistic regression when separating outcomes (i.e. successes from failures) becomes problematic. The results from this model (Table 5, Column 4) are consistent with our previous findings. We also use an alternate robustness check to re-estimate corrected odds ratios (not shown) using "prior corrected" odds approach proposed by King and Zeng (2002). This approach did not significantly change the odds ratios, which gives provides further robustness.

Endogeneity in Estimating the Effect of Repurposing/Disposal Ratio: Although OMWE presence is on the rise, the transactions undertaken through OMWEs account for a small percentage (less than 5%) compared to the overall repurposing in the county. Hence, the reverse causal effect of successful OMWE exchanges on *Repurposing/Disposal Ratio in Seller's County* is likely to be inconsequential. Yet, we cannot completely reject the possibility that *Repurposing/Disposal in Seller's County* is endogenous since it could simultaneously affect and be affected by the likelihood of exchange. To control for this possible effect, we ran a 2-stage least squares (2SLS) model, where *Repurposing/Disposal in Seller's County* was first estimated using annual county-level *Fertility Rate in Seller's County* as the instrumental variable. *Fertility Rate in Seller's County* is correlated with *Repurposing/Disposal in Seller's County* but is unlikely to have any relationship with the structural error terms (or the outcome variable "Exchange_Listing"), thereby satisfying the criteria for a good instrument (Wooldridge 2002). This model (results included in the Appendix) actually strengthened the impact of *Repurposing/Disposal in Seller's County* on likelihood of an exchange. We also conducted analysis using *Infant Mortality Rate in Seller's County* as the instrumental variable, which gave similar results.

Operationalization of Past Familiarity and Experience: As indicated in Table 3-2, our user experience variables (*Past Buyer-Seller Familiarity*, *Buyer's Experience as Seller* and *Seller's Experience as Buyer*) are not based on a specific time window. Specifically, *Past Buyer-Seller Familiarity* was coded 1 if buyers and sellers had interacted previously (anytime); 0 otherwise.

Similarly, for *Buyer's Experience as Seller* and *Seller's Experience as Buyer,* we coded '1' if buyers/sellers had previously (anytime) played the opposite party's role; 0 otherwise. Here, we re-operationalize these variables based on a retrospective two-year time window i.e. only buyer-seller interactions occurring over the last 2 years are considered to measure "experience". This approach (Appendix) does not qualitatively change our findings, although the coefficient values were affected to some extent. Further, our analysis was conducted assuming each interaction is independent. Hence, if the same (or different) buyer-seller pair interacted more than once, each interaction would be assumed to be independent of the previous. As an alternative approach, we only retained the 'final' interactions for each buyer-seller pair in circumstances where a buyer-seller pair had multiple interactions for the same item listing. This approach (Appendix) did not affect our results significantly.

3.5 Discussion

About 65% of all waste generated in the United States ends up in landfills or incinerators (EPA, 2011). To address this problem, we focus on the exchanges of low-valued, non-standardized and non-branded products between industrial and commercial facilities. Online Material and Waste Exchanges (OMWEs) facilitate repurposing such industrial materials and wastes. The 'last hurdle' problem in OMWEs relates factors that influence the seller's *commitment* and buyer's *uncertainty* to engage in a successful exchanges. Drawing on MNExchange.Org and other secondary sources, we develop a unique dataset to examine the 'last hurdle' problem in OMWEs. To our knowledge, this is the first empirical study to examine the factors that influence transactions in OMWEs. Broadly, our research contributes to the growing body of literature on repurposing (Toktay et al. 2000; Linton et al. 2007; Atasu et al. 2008; Guide & Van Wassenhove 2009; Gui et al. 2013), waste management (Wei & Huang 2001; Tsai & Chou 2004) and online markets (Boyer & Olson 2002; Johnson & Whang 2002; Balakrishnan & Geunes 2004; Pavlou et al. 2007; Dimoka et al. 2012; Subramanian & Subramanyam 2012). Below, we discuss how our findings can help inform OMWE policies.

3.5.1 Developing Regional Repurposing Markets and Policies

On the seller side, we show that access to alternatives affects seller commitment to OMWEs. Interestingly, we find that although disposal alternatives reduce online transactions, repurposing alternatives increase transactions. This is an important finding for environmental policy. Currently, state and regional environmental control agencies (e.g. EPA, MPCA) dedicate resources to develop local repurposing markets i.e. networks of buyers, sellers and recyclers at the county-level (MPCA Officer 2014). Our findings suggest that the presence of such local networks and access to repurposing options might have a complementary effect on OMWEs. Building on Porter's (1998) idea, regional "repurposing cluster" could help reduce the transaction and coordination costs in OMWEs. On the other hand, OMWEs can act as an informational medium which binds these networks more cohesively. Furthermore, stronger regional markets can successfully overcome the problem of geographical buyer-seller separation and lower transaction uncertainty. In summary, OMWEs could offer complementary benefits to other existing repurposing supply chains such as OEM remanufacturing, third-party demanufacturing and industrial recycling.

Along similar lines, we find that regional repurposing and disposal rates influence exchanges. Regional repurposing rates enhance exchanges, while disposal rates reduce exchanges. Many states today spend millions of dollars developing repurposing programs. For example, in Minnesota, the Select Committee on Recycling and the Environment (SCORE) Act has led to increased funding for recycling programs, waste reduction, management of hazardous wastes, and problem materials. In 2012, Minnesota counties spent nearly $61 million in state and local funds for SCORE-related programs (MPCA 2012). Our findings suggest that such policies have significant spillover effects (through better repurposing infrastructure and policies) on the success of online markets for used and surplus materials, by-products and wastes. This research contributes to the understanding of how regional factors affect repurposing operations through OMWEs, which can help inform environmental policy (Atasu et al. 2008; Gui et al. 2013) for the future.

3.5.2 Developing OMWE platforms

On the buyer side, we show that product and transaction information richness positively affects exchanges. This finding is in line with past literature on online markets (Pavlou & Gefen 2004; Pavlou et al. 2007; Overby & Jap 2009). The next step for OMWEs is to improve online platforms by increasing transparency and information richness. As already mentioned, reputation mechanisms are not widely used in OMWEs today. Infrequent listings by each seller in OMWEs translates into few opportunities for a given supplier to be rated and also for the supplier to be effected by the reputation implied by the rating. A potential alternative being explored by MNExchange.Org to improve information credibility and reduce uncertainty is manual verification of each item description before it is listed online. Such a verification process, while costly, could ensure the listing has a threshold level of information to reduce product uncertainty. As OMWEs grow in scale, this verification process could be replaced by automated feedback mechanisms.

This study also has implications for understanding user behavior in the absence of online reputation mechanisms (Bolton et al. 2004; Pavlou & Gefen 2004). The results show that previous experience (i.e. familiarity) between the buyer and seller increases the likelihood of an exchange. The analysis also shows that the buyers' previous experience as a seller further increases exchanges. Users rely extensively on past experiences to make decisions; consequently exchanges should encourage long-term relationships between buyers and sellers. This topic of relationship-building is currently being addressed by many OMWEs. A potential solution being proposed is that certain types of items and transactions might necessitate "personal intervention" by the OMWE staff/experts to facilitate contracting and develop long-term relationships (Director at iWasteNot Systems 2014). Interestingly, our analysis shows that recurring items (which need long-term contracting) have a lower likelihood of being exchanged. This validates concerns expressed by OMWE staff at MNExchange.Org that exchanges of recurring items have higher initial transaction costs. To develop long-term buyer-seller contracts, OMWEs should consider some form of personal intervention that reduces uncertainty and builds trust. Potentially, this could lead to a self-sustaining industrial symbiosis between multiple collocated OMWE users, with OMWEs serving as the supporting platform.

3.6 Limitations

One limitation of this study is our choice of waste exchange. MnExchange.Org is a mixed waste exchange that consists of products with different levels of reusability. To account for this we controlled for the 14 material classes and conducted additional *post hoc* analysis based on various product attributes. However, there may be significant variance in the quality and usability of items within these 14 categories which our models do not capture. Also it is possible that product specific legislations and policies affect exchange success on OMWEs. For example, various states have now passed electronics recycling acts that might affect how electronics are traded through OMWEs. Future research is needed to examine exchanges of specific products (e.g. packaging materials, rubber, electronics etc.) to verify the generalizability of our results. Also, OMWEs can undergo technological and policy changes that may not have been captured entirely by our models. For example, although we control for year effects, intermittent changes to the online interface are not captured by our models. Also, our inferences are limited to the registered organizations in our sample, and may not extend to the general population of firms.

Although we used the best measures available from the data source, some of our independent measures have limitations, as is the case with most studies that rely on secondary data. For example, *Textual Information Length* is measured as the total number of characters in the description. However, one could argue that a lengthy description may not necessarily provide a richer explanation of the product details. Furthermore, the quality of *Visual Information Content* may also vary across items. Our data on *Access* to disposal and repurposing alternatives comes from a separate secondary source (e.g. Minnesota Pollution Control Agency), which may have limitations. For example, the county-level statistics on repurposing and disposal comes from annual survey responses, which could be prone to reporting errors (Bertrand & Mullainathan 2001). At the interaction level, it is possible that some interactions represented serious buyers, whereas others might represent curious users simply surfing the database. Unfortunately, we cannot capture buyers' true intention which could potentially lead to biases in evaluation of transaction frequency. Finally, this study looks at the 'last hurdle' (i.e. actual exchange) problem since this is the most pertinent metric for evaluating OMWEs. Yet, we do not focus on many other crucial metrics such as final usage of exchanged items, user membership, hits on listings etc. While this paper lays the foundation for additional research on Online Materials & Waste Exchanges (OMWEs), we hope some of the limitations and open questions trigger more research in this area.

Chapter 4

ESSAY 3 - The Role of Online Intermediaries in Coordinating Industrial Surplus Chains: Operational Policy Change and Adverse Outcomes[13]

Summary

Online Material & Waste Exchanges (OMWEs) are internet-based B2B markets that coordinate transactions of surplus materials, by-products and waste across industrial facilities. Collectively, OMWEs possess the potential to repurpose millions of lbs. of industrial materials and save billions of dollars in disposal fees and inventory costs. Many OMWEs have traditionally relied (at least partly) on *human intermediaries* to match producers and consumers, facilitate negotiations and coordinate transactions. Today, most OMWEs have transitioned into decentralized *online* platforms, which parallels the "move-to-the-market" or "disintermediation" trends observed in many industrial sectors. In this paper, we question such sole reliance on internet-based technologies. Using a quasi-experimental design afforded by a unique empirical setting (MNExchange.Org), we examine the effects of an *operational policy change* which eliminated *human intermediaries*. We show that elimination of this form of intermediary had dire consequences on the market efficiency as measured by (i) likelihood of successful transactions and (i) time to a successful transaction. Although the overall effect was significant, we also find more nuanced effects for certain types of items. Specifically, process-use (relative to end-use), negotiable (relative to free) and one-time (relative to recurring) items faced significantly greater transactional challenges. We discuss the implications of these findings for supply chain intermediaries and internet-based marketplaces.

Keywords: *Surplus Chains, Materials & Waste Exchanges, Quasi-Experiment, B2B Online Markets, Intermediaries*

4.1 Introduction

"Technology [is] our planet's last best hope" (The Guardian Environmental Network 2013).

"Technology cannot solve all environmental problems" (European Environmental Agency 2014).

Industrial facilities abound with surplus materials, by-products and waste. For example, U.S. companies cumulatively generate more than 7.5 billion tons of by-products and waste annually[14]. The annual overstock of unused materials and inventory in U.S. companies exceeds $350 billion[15] and large portion of this eventually reaches obsolescence[16]. This problem calls for

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[14] http://www.epa.gov/osw/nonhaz/industrial/

[15] http://www.dmnews.com/e-surplus-market-to-boom/article/63516/

[16] http://www.enxmag.com/twii/feature-articles/2013/06/the-overstock-parts-network-adds-new-life-to-old-parts/#.VDACj_ldWIM

innovative approaches to coordinate supply chains to better facilitate transactions of these materials. Although challenging, effective management of industrial "surplus chains" increases repurposing of materials, by-products and wastes, which may have otherwise ended up being disposed. Recently, Material & Waste Exchanges have emerged across the U.S. and Europe as a means to facilitate exchanges of industrial surplus materials, by-products and waste. According to the EPA (2013a), "Materials and Waste Exchanges are [B2B] markets for buying and selling reusable and recyclable commodities. Some are physical warehouses that advertise available commodities through printed catalogs, while others are simply web sites that connect buyers and sellers". While few Material & Waste Exchanges still operate as physical warehouses, most have transitioned to internet-based platforms (i.e. OMWEs) that connect industrial buyers and sellers (see Figure 1). If managed well, OMWEs can enable efficient transfer of surplus materials, by-products and waste across industrial facilities, thereby generating substantial environmental and economic benefits.

More than 100 OMWEs operate in the U.S. today[17] (EPA 2013a). Collectively, OMWEs possess the potential to repurpose millions of lbs. of industrial materials and save billions of dollars in disposal fees and inventory costs. Large-scale OMWEs (e.g. MNexchange.org, Reusemarketplace.org) typically host hundreds of industrial materials, by-products and wastes. A major challenge in these exchanges is efficient matching of buyers and sellers. Traditionally, many OMWEs relied, at least partly, on expert *human intermediaries* (henceforth also referred to as *intermediaries*) to match producers with consumers, facilitate negotiations and coordinate transactions. Today, most OMWEs have almost completely transitioned to pure internet-based *online* platforms, allowing sellers to directly post listings and buyers to directly negotiate transactions. As a result, the role of *human intermediaries* has almost entirely been substituted by pure *online* platforms. For most OMWEs, the move towards internet-based platforms is driven by resource constraints[18]. The shift towards pure internet-based platforms also parallels the "move-to-the-market" or "disintermediation" trends observed in many other sectors, where traditional brick-and-mortar business models are either being complemented (Gallino & Moreno 2014) or entirely substituted (Brynjolfsson & Mcafee 2012) by internet-based platforms. Internet-based platforms are expected to improve scalability and lower coordination costs (Malone et al. 1987; Bakos 1991; 1998), potentially providing a more efficient matching between buyers and sellers.

[17] The number of operating OMWEs is far greater (conservative estimates indicate at least 200) when local/county-level exchanges are included. OMWEs are common in other regions such as Canada (British Columbia IMEX), U.K. (Eastex), Singapore (Waste is Not Waste) and India (CII Waste Exchange).

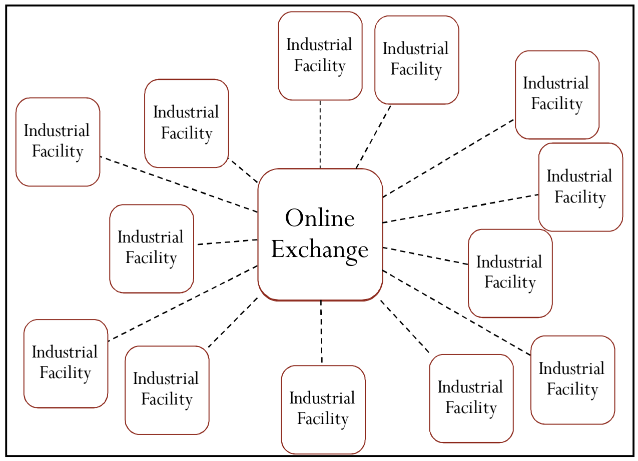
[18] Most Material & Waste Exchanges are managed by state environmental agencies and are offered as a free service. Although some exchanges charge a nominal fee to cover basic costs of hosting the platform, almost no Material & Waste Exchange has a profit-driven business model. As a result, resource constraints often lead exchanges to reallocate expert *human intermediaries* to other tasks related to environmental enforcement, recycling market development etc.

Evidently, a complete reliance on pure internet-based platforms is seen as the next "logical step", which can allow OMWEs to "…operate with less than one FTE" (2005 Annual Report of large-scale OMWEs in U.S.). This study challenges this sole reliance of OMWEs on internet-based platforms, by highlighting the advantages of using the expertise of *human intermediaries.* We examine the downside of eliminating *human intermediaries* on transactions in OMWE.

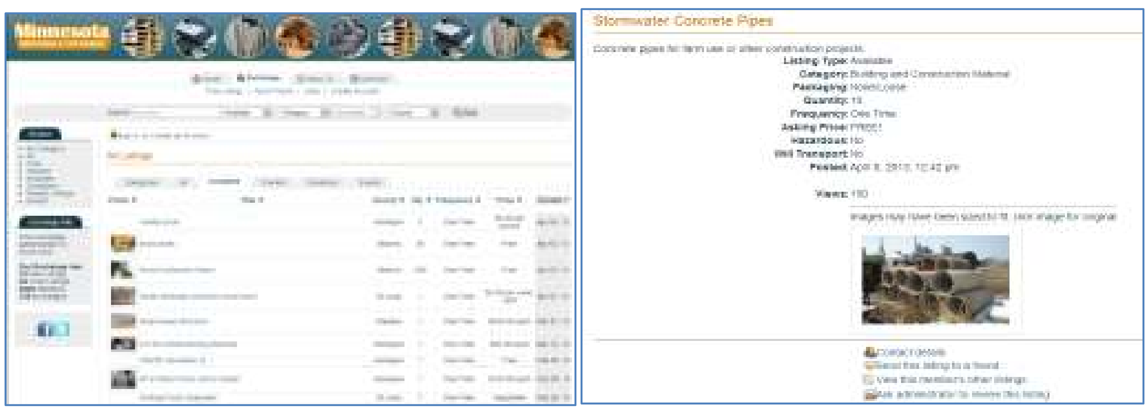
As an empirical setting, we use a large-scale state-level OMWE – MNExchange.Org – located in Minnesota, U.S. Taking advantage of a unique quasi-experiment (Shadish et al. 2002), we study the effects of an operational policy change that eliminated the *human intermediaries* in MNExchange.Org. Using longitudinal data spanning nine years and more than 4000 item listings, we show that the policy change had significant implications for MNExchange.Org. In particular, the operational policy change had substantial adverse effects on two metrics of transaction success: (i) likelihood of transaction and (ii) time to successful transactions. Furthermore, we show greater adverse effects on specific categories of items. Transactions of *process-use* items (e.g. plastics, rubber, wood, leather and equipment) suffered much more compared to transactions of *end-use* items (e.g. electronics, furniture, paper and supplies). Along similar lines, we find a significantly greater decline in transactions of *negotiable* (i.e. non-free) items compared to *free* items; a significant decline in transactions of *one-time* items compared to *recurring* items. Similarly, the time to a successful transaction increased for *process-use* (compared to *end-use*), *negotiable* (compared to *free*) and *one-time* (compared to *recurring*) items. Further investigation into the mechanisms reveals shifts in seller and buyers behaviors. The analyses highlight the negative consequences of relying solely on internet-based technologies, while highlighting the importance of *human intermediaries* to facilitate exchanges.

Our study provides important insights into the design of OMWEs, which have been widely recognized by environmental agencies as a "unique tool" to overcome the waste problem and generate savings (EPA 1978; EPA 1994; EPA 2013a; MPCA 2011). Undoubtedly, unpacking the potential of OMWEs can generate immense environmental and economic benefits. In this paper, we present a practical problem of coordination (Cachon 2003) in industrial surplus chains and illustrate the effectiveness and limitations of an internet-based solution - OMWEs. Our study also questions the "move to the market" (Malone et al. 1987) hypothesis which argues in favor of internet-based technologies "substituting" (Brynjolfsson & Mcafee 2012) for human intermediaries. Recently, the "flat world" hypothesis has been questioned by scholars based on the increasing presence of supply chain intermediaries (Belavina & Girotra 2012). Using OMWEs as an empirical setting, our study shows that sole reliance on internet-based technologies may have shortcomings in coordinating surplus chains. Furthermore, we show that *human* *intermediaries* provide greater transactional advantages for process-use, negotiable and one-time items, and eliminating such intermediaries can result in a market favoring low-cost, end-use items offered on a recurring basis. This provides practical implications for the management and design of B2B marketplaces serving waste and surplus markets.

Figure 4-1. Conceptual Model for OMWEs



Snapshots for MNExchange.Org



4.2 Literature Review

This study builds on literature from three separate domains related to environmental supply chains, online marketplaces and supply chain coordination. A review of the related literature follows.

Environmental supply chains have received increasing attention from OM scholars (Atasu, Guide, et al. 2008). Researchers in this area have addressed various problems related to OEM remanufacturing including disassembly and recovery (Guide & Wassenhove 2001), production planning (Guide 2000), inventory management (Toktay et al. 2000) and marketing (Atasu, Sarvary, et al. 2008). Recent research has also begun to examine the benefits of third-party de-manufacturing (Savaskan et al. 2004; Tibben-Lembke 2004) which consist of the logistics, sorting and materials recovery processes performed by third-party providers (Spicer & Johnson 2004). Finally, researchers (Desrochers 2004; Chertow 2007; Lee 2012) have also examined the industrial symbiosis perspective which views the industrial processes as a biological ecosystem that can survive on its own by-products. Broadly, this study shares the spirit of these papers by "integrating issues at the interface of environmental sustainability and supply chains" (Linton et al. 2007). Yet, this paper makes a unique contribution to this literature by examining an online market-based approach for addressing environmental challenges. In doing so, our paper extends the exploratory work of Dhanorkar et al. (2014), which identified buyer- and seller-side factors that lead to transaction success on OMWEs. In this paper, we focus on a specific operational problem in the design of OMWEs.

The literature on *online markets* is also relevant to our study. OMWEs are online B2B markets that facilitate transactions of reusable and recyclable materials. Online marketplaces have long been a subject of attention for IS scholars (Bakos 1991; Bakos 1998). Information asymmetry has been recognized as one of the most important obstacles in achieving efficient online transactions (Lee & Whang 2001). This paper borrows from the IS literature and builds on previous research on information asymmetry in online marketplaces. More recently, scholars have highlighted the informational challenges in transacting used goods. For example, Ghose (2009) shows that despite the presence of reputation mechanisms, online transactions of used goods are prone to adverse selection. Similarly, Dimoka et al. (2012) showed that used goods have more product-related uncertainty, which subsequently affects sellers' price premiums. In general, these studies highlight challenges in achieving higher social welfare (Bapna et al. 2008) through online transactions, especially in the context of used products with high uncertainty. Recently, Overby and Jap (2009) showed that online channels are better for transacting products with low uncertainty, while physical channels work better for products with high uncertainty. Although these papers (Ghose 2009; Overby & Jap 2009; Dimoka et al. 2012) are relevant to our context, they primarily focus on B2C marketplaces for commodity products. Poundarikapuram and Veeramani (2004) develop a distributed decision-making framework for users in an e-marketplace to collaboratively arrive at a global Pareto-optimal solution, while maintaining the information privacy of supply chain partners. Yet, much of the research on e-commerce focuses on B2B transactions of primary products – raw materials and finished goods. In contrast, our study focuses on challenges in facilitating B2B transactions of industrial surplus materials, by-products and waste. Our study is also very relevant to previous work on e-commerce. For example, companies experience various challenges driven by information asymmetry in e-commerce transactions (Balakrishnan & Geunes 2004). Transactions on OMWEs are often more challenging due to a lack of seller reputation mechanisms,[19] which results in high information asymmetry.

A large body of research exists on the topic of *supply chain coordination* through contractual arrangements (Cachon 2003). Intermediaries offer one approach to better coordinate supply chains. Earlier research has highlighted the advantages and disadvantages of supply chain intermediaries in B2B transactions (Wu 2004). With the advent of internet-based technologies, the "disintermediation" (i.e. the elimination of human intermediaries) hypothesis has been strongly argued over the past few decades (Benjamin & Wigand 1995). While disintermediation was first used with reference to financial services (Wu 2004), it more broadly predicted that significant efficiencies can be achieved in buyer-seller interactions by cutting out the middlemen and replacing them with internet-based/digital platforms (Hoffman 1995; Malone et al. 1987). Yet, research has also highlighted the usefulness of intermediaries (Sarkar et al. 1995) despite the rapid growth in e-commerce. For example, Belavina and Girotra (2012) showed that large-scale human-supported intermediaries (e.g. Li & Fung Ltd., Olam International) continue to exist in the traditional supply chain context. Often supply chain intermediaries provide transactional (reducing search and bargaining costs) and informational (enabling trust and reducing adverse selection) benefits, which justify their presence in B2B transactions (Wu 2004). Consequently, some researchers (Bakos 1998; Bailey & Bakos 1997) have proposed that intermediation and` disintermediation are both potential solutions, albeit under different contextual settings. On a related note, Kleindorfer and Wu (2003) integrate concepts from B2B market and supply chain contracting to show the conditions under which online spot markets versus contractual arrangements are more appropriate. Our paper contributes to this debate by testing the effectiveness of a "disintermediation" (i.e. elimination of *human intermediaries*) strategy in a unique OMWE quasi-experimental setting. Furthermore, we show how specific product categories may necessitate the presence of human intermediaries to overcome transactional challenges in online markets.

4.3 Quasi-Experimental Setting

The Environmental Protection Agency (EPA) identifies OMWEs as a way to exchange industrial materials and avoid disposal (EPA 2013a). Today, almost every state in the U.S. has an OMWE. For example, The Reuse Marketplace in New England is an example of an OMWE supported by state agencies and private businesses. It is administered by Northeast Recycling Council, a

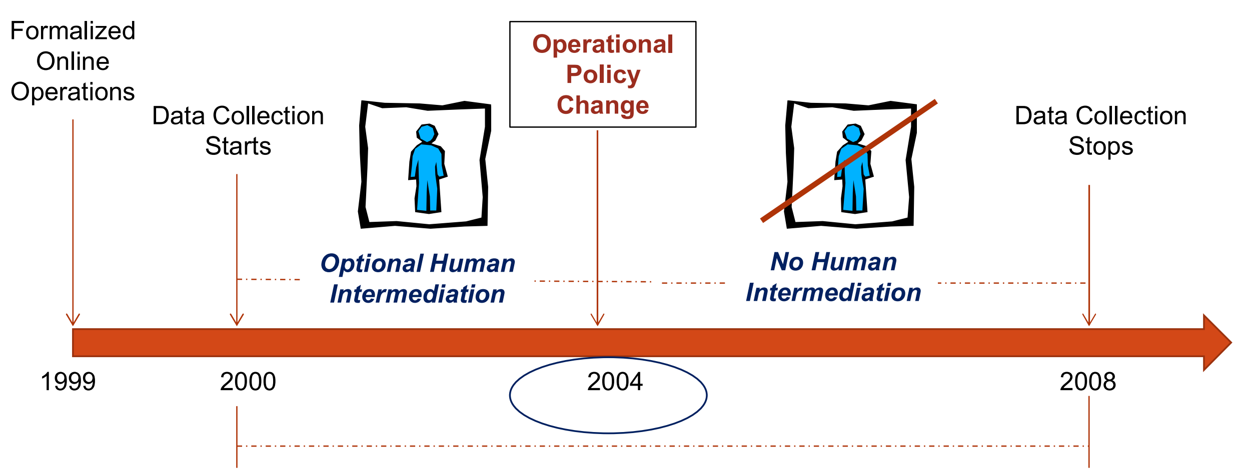
[19] Seller reputation mechanisms are effective when sellers participate frequently and the volume of transactions is adequately high (Heski & Tadelis 2008). Both these conditions are often not satisfied in OMWEs. As a result, no OMWEs currently offer seller reputation/ feedback mechanisms.

regional nonprofit dedicated to an environmentally sustainable economy through reuse, recycling, and green purchasing. The Resource Exchange Network for Eliminating Waste (RENEW) in Texas was established by the Texas legislature in 1987. This exchange covers Arkansas, New Mexico, Oklahoma, Louisiana, and Texas. The Minnesota Materials Exchange Program (MNExchange.Org) is a grant-funded exchange that connects industrial and commercial facilities across Minnesota. It is hosted by the Minnesota Technical Assistance Program. While the format of each OMWE may vary slightly, there are several commonalities. In a typical OMWE, sellers list items they no longer need while potential buyers browse listings and request exchanges. The overwhelming majority of OMWEs are offered as free services open to industrial facilities. Sellers on the exchange list the items available for sale, typically with a brief description and visual illustration of the product. Contact information is made available to allow interested buyers to connect with the seller. OMWEs do not offer an online payment option; pricing (product and transportation) is negotiated by buyers and sellers offline.

The empirical setting for this study is the Minnesota Materials Exchange - MNExchange.Org (henceforth also referred to as "the exchange"). This exchange provides a useful empirical context for the following reasons. First, MNExchange.Org has been operational since 1999 and has thousands of registered users, which makes it a mature exchange. It has helped divert more than 25 million lbs. of waste from being disposed in landfills or incinerators, and reduced disposal fees and material costs exceeding $6 million. As of 2010, the exchange had 12,256 registered members representing approximately 8000 industrial and commercial facilities. MNExchange.Org is therefore an appropriate empirical context, given its scale and longevity. MNExchange.Org operates in a similar manner to many other exchanges across the United States and abroad, which improves applicability of our findings. Dhanorkar et al. (2014) also used the MNExchange.Org as an empirical setting in their exploratory study to examine buyer-side (information, uncertainty) and seller-side (access to alternatives, regional policies) factors that influences exchanges on OMWEs. Although our paper overlaps with Dhanorkar et al. (2014) in the choice of empirical setting, we examine the problem of OMWE design (specifically intermediation) using a quasi-experiment to understand the adverse effects of sole reliance on internet-technology on exchange likelihoods and durations. As a result, our conceptual, measurement and analysis approach is substantially different.

MNExchange.Org became operational in 1999 with the intention of matching industrial facilities to promote reuse of surplus materials, by-products and waste (**Figure 4-2**). Between 1999 and 2004, MNExchange.Org (the web interface) acted as an information portal where buyers and sellers could establish contact and negotiate contractual terms offline. During this period, users could also seek help from expert *human intermediaries* (employees of MNExchange.Org), who helped match potential buyers with sellers, facilitated bargaining, and coordinated transactions. The *human intermediaries* did not actively target specific categories of materials or users on the market; users sought services from *human intermediaries* when necessary. Internet-based technologies were picking up during this period, with rapid growth in internet usage and e-commerce [for details on growth in B2C and B2B platforms, see (Ho et al. 2007)]. In line with these trends OMWEs had begun transitioning into completely decentralized online platforms. Like many other OMWEs, MNExchange.Org revised their operational policy in late 2004, which gave emphasis to the *online* aspects of the exchange while eliminating *intermediaries*. As a result, starting 2005, *"...service improvements and database streamlining finally allowed operations by less than one FTE"* (MNExchange.Org Report, 2008). We examine the effect of this operational policy change on two transaction outcomes that drive OMWE efficiency. We use the quasi-experimental design (Shadish et al. 2002) in this empirical setting. Earlier studies have adopted a similar approach to investigate operational policy changes in the online/offline environments (Hann & Terwiesch 2003; Overby & Jap 2009; Gallino & Moreno 2014). For example, Hann & Terwiesch (2003) examine the effect of an operational policy change in a Name-Your-Own-Price online retailer; Overby and Jap (2009) examine the effects of adding an online channel to vehicle auctions; Gallino and Moreno (2014) studied the implementation of a "buy-online, pickup-in store" alternative in retail operations. We use a similar approach to show the effect of an *Operational Policy Change* that eliminated physical *human intermediaries* in MNExchange.Org. Further, we also compare and contrast the effect of the *Operational Policy Change* on specific categories of items based on usage (process-use vs. end-use), asking price (free vs. negotiable) and frequency (one-time vs. recurring).

Figure 4-2. Quasi-Experimental Setting



4.4 Hypotheses Development

4.4.1 The Role of Human Intermediaries in Coordinating Surplus Chains

The unpredictable supply of industrial surplus materials, by-products and waste can make buyer-seller matches especially challenging on OMWEs (Dhanorkar et al. 2014). On the buyer side, high variability in supply of materials can be disadvantageous since it adds variability to processes (Lee et al. 2004). As a result, buyers may be reluctant to source from OMWEs, partly due to the unpredictability of supply. OMWEs need to overcome this problem in order to increase transaction rates and allow easier flow of surplus materials across industrial facilities. Human intermediaries can play an important role in reducing the unpredictability of the supply on OMWEs. In situations with high supply unpredictability, "mixed mode" (that is, a combination of online and human intermediaries) platforms (Holland & Lockett 1997) have advantages over purely internet-based platforms. Mixed mode platforms offer informational and transactional benefits of intermediation (Wu 2004) along with scale benefits of internet-based platforms (Bakos 1997). Furthermore, expert intermediaries can enhance[20] the search and matching function of OMWEs to identify dormant buyers (i.e. those not actively searching). This can improve the overall market efficiency. Hence, human intermediaries can provide complementary benefits (Bailey & Bakos 1997) to OMWE exchanges.

A second benefit of human intermediaries is that they can help reduce product uncertainty. Product uncertainty in online markets is defined as "the buyer's difficulty in evaluating the product and predicting how it will perform in the future" (Dimoka et al. 2012). Online exchanges of secondary products (Ghose 2009) have high uncertainty for buyers, which can lead to transactional challenges (Dhanorkar et al. 2014). Materials traded on OMWEs can have a high degree of quality heterogeneity (Ghose 2009). As a result, product uncertainty can be extremely high in OMWEs, which makes evaluations difficult. A related problem that amplifies product uncertainty is the buyer's inability to evaluate the seller. In conventional online markets, reputation- and trust-building mechanisms reduce seller reputation concerns (Pavlou et al. 2007). However, the infrequent and low-volume nature of OMWE transactions does not allow for effective use of reputation- and trust-building mechanisms. Consequently, OMWE's have high levels of product uncertainty. Intermediaries can provide informational benefits in supply chains (Wu 2004). In the OMWE context, *human intermediaries* can help reduce buyer's concerns about quality due to information asymmetries. Essentially, the intermediary may act as a third-party

[20] We had a related discussion with an expert intermediary from an exchange in Minnesota (MNExchange.Org). She explained a situation where a process-use items item (10 tons of rubber pellets) was in stock with a seller. After waiting two weeks for online buyers, the seller contacted the intermediary. The intermediary was able to find a registered buyer who was not actively searching on the OMWE (i.e. was dormant) but had a demand for the rubber pellets.

assurance that the seller's product quality meets the buyer's quality expectations. Intermediaries also bring to the table, relational advantages (Belavina & Girotra 2012) through their industry networks and process knowledge. In the context of OMWEs, intermediaries have in-depth knowledge of company policies towards material sourcing, product reuse and recycling markets. In summary, by reducing information gaps and providing relational benefits, intermediaries can significantly alleviate buyers' uncertainty.

Thirdly, human intermediaries can also help industrial facilities navigate regulatory policies. State and regional environmental authorities often regulate the transfer, sale and disposal of potentially hazardous materials such as chemicals, rubber, paint etc. As per the federal (EPA 2012) and state (MPCA 2013) regulations, the producer (i.e. seller) bears significant responsibility for the management and/or disposal of hazardous waste/by-products. As a result, the seller may be held responsible for any misuse of hazardous materials by the transporter or the buyer (MNExchange.Org Staff 2013). This can lead to a moral hazard problem where the costs of potential material mishandling will be disproportionately borne by the seller (Logue & Ben-Shahar 2012). Consequently, sellers may choose alternative disposal options over OMWEs in anticipation of a buyer's potential misuse of exchanged items. In addition, the shipping and handling of hazardous waste/by-products is subject to regulations (EPA 2012). Transporters of solid waste and industrial materials classified as hazardous typically require special operating permits, which increases the transaction costs of an exchange (MPCA 2013). Consequently, there are significant concerns about regulatory compliance in OMWEs. However, expert intermediaries typically possess in-depth knowledge about regional disposal, reuse and recycling policies. Since OMWEs are typically managed by state/regional environmental agencies, intermediaries (as employees of the agencies) are up-to-date with environmental rules and regulations. As a result, human intermediaries bring greater regulatory legitimacy (Bloomfield & Best 1992) to OMWE transactions. Given the above advantages of *human intermediaries* in OMWE transactions, we predict that eliminating human intermediaries will have a negative effect on transaction outcomes.

H1: *Eliminating Human Intermediaries will be associated with (a) a decline in the likelihood of successful transactions and (b) an increase in the duration to a successful transaction.*

4.4.2 Usage – Process-Use versus End-Use Items

As predicted in H1, *human intermediaries* in OMWEs can affect transaction outcomes. However, the usefulness of human intermediaries may depend on the type of item being exchanged.

OMWEs broadly categorize items[21] as *end-use* (commodities and consumer durables such as electronics, office supplies, furniture etc.) and *process-use* (raw materials and by-products such as wood, rubber, plastics etc.). The three challenges discussed above (supply unpredictability, quality uncertainty, and regulatory compliance) may depend on the material exchanged. We argue that the elimination of *human intermediaries* has a more negative impact on *process-use* item transactions compared to *end-use* item transactions for the following reasons.

First, the potential impact of supply unpredictability is relatively low for end-use items since they do not typically comprise inputs to buyer-side processes. On the other hand, fluctuations in supply of process-use items can lead to higher transactional challenges. The unpredictable generation (i.e. supply) of process-use items can create challenges in finding the appropriate buyers. Unlike most end-use items which have a general purpose applications, process-use items often have only specific applications. For a process-use item to be exchanged on an OMWE, it needs to match specifications of an interested buyer who has demand and engages in online search on the OMWE. All these reasons make process-use item transactions highly difficult in the absence of human intermediaries. Second, any deviations from expected process-use item quality can introduce quality defects in the buyer's products and processes. On the other hand, any quality shortcomings in end-use items quality can only affect/limit its end-usability. Evidently, process-use item quality has greater implications for buyers. It can therefore be argued that buyers' concerns about product uncertainty are relatively higher for process-use items than for end-use items. A policy that eliminates intermediaries will therefore have a greater negative effect on process-use item transactions. Finally, transactions of process-use items (raw materials and by-products such as wood, rubber, plastics etc.) often require greater knowledge about regional policies and regulations about disposal, transportation, handling, reuse and recycling (MPCA 2013). Typically, OMWE transactions are managed by purchasing/inventory departments[22] in industrial facilities, which often lack the required knowledge related to environmental benefits and costs of industrial exchanges of surplus materials, by-products and wastes. Environmental compliance requirements associated with exchanges of process-use items can burden facilities with additional transaction costs (Tadelis & Williamson 2010). Elimination of intermediaries will therefore have a more dire consequence on process-use item transactions.

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[21] The classification scheme in this study was developed through many discussions with large-scale OMWEs in Minnesota, Alabama, Texas and New York (United States) and British Columbia, Ontario (Canada). In addition, a research assistant browsed and studied more than 30 OMWEs across the U.S. to compare the type of items being exchanged. The process-use and end-use classification was also confirmed during a formal presentation to the Minnesota Pollution Control Agency's Solid Waste and Reuse Markets divisions.

[22] Although uncommon, OMWE transactions are sometimes handled by the waste management/environmental & health safety divisions in industrial facilities. In such cases, knowledge about regulatory compliance issues might be internally available. Discussions with companies revealed that the intermediaries' "expert advice" can still be valuable.

H2: *Eliminating Human Intermediaries will be associated with (a) a greater decline in the likelihood of successful transactions of process-use items compared to end-use items and (b) a greater increase in the duration to a successful transaction of process-use items compared to end-use items.*

4.4.3 Price – Free versus Negotiable

Buyers face significant product-related uncertainty in online markets (Bakos 1991) such as OMWEs, since various product attributes (condition, quality etc.) are unobservable. Online electronic markets are extremely susceptible to problems related with uncertainty, since information asymmetries emerge when buyers and sellers are separated by time and space (Dewan & Hsu 2004). In other words, while sellers themselves are aware of the true quality of the products, buyers can only rely on seller-provided information to make evaluations of the unobserved quality. In such circumstances, buyers expect higher price discounts to overcome their uncertainty and engage in transactions. This behavior results in adverse selection (or the "lemons market" problem) (Akerlof 1970), which refers to a market equilibrium where lower quality (and lower price) products get exchanged as a result of high information asymmetry. The result of such user preferences is a downward spiral towards lower price and quality items being favored in the market.

Since quality is difficult to assess in our context, we examine the listings and transactions of free (vs. negotiable) items. On OMWEs, sellers often refrain from providing exact prices (in MNExchange.Org barely 2% item listings have an associated asking price; the rest are listed as either 'negotiable' or 'free'). For items listed as 'negotiable', buyers and sellers bargain offline to arrive at a price; for 'free' items, buyers merely bear the transportation costs while the incentive for sellers comes from reduced disposal costs. On OMWEs, intermediary services can reduce (if not entirely eliminate) information asymmetries about product quality (Dewan & Hsu 2004). However, in the absence of human intermediaries, information asymmetries between buyers and sellers (Koch & Schultze 2011) will lead to higher uncertainty and consequently, greater adverse selection. The resulting effect on OMWEs will drive out the negotiable (higher quality and price) items in favor of free (lower quality and price) items. This suggests the following hypothesis.

H3: *Eliminating Human Intermediaries will be associated with (a) a greater decline in the likelihood of successful transactions of negotiable items compared to free items and (b) a greater increase in the duration to a successful transaction of negotiable items compared to free items.*

4.4.4 Frequency – One-time versus Recurring

Research shows that transaction costs in physical (Tadelis & Williamson 2010) and online markets (Bakos 1991) reduces the buyers and sellers incentives to exchange with one another.

Transaction costs play an important role in determining outcomes of online interactions. In the OMWE setting, transaction costs comprise of *search* (identifying a transacting partner) and *bargaining* costs (negotiating the contract) incurred by buyers and sellers during a transaction (Dahlman 1979; Williamson 1995). As with any other transaction (Kleindorfer & Wu 2003), user decisions in OMWEs are likely to be driven by the motivation to minimize transaction costs (Dhanorkar et al. 2014). Human intermediaries can enhance search efficiency while also improving bargaining through higher information transparency (Wu 2004). As a result, exchanges combining both online markets and human intermediaries (Holland & Lockett 1997) helps reduce transaction costs.

Sellers on MNExchange.Org (and most other OMWEs)[23] offer items either on a one-time basis or a recurring basis. One-time items, as the label suggests, comprise of items offered by sellers for a single transaction with interested buyers. Recurring transactions usually involve the possibility of ongoing exchanges on a daily, weekly or monthly basis.[24] Although both types of transactions can have associated transaction costs, they may vary substantially depending on the presence of an intermediary. For example, both parties (buyers and sellers) incur *search* and *bargaining* costs for each one-time transaction. These costs are incurred, as described by Kleindorfer and Wu (2003), in establishing one-time transactions. On the other hand, *search* costs can be virtually eliminated (for subsequent transactions) and *bargaining* costs can be substantially minimized in recurring exchanges since the same parties are engaged in long-term exchanges. Since *search* and *bargaining* costs can be substantially high for one-time exchanges in the absence of human intermediaries in OMWEs, users will avoid transactions of one-time items. On the other hand, *search* and *bargaining* costs for recurring items will be distributed over multiple exchanges (Kleindorfer & Wu 2003), therefore driving down the cost per transaction for buyers and sellers. As a result, transactions for recurring items (longer-term arrangements) will be favored after the operational policy change.

H4: *Eliminating Human Intermediaries will be associated with (a) a greater decline in the likelihood of successful transactions of one-time items compared to recurring items and (b) a greater increase in the duration to a successful transaction of one-time items compared to recurring items.*

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[23] We surveyed 20 other OMWEs in other regions such as Canada (British Columbia IMEX), U.K. (Eastex), Singapore (Waste is Not Waste) and India (CII Waste Exchange). Most of these have very similar operations.
[24] Information regarding the frequency of recurring transactions is typically provided by the seller. However, this may be negotiated as per the availability (supply) and demand for the materials.

4.5 Econometric Analysis

4.5.1 Data

The available archival data spans 1999-2008 and consists of product listings, buyer views (i.e. hits), and product-, seller- and buyer-specific information. We exclude data prior to 2000 since the exchange was still evolving at that time. Out of the total 4500 item listings available, we were missing information for various measures on approximately 460 listings. Most of the missing information was due to recording errors (for user size, county, organization type etc.). We resolved 215 of these cases through discussions with MNExchange.Org and other data sources (Hoover's and ORBIS). Finally, we dropped listings where information was missing on more than two control or independent variables. Since the listing and exchange dates are extremely important in our study, we dropped cases where this information was not accurate or missing. For example, some listings only had information about the month but not the exact date; these cases were dropped. The final sample consisted of 4055 listings and 869 successful transactions. We matched other county-level data from Minnesota state public records and Minnesota Pollution Control Agency (MPCA) reports on county-level statistics. **Table 4-1** shows the description and statistics of all variables. Product classifications (free/negotiable and one-time/recurring) were based on listings submitted by sellers in the respective fields. Classification based on use (process-use/end-use) was made based on discussions with MNExchange.Org staff (specifically the Director, administrators and intermediaries) as well as regulatory experts at the MPCA.

Table 4-1. Variable Descriptions & Summary Statistics

Variable	Variable Description	Mean	Std. Dev
Exchange	Binary [Outcome] Variable indicating whether the listed item was exchanged successfully	0.20	0.40
Time to Exchange	For successfully completed transactions, this [Outcome] variable captures the time (days) since the item was listed by the seller to the time when it was exchanged.	17.50	75.91
Operational Policy Change	This is a binary [0, 1] variable based on the time when policy change was initiated. Following the Figure 1, we record policy change as the years after 2004. The Operational Policy Change led to the elimination of *human intermediaries*.	0.46	0.49
Process-Use/ End-Use	This classification was based on discussions with MNExchange.Org and Minnesota Pollution Control agency officials. We classify Process-use items as following: Equipment & Machinery, Construction Materials, Plastics and Rubber, Textiles & Leather, Wood Products. We classify End-use items as following: Electronics, Office Furniture, Office Supplies, Paints & Cleaners, Boxes & Containers, Paper Products.	0.34	0.47
Free/Negotiable	Binary Variable representing whether item listed was offered for 'free' by the seller. Apart from the environmental benefits, sellers benefit through reduced disposal fees despite 'free' exchanges.	0.52	0.50
One-Time/ Recurring	Binary variable indicating if the item was being offered by the seller on a recurring basis (i.e. weekly/ monthly etc.). For e.g. furniture manufacturer (seller) could list wood chips as recurring.	0.27	0.44
Total Hits on Listing	Log total number of buyer web hits on the listed item. Captures overall interest in the listing i.e. "potential demand".	2.46	1.26
Total Hits on Listing^2	Squared logarithm of total buyer hits on the listed item. Interviews and exploratory analysis showed that successfully exchanged items tended to have either low hits (indicating fast exchange) or high hits (indicating high potential interest). This suggested a curvilinear relationship.	7.65	6.35
Textual Information Length	Sellers provide a textual description along with the item listing. This variable is the Logarithm of the number of characters in the textual information provided by sellers for the listed item.	3.92	0.94
Visual Information Dummy	Binary variable indicating if seller provided any visual information content (e.g. picture, user manual etc.) along with listing. This can alleviate uncertainty (Dimoka et al. 2012)	0.10	0.31
Hazardous	Binary variable indicating if the item posed any safety hazard. This was controlled for because such materials were less likely to get exchanged due to risks and higher transportation costs.	0.04	0.20
MNExchange.Org Diffusion in Buyer/Seller County	Log of the number of registered MNExchange.Org users in seller's/buyer's county, accounts for diffusion of OMWEs. This variable was estimated based on annual registrations data obtained from MNExchange.Org	6.45	1.03
Buyer-Seller Familiarity	Prior Experience between transacting parties can affect transaction outcomes. We therefore control for this by including an indicator variable that captures whether the buyer and seller had interacted before. We assume that any previous interaction occurring at any point in time increases familiarity.	0.39	0.48
Seller/Buyer Size Dummies	Ordinal Variable for Size of the organization. Data available was Categorical based on # of employees: Small (<500); Medium (501 - 3000); Large (>3000) Companies	NA	NA
Buyer/Seller Type Dummies	We include dummy variables for different types of users on MNExchange.Org. Users were one of the following: Manufacturing, Commercial, Non-Profit, Government, Education and Undeclared	NA	NA

4.5.2 Estimation Strategy

In our context, H1 examines the overall effect of an *Operational Policy Change*. To estimate the effect on likelihood of exchange as predicted by H1a, we use logistic regression models; to estimate the effect on time to exchange as predicted by H1b, we use OLS regression models with the logarithm of time (days) to an exchange as the dependent variable. All models include various buyer and seller dummies, product-level controls and transaction-level controls.

Hypotheses H2-H4 examine the effect of the *Operational Policy Change* on 'exchange likelihood' and 'time to exchange' subject to items from various categories – end-use/process-use, free/negotiable and recurring/one-time. A common problem with such comparisons is the 'omitted variable bias', which occurs due to unobserved confounding factors that makes each category different from the other. Therefore, we use an estimation strategy similar to the differences-in-differences (DID) approach in a regression framework. This strategy has been extensively used to examine the effects of exogenous shocks on various economic (Card & Krueger 1993), and organizational (Dahl 2011) outcomes, as well as to study online markets (Forman et al. 2009). In our context, the *Operational Policy Change* represents an exogenous shock to MNExchange.Org and its users, and we are interested in the post-shock transaction outcomes compared to the pre-shock transaction outcomes. For H2-H4, we examine the 'treatment' effects of the *Operational Policy Change* on process-use, negotiable and one-time items. As a result, end-use, free and recurring (respectively) items act as our 'control groups' in the DID model. As a result, The DID estimation strategy amounts to comparing the 'change' in outcome variables (before versus after) in one category to the 'change' in outcome variables in the other category. In standard notation, the DID estimator is:

$$Outcome_{it} = \beta_0 + \beta_1\, Treatment\ Category_i + \beta_2\, Operational\ Policy\ Change_t + \beta_3\, (Treatment\ Category \times Operational\ Policy\ Change)_{it} + \varepsilon \quad \ldots(1)$$

…where *Treatment Category* is a 'treatment group' dummy for categories process-use, negotiable or one-time; *Operational Policy Change* is a 'treatment time' dummy. The estimated coefficient (β_3) on the interaction term gives the DID estimate. Conventional standard errors from DID estimation often understate the standard deviations of estimators. As a result, we use clustered standard errors (Bertrand et al. 2003). Finally, we conduct additional analyses and robustness checks to alleviate any concerns related to causality in our empirical setting. Below, we provide details about the estimation strategy for the two outcome variables – (i) likelihood of exchange and (ii) time to exchange.

4.5.3 Effects of Policy Change on Likelihood of Transactions

Recall that the main objective of this study is to examine the impact of the change in MnExchange.Org's operating policy. Two important metrics for evaluating the usefulness (i.e. efficiency) of the MNExchange.Org are (i) the likelihood of successfully completed transactions and (ii) time taken to complete successful transactions. Table 2 shows the results for hypotheses H1a, H2a, H3a and H4a related to the effect of operational policy change on likelihood of successful transactions. The logit model is:

$$\begin{aligned} Pr(\textit{Exchange Success} = 1|X) = {} & \beta_0 + \beta_{CL}X_{CL} + \beta_1 \textit{Operational Policy Change} + \beta_2 \\ & \textit{Operational Policy Change} \times \textit{Process-Use} + \beta_3 \\ & \textit{Operational Policy Change} \times \textit{Negotiable} + \beta_4 \\ & \textit{Operational Policy Change} \times \textit{One-Time} + \beta_5 \\ & \textit{Process-Use} + \beta_6 \textit{ Negotiable} + \beta_7 \textit{ One-Time} \qquad \ldots (2) \end{aligned}$$

...where X_{CL} is the vector of controls, while βs are respective coefficients. We use clustered standard errors to avoid problems with heteroskedasticity (Wooldridge 2002) and understated standard errors in DID estimation (Bertrand et al. 2003). For H1a, we use a reduced form of equation 2 without the DID interaction terms for the item categories, while still retaining the dummy variables.

Table 4-2 shows that the *Operational Policy Change* has a significant negative effect (β=-0.23, $p<0.10$) on the likelihood of exchange for all items (Column 1). This supports H1a. The effect of *Operational Policy Change* is significant for process-use items (Column 2, β=-0.38, $p<0.05$), which suggests a significant decline in process-use item (versus end-use item) transactions following the *Operational Policy Change*. Overall, the results support H2a. We do not find a significant effect of *Operational Policy Change* for transactions of negotiable (versus free) items (Column 3, β=-0.13, $p>0.10$), although it does seem that the market could be eventually converging to free items in the absence of human intermediaries. H3a is not statistically supported. Finally, there was a significant effect of *Operational Policy Change* on transactions of one-time (versus recurring) items (Column 4, β=-0.37, $p<0.05$). We find substantial support for H4a; users might be inclined towards recurring transactions indicative of preference for "longer-term contracts" (Kleindorfer & Wu 2003). Although the initial probabilities could, and do differ across categories (which is expected), the DID estimation approach confirms that the "change" in likelihoods of transaction was substantially different across the categories following the operational policy change.

Table 4-2. Likelihood of Successful Transactions

Variables	Hypotheses	Including All Years of Data Full (1)	 Use (2)	 Price (3)	 Frequency (4)	Excluding Implementation Year (2004) Full (5)	 Use (6)	 Price (7)	 Frequency (8)
Operational Policy Change	**H1a**	-0.23*	-0.14	-0.19	0.04	-0.50***	-0.41	-0.43*	-0.26
		(0.12)	(0.21)	(0.25)	(0.38)	(0.14)	(0.32)	(0.25)	(0.35)
Operational Policy Change	**H2a**		-0.38**				-0.46***		
× Process-Use			(0.17)				(0.17)		
Operational Policy Change	**H3a**			-0.13				-0.19*	
× Negotiable				(0.08)				(0.10)	
Operational Policy Change	**H4a**				-0.37**				-0.35**
× One-Time					(0.17)				(0.16)
Process-Use		0.88	0.99	0.89	0.86	0.96	1.16	0.99	0.91
		(0.61)	(0.80)	(0.78)	(0.79)	(0.80)	(0.73)	(1.08)	(1.08)
Negotiable		-0.44***	-0.42***	-0.41***	-0.45***	-0.41***	-0.41***	-0.32*	-0.42***
		(0.10)	(0.07)	(0.11)	(0.09)	(0.12)	(0.10)	(0.18)	(0.12)
One-Time		0.25**	0.24	0.24*	0.46***	0.23**	0.21*	0.22	0.44***
		(0.10)	(0.16)	(0.14)	(0.11)	(0.11)	(0.11)	(0.15)	(0.08)
Total Hits on Listing		-0.70***	-0.63	-0.69*	-0.69*	-0.75***	-0.70**	-0.75*	-0.75*
		(0.09)	(0.42)	(0.41)	(0.41)	(0.10)	(0.32)	(0.42)	(0.42)
Total Hits on Listing^2		0.11***	0.10	0.11	0.11	0.12***	0.11	0.12	0.12
		(0.02)	(0.07)	(0.07)	(0.07)	(0.02)	(0.07)	(0.08)	(0.08)
Hazardous		-0.36	-0.38	-0.37	-0.37	-0.17	-0.12	-0.17	-0.17
		(0.26)	(0.53)	(0.53)	(0.52)	(0.28)	(0.20)	(0.61)	(0.60)
Textual Information Length		0.00	-0.00	0.01	-0.00	-0.02	-0.03	-0.02	-0.03
		(0.04)	(0.02)	(0.02)	(0.02)	(0.05)	(0.06)	(0.03)	(0.02)
Visual Information Dummy		-0.12	-0.11	-0.11	-0.12	-0.21	-0.17	-0.21**	-0.21**
		(0.13)	(0.09)	(0.11)	(0.10)	(0.15)	(0.29)	(0.09)	(0.09)
Buyer-Seller Familiarity		0.21**	0.17	0.21	0.20	0.21**	0.14*	0.22	0.21
		(0.08)	(0.20)	(0.21)	(0.21)	(0.09)	(0.08)	(0.18)	(0.18)
MNExchange.Org Diffusion in Seller County		0.04	0.05	0.04	0.04	0.02	0.03	0.02	0.02
		(0.04)	(0.03)	(0.04)	(0.04)	(0.05)	(0.07)	(0.02)	(0.02)
MNExchange.Org Diffusion in Buyer County		0.01	0.00	0.01	0.00	-0.01	-0.01	-0.00	-0.01
		(0.03)	(0.05)	(0.04)	(0.04)	(0.03)	(0.07)	(0.06)	(0.06)
Constant		-1.07	-1.18	-1.12	-1.17	-0.87	-0.95	-0.98	-0.96
		(0.68)	(0.99)	(1.06)	(1.15)	(0.87)	(0.89)	(1.13)	(1.20)
Observations		4055	3609	4055	4055	3370	2977	3370	3370
Log Likelihood		-2044.85	-1820.82	-2044.67	-2043.18	-1707.44	-1509.45	-1707.13	-1706.11

*Logit Models shown; Dependent Variable is 'Likelihood that Listed Surplus is Exchanged; Clustered Standard Errors in parentheses; *p<.10, **p<0.05, ***p<0.01; Material Code dummies included for each model; Buyer/Seller Type dummies and Buyer/Seller size dummies added to all models; Reduced sample size for analysis of Item-use is due to omission of Miscellaneous items which were not listed under specific material codes. This did not allow classification as either process- or end-use.*

Table 4-3. Time to Successful Transactions

		Including All Years of Data				Excluding Implementation Year (2004)			
	Hypotheses	Full	Use	Price	Frequency	Full	Use	Price	Frequency
Variables		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Operational Policy Change	**H1b**	0.33**	0.33**	0.22	0.04	0.54**	0.69***	0.36**	0.31**
		(0.10)	(0.10)	(0.11)	(0.11)	(0.11)	(0.03)	(0.09)	(0.09)
Operational Policy Change	**H2b**		0.53*				0.33		
× Process-Use			(0.21)				(0.18)		
Operational Policy Change	**H3b**			0.56**				0.58**	
× Negotiable				(0.16)				(0.12)	
Operational Policy Change	**H4b**				0.40**				0.35*
× One-Time					(0.07)				(0.14)
Process-Use		0.29	0.32	0.22	0.39	0.14	0.22	0.07	0.22
		(0.31)	(0.30)	(0.31)	(0.29)	(0.30)	(0.25)	(0.29)	(0.31)
Negotiable		-0.05	0.11	-0.20**	-0.02	0.02	0.25	-0.22	0.06
		(0.09)	(0.05)	(0.05)	(0.09)	(0.17)	(0.14)	(0.17)	(0.17)
One-Time		-0.52***	-0.44***	-0.50***	-0.79***	-0.47***	-0.41***	-0.44***	-0.73**
		(0.02)	(0.06)	(0.02)	(0.07)	(0.03)	(0.04)	(0.03)	(0.16)
Total Hits on Listing		0.06	-0.05	0.03	0.06	-0.03	-0.16**	-0.06	-0.03
		(0.12)	(0.11)	(0.11)	(0.12)	(0.04)	(0.03)	(0.04)	(0.05)
Total Hits on Listing^2		0.06*	0.08**	0.07*	0.06	0.08**	0.10***	0.08**	0.08**
		(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)	(0.02)	(0.02)
Hazardous		0.31	0.35	0.32	0.33	0.43**	0.50**	0.43**	0.44**
		(0.15)	(0.15)	(0.15)	(0.16)	(0.13)	(0.12)	(0.13)	(0.13)
Textual Information Length		-0.09	-0.08	-0.10	-0.09	-0.09	-0.09	-0.10	-0.09
		(0.14)	(0.13)	(0.14)	(0.14)	(0.15)	(0.15)	(0.15)	(0.15)
Visual Information Dummy		0.29*	0.31*	0.26	0.28*	0.21	0.22	0.19	0.21
		(0.11)	(0.11)	(0.12)	(0.11)	(0.19)	(0.20)	(0.19)	(0.18)
Buyer-Seller Familiarity		-0.20	-0.23*	-0.20	-0.20*	-0.16	-0.19	-0.17	-0.17
		(0.09)	(0.08)	(0.09)	(0.08)	(0.10)	(0.09)	(0.10)	(0.10)
MNExchange.Org Diffusion in Seller County		0.01	0.03	0.01	0.01	-0.02	-0.00	-0.02	-0.01
		(0.02)	(0.04)	(0.02)	(0.02)	(0.01)	(0.04)	(0.01)	(0.01)
MNExchange.Org Diffusion in Buyer County		0.05	0.08**	0.04	0.05	0.04	0.07	0.04	0.04
		(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
Constant		1.65	1.28	1.90	1.77	1.93*	1.61	2.22*	2.03*
		(0.83)	(0.75)	(0.81)	(0.77)	(0.82)	(0.75)	(0.79)	(0.75)
Observations		869	779	869	869	701	630	701	701
Adjusted R-squared		0.292	0.299	0.297	0.294	0.291	0.305	0.295	0.292
Log Likelihood		-1263.57	-1113.80	-1259.85	-1261.60	-1047.69	-925.80	-1044.74	-1046.58

*OLS Models shown; Dependent Variable is Logarithm (Time to Exchange)'; Clustered Standard Errors in parentheses; *p<.10, **p<0.05, ***p<0.01; Material Code dummies included for each model; Buyer/Seller Type dummies and Buyer/Seller size dummies added to all models; Reduced sample size for analysis of Item-use is due to omission of Miscellaneous items which were not listed under specific material codes. This did not allow classification as either process- or end-use.*

Figure 4-3 plots the predicted probabilities against time using a local polynomial regression with an epanechnikov kernel. The plots illustrate the severity of negative impact on exchange outcomes due to the policy change. In general, the analysis provides three insights. First, the *Operational Policy Change* leads to significant drop (approximately 30%) in the overall likelihood of successful exchanges. Second, the decline is far more substantial for *process-use, negotiable* and *one-time* items (compared to *end-use, free* and *recurring* items respectively). Finally, Figure 3 shows that the likelihood of successful exchange declined over time following the operational policy change.

4.5.4 Effects of Policy Change on Time to Successful Transactions

Table 4-3 shows the results for hypotheses H1b, H2b, H3b and H4b related to the effect of operational policy change on time to successful transactions. The regression model used is:

$$Log\ [Time\ to\ Exchange] = \gamma_0 + \gamma_{CR}X_{CR} + \gamma_1 Operational\ Policy\ Change + \gamma_2\ Operational\ Policy\ Change \times Process\text{-}Use + \gamma_3\ Operational\ Policy\ Change \times Negotiable + \gamma_4\ Operational\ Policy\ Change \times One\text{-}Time + \gamma_5\ Process\text{-}Use + \gamma_6\ Negotiable + \gamma_7\ One\text{-}Time \quad \ldots (3)$$

where X_{CR} is the vector of controls and γs are respective coefficients. We use a DID regression approach with clustered standard errors. To examine H1b, we use a reduced form of equation 3 without the DID estimators for the items categories, while still retaining the dummy variables. The sample for the analysis of time to exchange consists of only those items that were exchanged at some point in time.

The *Operational Policy Change* has a significant positive effect (Column 1, β=0.33, $p<0.05$) on the time to exchange, which supports H1b. Also, the effect of *Operational Policy Change* is significant for process-use items (Column 2, β=0.53, $p<0.10$), which suggests a significant increase in time to exchange process-use (versus end-use) items following the *Operational Policy Change*. Overall, the results support H2b. We also find a significant effect of *Operational Policy Change* on time to exchange for negotiable (versus free) items (β=0.56, $p<0.05$), which suggests that free items exchange faster when compared to negotiable items in the absence of intermediaries. Hence, H3b is supported. Finally, *Operational Policy Change* had a significant effect on the time to exchange one-time (versus recurring) items (β=0.40, $p<0.05$), which supports H4b.

Figure 4-4 plots the predicted time to exchange using a local polynomial regression with an epanechnikov kernel. These trends illustrate the severity of negative impact on the time taken to establish successful exchanges after the policy change. In general, the analysis provides three insights. First, there is a significant rise (approximately 80%) in the overall time to reach successful exchanges following the operational policy change. Second, the rise is far more substantial for *process-use* (compared to *end-use*), *negotiable* (compared to *free*) and *one-time* (compared to recurring) items respectively. Finally, the increase in the time to successful exchanges was almost instantaneous, but reached a stable level over time. This clearly shows that eliminating intermediaries from MNExchange.Org created transactional difficulties. This finding has implications for designing hybrid or mixed-mode platforms.

Table 4-4. Non-parametric tests for Changes in Seller Listings

Type of Items	Listings per Week (Mean) Before	After	Difference in Means	Percentage Change	Kolmogorov Smirnov	Mann Whitney	Wilcoxon Sign-Rank
All Items	13.70	13.56	-0.14	-1%	*p>0.10*	*p>0.10*	*p>0.10*
End-use items	6.09	9.57	3.48	57%	*p<0.01*	*p<0.01*	*p<0.01*
Process-use items	6.06	2.41	-3.65	-60%	*p<0.01*	*p<0.01*	*p<0.01*
Free Items	4.59	9.22	4.63	101%	*p<0.01*	*p<0.01*	*p<0.01*
Negotiable Items	9.23	3.90	-5.33	-58%	*p<0.01*	*p<0.01*	*p<0.01*
Recurring Items	2.96	4.37	1.41	48%	*p<0.01*	*p<0.01*	*p<0.01*
One-Time Items	10.86	9.21	-1.65	-15%	*p<0.05*	*p<0.05*	*p<0.05*

Table 4-5. Non-parametric tests for Changes in Buyer Views

Type of Items	Hits per Week (Mean) Before	After	Difference in Means	Percentage Change	Kolmogorov Smirnov	Mann Whitney	Wilcoxon Sign-Rank
All Items	2.02	3.28	1.26	62%	*p<0.01*	*p<0.01*	*p<0.001*
End-use items	2.13	3.38	1.25	59%	*p<0.01*	*p<0.01*	*p<0.001*
Process-use items	2.12	3.11	0.99	47%	*p<0.01*	*p<0.01*	*p<0.001*
Free Items	2.31	3.49	1.18	51%	*p<0.01*	*p<0.01*	*p<0.01*
Negotiable Items	1.83	2.61	0.78	43%	*p<0.01*	*p<0.01*	*p<0.01*
Recurring Items	1.67	3.00	1.33	80%	*p<0.01*	*p<0.01*	*p<0.01*
One-Time Items	2.52	3.48	0.96	38%	*p<0.01*	*p<0.01*	*p<0.01*

4.6 Robustness checks

A major challenge in quasi-experimental designs is that of attributing the effects to the "intervention" i.e. *Operational Policy Change*. We alleviate these concerns by conducting a series of robustness checks that address potential alternative explanations.

4.6.1 Accounting for Policy Implementation Delays

It is common knowledge that operational policy changes do not take place overnight. Typically, such changes involve intense deliberation and beta testing before implementation. Even the process of implementation can take a few months. In our dataset, there were strong indications for delays in implementation of the *Operational Policy Change*. For example, archival records showed that new operational policy changes were initiated in early 2004, but were “formalized in October 2004”. To account for such implementation delays and their spurious effects on our findings, we eliminate all transactional data for the year 2004. We conducted our analysis using this reduced sample.

The results are shown in **Table 4-2** (Columns 5-8) and **Table 4-3** (Columns 5-8). Overall, our findings do not change qualitatively after eliminating the observations during 2004. All hypothesized effects are significant and stronger for the logit models estimating ‘likelihood of exchange’ (**Table 4-2**). The coefficients (**Table 4-3**) have slightly higher associated *p* values for the regression on Log (Time to Exchange); however, the coefficients are in the right direction. Yet, our results find substantial support overall, after accounting for the implementation delays.

4.6.2 Potential Changes in Seller Composition & Usage Frequency

Another factor that could bias the results is the potential change in the composition of sellers. For example, certain types of sellers (characterized by the industry they represent) entering or exiting the market might lead to changes in the nature of transactions. **Figure 4-5** shows the seller composition before and after the policy change. The results show that there were minor fluctuations in the number of sellers representing education, government, manufacturing and non-profit sectors. The composition of sellers from the commercial sector underwent large change (>100%). Interviews with the MNExchange.Org Director suggested that these changes may be due to more sellers declaring their ‘industry type’ after the policy change (as observed in the lower number of ‘undeclared’ sellers in **Figure 4-5**). Discussions with MNExchange.Org staff confirmed that this trend was due to minor ongoing changes in the registration policies, which induced more users to declare information about their organization. This is seen in the reduction of ‘undeclared’ users. As a result, we did not find any reason to believe that changes in seller composition were the causal mechanism underlying aggregate-level changes in transactions.

In online markets, it is common to observe long tails (Brynjolfsson et al. 2011), indicating few users accounting for a large amount of usage. We therefore examined potential changes in sellers’ online usage behavior. Changes in the sellers’ online usage could indicate that MNExchange.Org became either more concentrated or more diversified, which could partially explain changes in transactions for certain items. Figures 6a and 6b do not show any significant changes in seller usage patterns. Most sellers do not revisit the exchange after initial registration; barely 2% of sellers use (i.e. post an item) the exchange platform more than five times over the two years following registration. Similar trends persist after the policy change. Overall, usage frequency did not substantially change. A non-parametric comparison test indicated non-significant differences ($p>0.10$) between distributions for usage frequency (before vs. after).

Figure 4-3. Local Polynomial Regression Plots [Predicted Probabilities of Transaction]

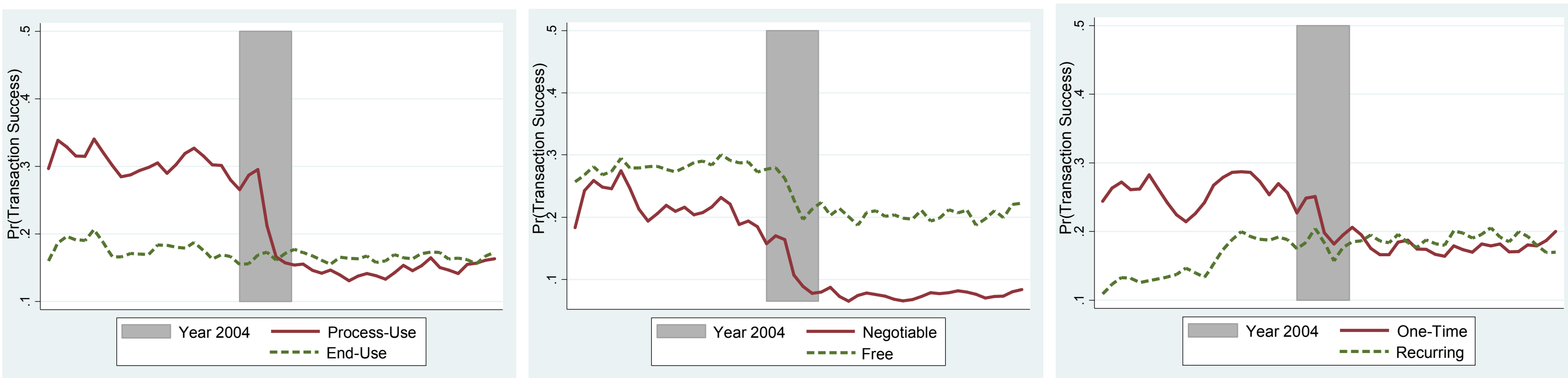


Figure 4-4. Local Polynomial Regression Plots [Predicted Times to Transaction]

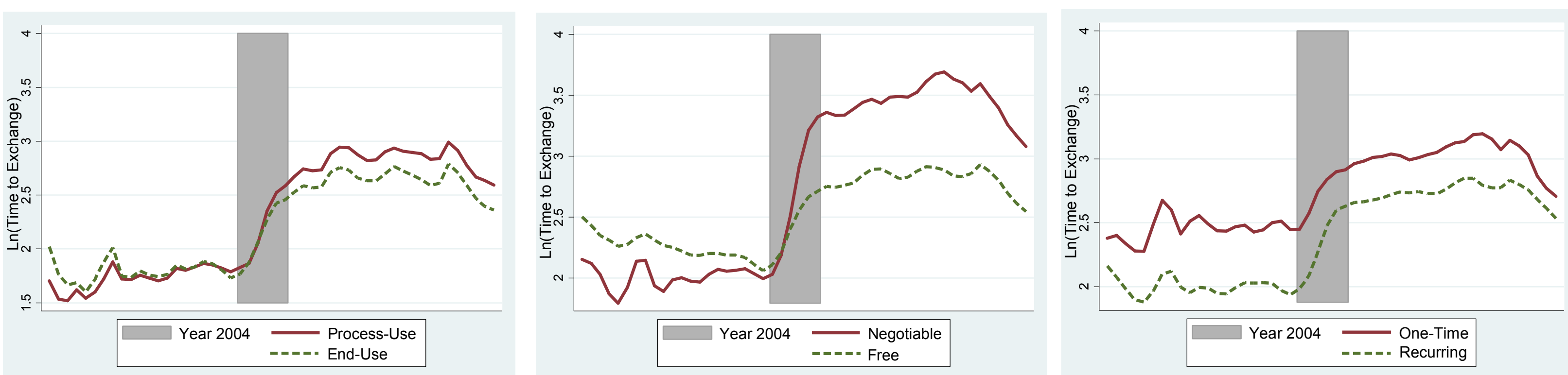


Figure 4-5. Seller Composition

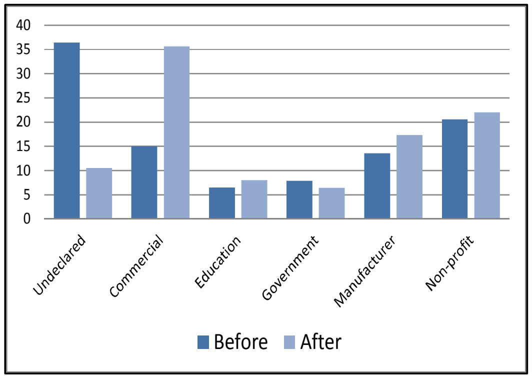


Figure 4-7. Buyer Composition

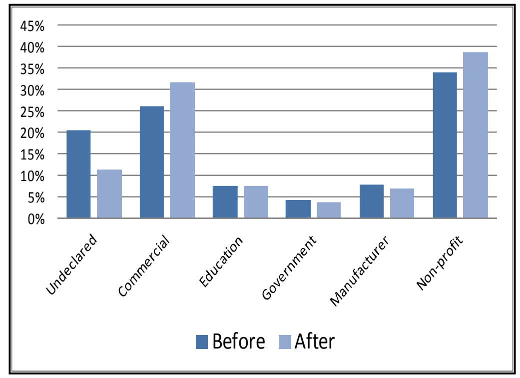


Figure 4-6. Sellers' Usage (Listing) Frequency

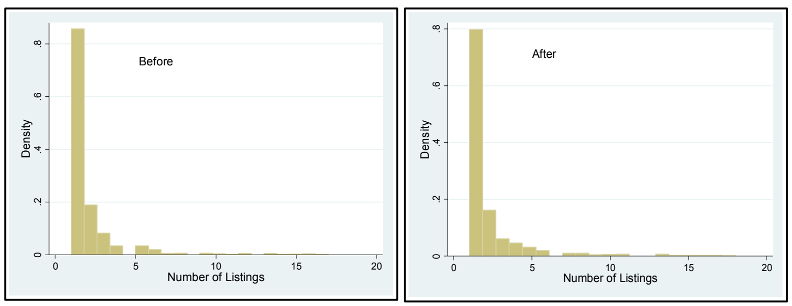
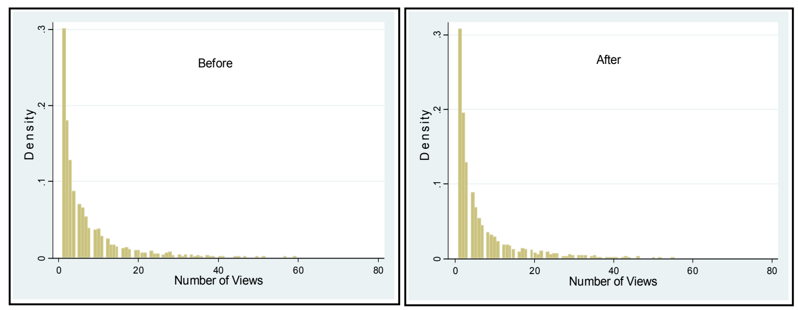


Figure 4-8. Buyers' Usage (Viewing) Frequency



4.6.3 Potential Changes in Buyer Composition & Usage Frequency

Another factor that could bias our results is the potential shift in the buyer composition. For example, certain types of buyers (characterized by the industry they represent) entering or exiting the market might lead to changes in the nature of transactions. **Figure 4-7** shows the buyer composition before and after the policy change. The results show some changes in the number of commercial and non-profit buyers. In discussions with MNExchange.Org, these increases (4-7%) could be almost entirely attributed to the fact that more number of buyers declared their type during registration in the latter years. The composition of buyers from the education, government and manufacturing sector remained largely unchanged. Overall, we conclude that changes in buyer composition are unlikely to have caused a drop in transactions.

We next also examined whether the policy fundamentally changed buyer usage patterns. **Figure 4-8** does not show any sudden shifts in buyer usage patterns. Most buyers do not revisit the exchange after initial registration; barely 2% of buyers engage in online search activity on MNExchange.Org more than 20 times after registration. These trends persist after the policy change, suggesting that buyers' usage behavior was not likely the reason behind the drop in transactions and increases in transaction times. A non-parametric comparison test indicated non-significant differences ($p>0.10$) between distributions of buyer usage frequency (before vs. after).

4.6.4 Changes in Information Content

Sellers typically provide a textual description of the item being offered. The textual description provides information that can reduce buyers' uncertainty about the product quality (Dimoka et al. 2012) and increase exchanges (Dhanorkar et al. 2014). A reduction in the information provided by sellers (especially after the policy change) could elevate the buyers' concerns uncertainty about the product. This may lead to lower exchanges as observed in our findings. In other words, the lower transactions could be due to the lack of *information* rather than the lack of *intermediation*. **Figure 4-9** shows the information (in number of characters) provided by sellers before and after the policy change. Surprisingly, we observe a greater increase in the sellers' information content for process-use items (compared to end-use items) and negotiable items (compared to free items). This could mean that, anticipating problems with the lack of intermediaries, sellers compensated by providing more information. Interestingly, even the increased information content for process-use items was not able to overcome the lack of *intermediaries*. Evidently, intermediaries provide transactional benefits that go beyond merely reducing information asymmetries. We do not observe a large increase in information content for one-time items (compared to recurring items).

Figure 4-9. Changes in Description Length

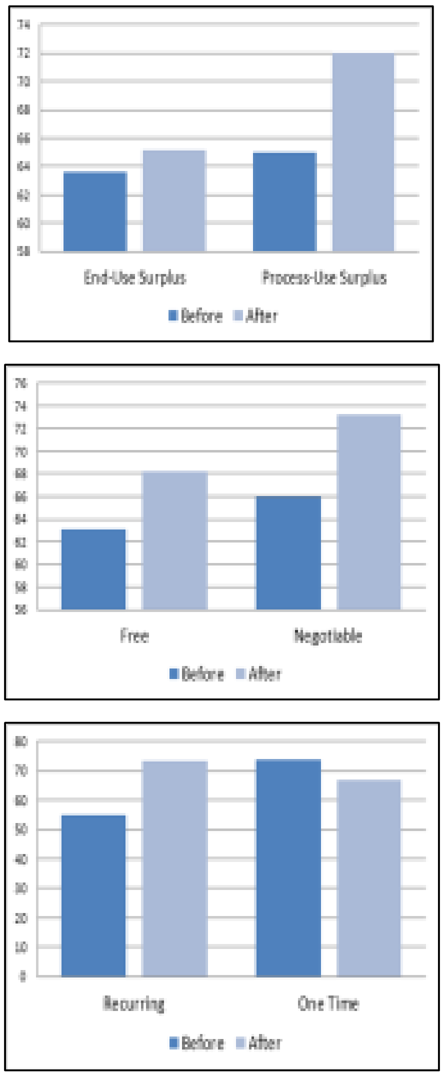


Figure 4-10. Cumulative Registrations by Region

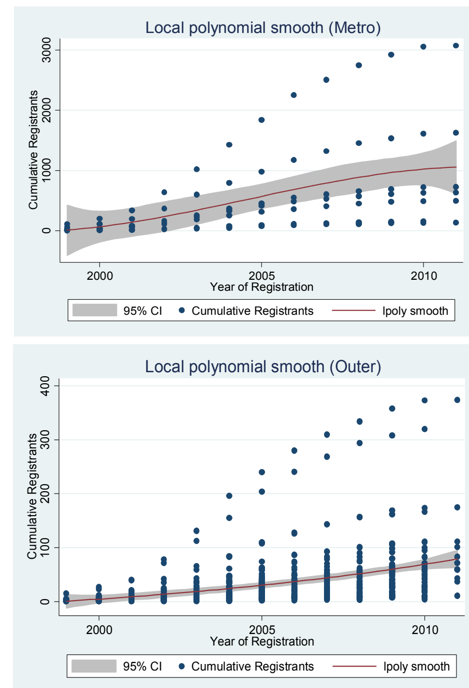
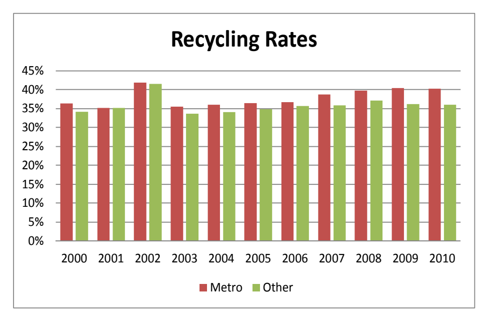


Figure 4-11. Recycling Rates in Minnesota



4.6.5 Exogenous Shocks

The above results provide a convincing argument for the existence of the Intermediation Problem. However, the decline in transactions (and supply) could also be caused by other exogenous effects during the study period. To test for these exogenous effects, we search for evidence for any sudden regulatory changes shifts in Minnesota. We also examined a potential second order effect of regulatory changes on registrations.

As a first step, we examine whether user registration patterns had any significant abnormalities during the 2003-2005 period, which could give erroneous results. One plausible reason for sudden changes in registration patterns is exogenous shocks (e.g. regulatory changes, industry-specific changes), which could also have a spillover effect on transaction outcomes. For example, exogenous shocks such as policy and regulatory changes can spur supply and demand for used materials and wastes (Atasu et al. 2009; Gui et al. 2013b). Also, increased regulatory stringency can be a resource- and time-intensive endeavor (Sadiq & Governatori 2010) for users, and is likely to delay transactions in the absence of a knowledgeable intermediary. We examine whether any such shifts can be observed in user registrations. **Figure 4-10** plots the time series of cumulative registrations by year, fitted with a local polynomial using an epanechnikov kernel (95% confidence interval). We intentionally cluster the data based on regions – metro counties and outer counties – to acknowledge differences in industrial activity. As expected, registration rates (per year) are significantly higher for the metro region. The trends suggest that there were no significant discontinuities in the registration patterns in either region. Rather, the local polynomial shows a uniform rise in cumulative registrations between 2000 and 2010. Hence, a change in total registrations is unlikely to have caused the drop in transactions.

Recycling policies could also alter transactions on OMWEs. In the state of Minnesota, the Minnesota Pollution Control agency (MPCA) sets rules and standards for waste disposal, reuse and recycling. These policies get implemented at the county-level. An important metric of environmental progress for MPCA (and counties) is recycling rates. Recycling rates can potentially affect exchanges on OMWEs. Increases in recycling rates suggest stronger environmental norms and improvements in recycling infrastructure (e.g. transportation, handling, sorting etc.). Hence, sudden increases in recycling rates could spur transactions through positive spillovers. On the other hand, a sudden decline in recycling rates could have a negative spillover effects on transactions. Figure 4-11 shows that year 2002 had a significant ($p<0.10$) spike in recycling activity. As such there is no reason to suspect that this spike would potentially bias our findings since the decline in transactions occurred almost three years later (in 2005). However, we still re-analyzed our data after dropping listings from 2002. This approach did not alter our findings qualitatively. Finally, we also conducted interviews with employees of MNExchange.Org and MPCA to confirm whether other regulatory interventions might have caused changes in transactions. The discussions revealed no reasons to attribute such dramatic shifts in transactions to regulatory factors.

4.7 Additional Evidence – Second Order Effects

If the adverse effects on transaction outcomes (as measured by likelihood of exchange and time to exchange) are actually due to the *Operational Policy Change*, we should be able to observe second order effects on buyer and seller behaviors as well. Such evidence of second-order effects can provide additional support for our hypothesized findings.

4.7.1 Second-Order Effects of Operational Policy Change on Seller Behaviors

Sellers have been known to alter online listing behavior based on their perceived expected transaction outcomes (Overby & Jap 2009). Apart from the aggregate effects, we had earlier predicted greater transactional challenges with *process-use*, *negotiable* and *one-time* items. Our results showed a 'lower transaction likelihood' and 'increased time to exchange' for these items. If our results are truly driven by transactional challenges and not by other factors, we should see sellers increasingly avoid listing item types that are likely to face higher transactional difficulties. Furthermore, under high uncertainty, sellers of lower quality (and lower price) products have a higher incentive to remain in the online market; while sellers of higher quality (and higher price) products will exit the online market in absence of intermediaries (Akerlof 1970). This should be observable though the second-order effect of a decline in the supply of *process-use*, *negotiable* and *one-time* items following the policy change.

To examine whether there was a decline in the supply of certain types of items, we rely on the number of *Listings per Week* for the different categories of items. Any drastic changes in the *Listings per Week* (i.e. supply) could indicate sellers' reluctance to engage in transactions of specific items. Table 4 shows the changes (within categories) in sellers' *Listings per Week* before and after the policy change. Not surprisingly, the overall supply rose, given the evolution of MNExchange.Org, but this rise is not uniform across item type. There is a significant rise in *Listings per Week* for end-use items (57%) and a sharp decline in *Listings per Week* for process-use items (-60%). There is also a significant rise in *Listings per Week* for free items (101%) but a sharp decline in *Listings per Week* for negotiable items (-58%). Finally, we observe an increase in the *Listings per Week* for recurring items (48%) but a small decline in the *Listings per Week* for one-time items (-15%). To statistically test these differences, we conducted a series of non-parametric tests[25] (**Table 4-4**), which provide support for a supply decline for certain categories of items.

Figure 4-12 graphs the results of a local polynomial regression (using epanechnikov kernel) for *Listings per Week* plotted against time. This plot provides a more granular illustration of the effect of *Operational Policy Change*. The trends suggest a rise in the *Listings per Week* for end-use items but a significant decline in process-use items supply following the operational policy change. Similarly, we see a decline in negotiable items while free items supply increased following the *Operational Policy Change.* We also see a rise in supply of recurring items but a decline in one-time items following the *Operational Policy Change*. These trends provide additional support for second-order effects resulting from the *Operational Policy Change*.

4.7.2 Second-Order Effects of Operational Policy Change on Buyer Behaviors

Often the rise or decline in supply and demand on online markets is a mutually evolving process (Overby & Jap 2009). Our results showed a 'lower transaction likelihood' and 'increased time to exchange' for *process-use*, *negotiable* and *one-time* items following the operational policy change. Such transactional challenges could lead to reduced buyer interest (as observed through views or hits) if buyers recognize the difficulties in engaging in OMWE transactions. Hence, an anticipation of transactional challenges may engender buyer disinterest in MNExchange.Org, at least for certain item categories. In addition, reduced supply of certain categories could lead to further reduction in demand.

Unlike some other markets, B2B markets typically do not entail bids or auctions (Koch & Schultze 2011). As a result, we do not observe either the final seller/buyer prices or the book values of the items (Dewan & Hsu 2004). We therefore examine the second-order effects of *Operational Policy Change* on the *Hits per Week* (i.e. unique buyer views) for the different categories of items. Any drastic changes in the *Hits per Week* could indicate buyers' increased interest in certain items and reduced interest in other categories. Table 5 shows the changes (within item categories) in buyers' *Hits per Week* before and after the policy change. We can see higher *Hits per Week* following the policy change for all categories of items. As suggested earlier, this could largely be an artifact of greater diffusion of MNExchange.Org within the state i.e. more users viewing listing in general. There is a marginally higher rise in *Hits per Week* for process-use items (59%) compared to end-use items (47%). There is also a marginally higher rise in *Hits per Week* for free items (51%) compared to negotiable items (43%). Finally, we observe a

[25] The Kolmogorov-Smirnov and Mann-Whitney test are analogous to the independent samples t-test, where we assume distributions for *Views per Week (before and after)* to be independent. In our context, the independence assumption is likely to be violated. Hence, we also conduct a Wilcoxon Sign-Rank test (which is a non-parametric analog to the paired samples t-test) which assumes dependence between the samples taken 'before' and 'after' the policy change.

significantly higher rise in the *Hits per Week* for recurring items (80%) compared to one-time items (38%). To statistically test differences within categories, we conducted Kolmogorov-Smirnov and Mann-Whitney tests (shown in Table 4-5). Overall, the increase in buyer demand appears to have been lower for *process-use, negotiable* and *one-time* items.

Although the above analysis shows the differences in *Hits per Week* before and after the *Operational Policy Change,* it does not account for changes over time. **Figure 4-13** summaries results from a local polynomial regression (using epanechnikov kernel) for *Hits per Week* plotted against time. This plot provides a more granular illustration of the effect of *Operational Policy Change*. The trends suggest a consistent rise in the *Hits per Week* for all categories of items, which can be expected as MNExchange.Org gets more diffused into the local industry. Yet, we observe a dip in *Hits per Week* shortly after the policy change was implemented. We also find marginally higher declines in buyer views for *process-use, negotiable* and *one-time items*, which provides additional robustness to our hypothesized findings.

4.8 Discussion

More than 100 OMWEs operate in the U.S. today[26] (EPA 2013a). Collectively, OMWEs possess the potential to repurpose billions of lbs. of industrial materials, by-products and waste as well as save millions of dollars in disposal fees and inventory costs. MNExchange.Org alone has diverted more than 25 million lbs. of reusable and recyclable materials from landfills, saving businesses over $6 million over eight years. Needless to say, it is essential to exploit the full potential of OMWEs. Our research extends the exploratory work of Dhanorkar et al. (2014) and addresses an important question of *intermediation*. We show that human intermediaries play an important role in to establishing exchanges in OMWEs, especially for *process-use, negotiable* and *one-time* items. Interestingly, we find that *end-use item* exchanges have fewer transactional challenges even in the absence of intermediaries, which is further supported by the success of platforms such as Craigslist.com. Furthermore, we clearly show that B2B markets such as OMWEs gradually gravitate towards *free* items in the absence of intermediaries, which in a way symbolizes a "market for lemons" (Akerlof 1970). In the absence of human intermediaries and the resulting uncertainty, users on B2B markets also show a greater preference for *recurring* exchanges, to reduce their transaction costs (Kleindorfer & Wu 2003). While our research relates to the work of Belavina and Girotra (2012), we also generate unique insights on "surplus chain intermediaries".

[26] The number of operating OMWEs is far greater (conservative estimates indicate at least 200) when local/county-level exchanges are included. OMWEs are common in other regions such as Canada (British Columbia IMEX), U.K. (Eastex), Singapore (Waste is Not Waste) and India (CII Waste Exchange).

Figure 4-12. Changes in Item Listings per Week [i.e. Supply]

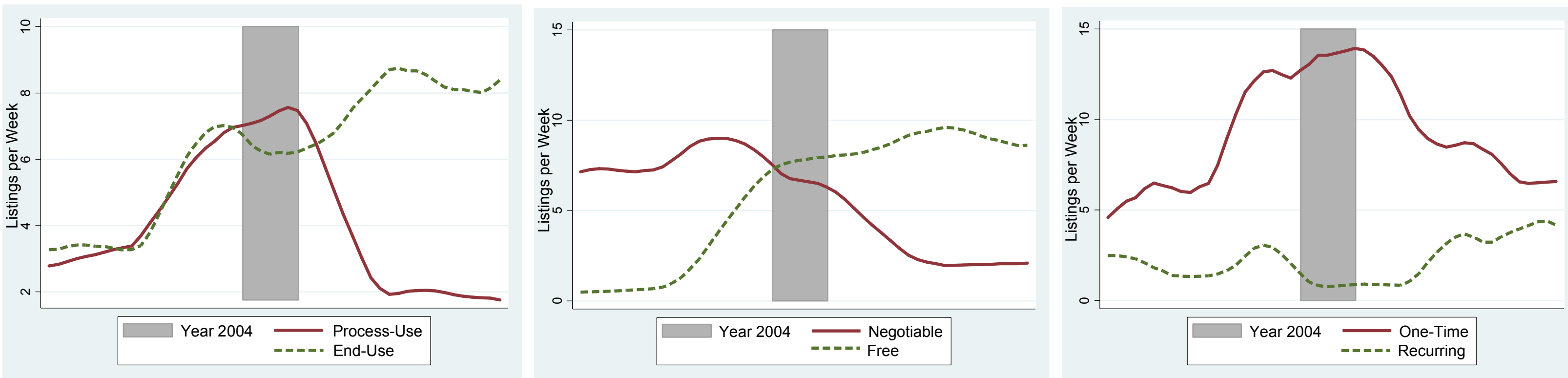
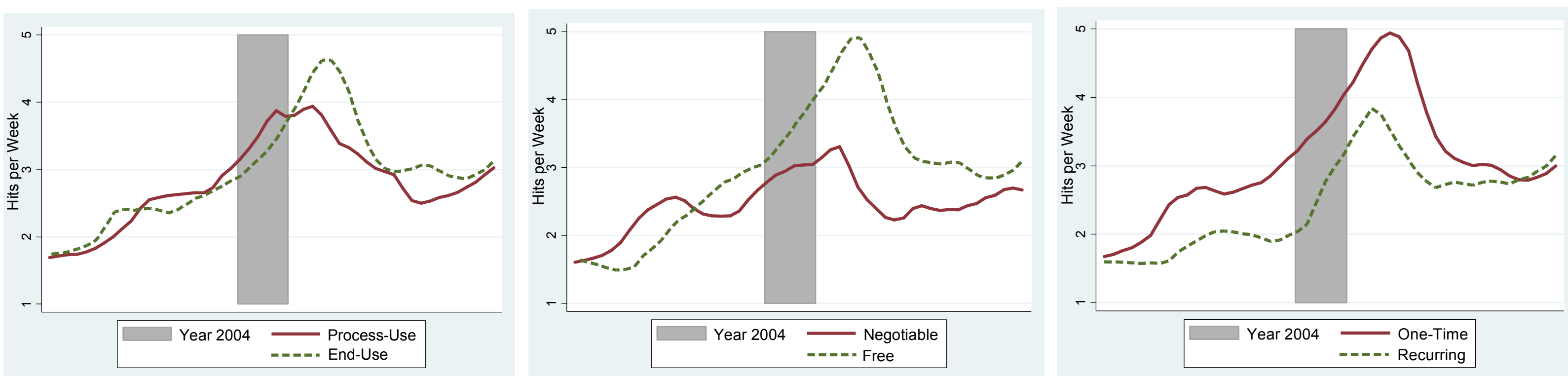


Figure 4-13. Changes in Item Hits per Week [i.e. Demand]



Our study highlights an important challenge faced by OMWEs. On the one hand, OMWEs have resource-constraints, which make decentralized online platforms favorable. Online platforms provide OMWEs with higher degrees of freedom to reallocate and manage human resources. Yet, our analysis suggests that this approach might be detrimental for process-use transactions. In the context of MNExchange.Org, the elimination of intermediaries led to increased transactional challenges i.e. higher "transactional" or "frictional" costs (Brynjolfsson & Smith 2000; Hann & Terwiesch 2003) of undertaking exchanges. The direct effect is seen on two primary transaction outcomes – transaction likelihood and transaction delays. Specifically, we observe a significant rise in time to successful transactions and a significant decline in the probability of successful transactions. We recommend that OMWEs should therefore adopt a hybrid policy which capitalizes the benefits of scale from internet-based platforms (Bakos 1998) while also providing informational and transactional benefits (Wu 2004) through *human intermediaries*.

End-use transactions of domestic surplus are already being facilitated by successful platforms such as Craigslist.Org (Seamans & Zhu 2013). Given the success of Craigslist.Org (and similar other platforms) with residential users, OMWEs need to fill a similar gap in surplus chains by facilitating transactions between commercial and industrial facilities. The most significant benefit of OMWEs often comes from their capability to redirect *industrial items* away from disposal options such as landfill, incineration etc. (MPCA Officer 2014). To successfully provide this service, OMWEs need to carefully develop their operating policies, potentially in favor of human intermediaries. This recommendation goes against the move-to-the-market hypothesis (Malone et al. 1987; Brynjolfsson & Mcafee 2012), but is still relevant for OMWE success in facilitating transactions.

From an environmental sustainability perspective, our paper also contributes to the technology debate. On the one hand, a commonly held belief by ecological modernists stresses that *"technology [is] our planet's last best hope"* (The Guardian Environmental Network 2013). This view hails technology as the solution to environmental and ecological problems. On the other hand, leading thinkers and scientists believe that *"technology cannot solve all environmental problems"* (European Environmental Agency 2014). Our study takes a perspective that technological solutions, especially online platforms, can have limited success when decisions are driven by unpredictability and uncertainty. Hence, this study provides a word of caution against the sole reliance on online technologies Rather, it is important to assess the context, products and users before developing operating policies in B2B online markets.

Our study has limitations and calls for future research in this domain. First, we use the MNExchange.Org platform as our empirical setting. Although MNExchange.Org operations are similar to various other OMWEs, there may be some differences (product types, web display etc.) which could potentially limit the generalizability of our research. Additional research can further establish the generalizability of our findings and the usefulness of OMWEs by examining other similar exchanges. As of today, several OMWEs exist in the U.S. and outside. In addition, parallel markets have emerged for fashion surplus (e.g. LikeTwice.com) and arts surplus (e.g. MNArtsMarket.com), which need careful examination. Second, our findings may also have limited applicability to other online B2B settings (Koch & Schultze 2011) for primary/virgin products, since quality heterogeneity and regulatory concerns might play a less important role. In these settings, the presence of human intermediaries might be less critical for maintaining high market efficiency. Finally, we focus on two primary metrics of OMWE efficiency – likelihood of exchange and time to exchange. Although our conversations revealed that these metrics were most useful for evaluating OMWEs, other conversion metrics based on clickstream data might also be useful for future research purposes.

Chapter 5

MANAGERIAL IMPLICATIONS

5.1 Implications for Environmental Policies to Promote Source Reduction

Research in environmental management has explored various organizational and behavioral motivations (DeCanio 1993; 1998; Muthulingam et al. 2013) that affect the adoption of EI initiatives. Unfortunately, academic research has focused less on the role of external influences in improvement projects. We show that punitive and supportive external influence tactics can have a significant influence on improvement projects. This finding is especially pertinent, given that not only environmental but also quality systems are, today, being shaped by various external regulatory bodies such as the FDA (for food and pharmaceutical companies), CPSC[27] (for consumer products companies) and the HHS[28] (for healthcare facilities). Accounting for external influences is increasingly important today given the degree to which regulations shape operational activity. Furthermore, there is increasing interest in exploring effective tactics that ensure supplier conformance to quality and environmental standards. Recent evidence shows that traditional command-and-control approaches (e.g. supplier audits by buyers) can have limitations in ensuring product, process and environmental quality. For example, professional auditors and "gatekeepers" exhibit various behavioral biases (Ball et al. 2013; Short et al. 2010) and suppliers tend to evade buyers' enforcement efforts (Plambeck & Taylor 2012). Our study contributes to this literature by showing that command-and-control approaches can have significant limitations when inappropriately timed. However, support-oriented intervention schemes could be effectively integrated with traditional punitive actions to ensure compliance. While a poor integration between these two polar tactics is counterproductive, a well-planned execution could lead to higher and faster compliance.

The problem of ineffective switching between production-related and improvement-related tasks can lead to abandonment of improvement efforts (Tyre & Orlikowski 1994; Victor et al. 2000). If applied appropriately and in a timely manner, external influence tactics help encourage switching behavior and reduce abandonment of improvement programs. For example, ailing companies with dysfunctional processes might need intermittent *punitive* actions to trigger new improvement programs. These punitive actions might create a conducive climate (Klein & Sorra 1996) for initiating *supportive tactics*. Once initiated, improvement efforts are constantly in need of *reinforcing supportive tactics* (e.g. reminders) to ensure completion. For external

[27] Consumer Products Safety Commission
[28] US Department of Health and Human Services

consultants and policy-makers, this finding has implications for better planning and anticipation of the disruptive and refocusing effects of their actions. Hence, when used well, both *punitive* and *supportive tactics* are useful tools for managers and policy-makers. While earlier studies have largely overlooked the factors that affect the evolution of improvement efforts across time, our study highlights the importance of a longitudinal perspective to understand the dynamic nature of improvement adoptions.

Broadly, our study considers two different approaches - *punitive* and *supportive* to ensure compliance. Earlier research has highlighted the differences in these approaches. For example, research in cognitive and behavioral sciences has shown that people can form different perceptions depending on the punitive/authoritative versus supportive/enabling dimensions of their interactions (Fiske et al. 2007). Earlier studies in organizations (Adler & Borys 1996), criminology (Colvin et al. 2002) and education (Mainhard et al. 2011) have also alluded to these two general types of approaches while highlighting their pros and cons. However, these two types of approaches have been traditionally thought of as being independent. Our study shows that punitive and supportive approaches can be introduced and implemented in a complementary manner. It is however essential to take into account the timing of such approaches and interventions to achieve the desired behavioral changes.

Final Recommendations:

- *<u>Recommendations for Policy-Makers:</u> Policies should be geared toward using the most effective aspects of supportive and punitive tactics. Often, one type of approach falls short of providing short- and long-term environmental benefits. In such circumstances, a hybrid approach can be effective. Yet, the timing of events and interventions plays a critical role in driving positive environmental change. Hence, coordination between punitive and supportive tactics is important. Policy-makers can develop policies that take into account other existing policies and initiatives to provide the most effective and long-standing solutions.*
- *<u>Recommendations for Supply Chains:</u> The challenge of externally promoting change is also ubiquitous in supply chains. In supply chains, punitive tactics such as performance evaluations, inspecting/certifications, as well as more supportive forms, such as joint process improvement initiatives are commonly implemented. Such approaches need not be viewed as polar opposites, but as complementary tactics that can be used to achieve supplier conformance and reliability. Gatekeeper institutions, downstream buyers and auditing firms can revisit their policies to drive positive environmental and process change through a complementary use of punitive and supportive tactics.*

5.2 Implications for Developing Online Markets to Promote Reuse

The problem on information asymmetry and the ensuing challenges are extremely relevant to the OMWE context. On the one hand, online markets are expected to lower the buyer's costs incurred in searching for the appropriate product and seller (Bakos 1991). Yet, the transaction of secondary products such as industrial surplus is especially difficult (Ghose 2009) due to information asymmetries between buyers and sellers. It has been long established that high information asymmetry leads to a "lemons" problem where low-quality goods dominate the market and drive out high quality products (Akerlof 1970). In the context of OMWEs, the lemons problem can result in increased transactions of 'free' products with relatively lower quality while the (potentially) higher quality, non-free products become less attractive. This could mean that higher quality yet higher uncertainty products (e.g. materials such as rubber, chemicals, wood etc.) are less frequently traded in OMWEs. Consequently, OMWEs will need to focus on reducing the buyers' uncertainty through the better user interfaces[29] and richness of product and transaction information[30]. From an OMWE user standpoint, higher transparency can lead to a higher likelihood of successful surplus exchange. Sellers on OMWEs need to provide adequate and accurate product (description, visuals, manuals etc.) and transaction (transportation, availability, quality etc.) information to alleviate buyer uncertainty.

Each party involved in the exchange of surplus is likely to choose a contract that will economize their costs of doing a transaction i.e. they will attempt to minimize their search costs, bargaining costs, and enforcement costs (Dahlman 1979). Search costs are incurred in the process of identifying a transacting partner. Bargaining costs are incurred in the process of negotiating the contractual terms and conditions. Finally, enforcement costs include monitoring the transacting partner's behavior and outcomes of the exchange[31]. Furthermore, product- and seller-related uncertainty can escalate transaction costs, which then reduces the intent to engage in transactions (Teo & Yu 2005). Finally, customer acceptance of an online product depends on the transaction costs incurred when purchasing online relative to purchasing in a physical channel[32]. Hence,

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[29] For a discussion on user interfaces and E-commerce, see Lee, Hau L, and Seungjin Whang. 2001. "Winning the Last Mile of E-Commerce." MIT Sloan Management Review 42 (4): 54–62.

[30] For a discussion on the importance of information richness, see Dimoka, Angelika, Yili Hong, and Paul Pavlou. 2012. "On Product Uncertainty in Online Markets: Theory and Evidence." MIS Quarterly 36.

[31] For details about the TCE perspective, see Williamson, O E. 1995. "Transaction Cost Economics and Organization Theory." Organization Theory: From Chester Barnard to the Present and beyond: 207–256. For a discussion of the costs involved in transactions, see Dahlman, Carl J. 1979. "The Problem of Externality." Journal of Law and Economics 22 (1): 141–162.

[32] For a discussion on the quantification of transactions costs of online versus physical channels , see Chintagunta, Pradeep, Junhong Chu, and Javier Cebollada. 2012. "Quantifying Transaction Costs in Online/Off-Line Grocery Channel Choice." Marketing Science 31 (1): 96–114. For a discussion on what drives consumer acceptance of online products, see Liang, Ting-Peng, and Jin-Shiang Huang. 1998. "An Empirical Study on Consumer Acceptance of Products in Electronic Markets: A Transaction Cost Model." Decision Support Systems 24 (1): 29–43.

regulatory policies should be shaped to minimize the transaction costs of using OMWEs. Since established supply chains rarely exist for exchanging industrial surplus, producers and consumers of surplus can incur significant transactions costs in surplus exchanges. From a policy perspective, this has implications for reducing industrial access to traditional disposal alternatives in order to spur OMWE usage. Similarly, the positive externalities from investments in regional repurposing norms and infrastructure could lead to reduced transaction costs in OMWE exchanges for users. For companies, OMWEs might still not be optimal when making ad-hoc transactions. Ad-hoc transactions have higher search-, bargaining- and enforcement-related transactions costs. Rather, OMWEs could be more effectively for transactions involving recurring (e.g. weekly, monthly) surplus transactions. For users, an appropriate strategy is using OMWEs to identify transactions with long-term trading potential.

A major challenge in OMWE exchanges is efficient matching of buyers and sellers of surplus items. To this end, OMWEs need to identify their role in efficiently coordinating surplus chains. Traditionally, many Materials & Waste Exchanges relied on *centralized expert intermediation* to match generators of surplus items with consumers. Experts performed the matching function, facilitated bargaining and coordinated transactions. Today, most OMWEs have almost completely transitioned into *decentralized online platforms*, thus allowing sellers to directly post listings and buyers to directly negotiate transactions. As a result, the role of the expert as an intermediary is being played by the online platform. However, many OMWEs continue to struggle with the question of whether 'centralized expert intermediation' or 'decentralized online platforms' is a better approach? Apparently, there exists a trade-off between increased scalability versus reduced uncertainty, especially in markets with products of high quality uncertainty such as OMWEs. Decentralized online platforms are expected to improve scalability and lower the buyer's search costs, potentially providing a more efficient matching between buyers and sellers (Bakos 1991). Such internet facilitated dis-intermediation i.e. elimination of intermediaries has also been predicted by the popular press(Friedman 2007). Yet, there has been an unprecedented rise of physical intermediaries in supply chains despite the advancements in technology and internet (Belavina & Girotra 2012). The challenge for OMWEs therefore lies in recognizing the circumstances (e.g. product usage, product types, user characteristics) under which online platforms versus expert intermediation strategies can be successful.

Final Recommendations:

- <u>*Recommendations for Companies:*</u> *Companies should adopt OMWEs as a complementary alternative to conventional repurposing and disposal options. Most states in the U.S. now have OMWEs. Also, most European and Asian countries have OMWEs or similar platforms. Major benefits of using OMWEs include reduced disposal fees, lower compliance costs and higher environmental visibility. Yet, these benefits might accrue with increased experience and active usage. Sellers on OMWEs should focus on providing accurate and adequate product and transaction information to reduce buyers' uncertainty. Buyers should account for short- and long-term transaction costs when identifying trading partners. Finally, all users should carefully evaluate regulatory implications of trading (or disposing) their surplus. Many OMWEs provide regulatory assistance, advice and intermediary services, which users can benefits from.*
- <u>*Recommendations for Policy-Makers:*</u> *Policies should be geared toward encouraging OMWE adoption and usage, especially in urban regions with higher industrial activity. The regulatory uncertainty with surplus exchange (especially hazardous materials) will need to be reduced to allow clear directions on what can and can't be exchanged through OMWEs. Regional administrative offices can have a strong influence on OMWE usage by building positive repurposing norms within local communities and businesses. For example, various statewide and county-level environmental initiatives (e.g. education, market development) are critical for promoting a favorable atmosphere for encouraging OMWE usage. Peripheral services (e.g. transportation, hazardous waste management, technical assistance) need to also be developed for OMWEs to flourish and succeed.*
- <u>*Recommendations for OMWEs:*</u> *OMWEs need to work on (i) reducing information asymmetries through easy access to textual, visual and seller information (ii) building in technological features that allow integration with user systems and peripheral services (e.g. easy listing, transportation and handling, mobile access) (iii) provide intermediary services where transactions entail extremely high uncertainty for the buyers and (iv) engage policy-makers to provide incentives for OMWE usage over other disposal options. Some of these proposed strategies overlap with other conventional online markets (eBay, Amazon) and classifieds (Craigslist), yet others are unique to OMWEs. Especially given the regulatory complexity in some OMWE transactions, intermediary services and regulatory partnerships are unique strategies that will need to adopted by mature, as well as emerging OMWEs.*

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Appendix

Appendix A2-1. Sample Recommendations

Procedural Improvements (Low Technological Complexity)
Recycle vacuum pump seal water back to the seal with some purge.
Segregate food waste for animal feeding or composting.
Collect usable material by sending air through equipment without atomization, collect waste acetone from clean-up of metal paint equipment.
Painting, Gun washer solvent reduction. Modify change out procedure to maximize use of gun wash solvent before disposal.

Equipment Improvements (High Technological Complexity)
Replacement of poor function Liquid Measuring Equipment with one that is leak proof, covered, color-coded, accessorized.
Switch to reusable sprays, instead of more costly manufactured aerosols requiring labor for disposal processing.
Install (plumb) a reservoir (old purge tank) for recycling cooling water for large walk in coolers and one freezer.
Replace Trim coolers on the compressors which use a lot of water when it is hot outside.

Material Improvements (High Technological Complexity)
Procure re-refined oils from commercial supplies/Defense Logistics Agency (DLA) to generate savings.
Consider nickel plated fasteners instead of zinc plated parts (hinges, etc.)
Eliminate testing waste and production downtime by selecting an acetone/NMP mixture composition in equilibrium with vapor for a precision cleaning application
Explore ways to formulate low/no P formulations which have greener/cleaner formulation.

Appendix A2-2. EI Ownership

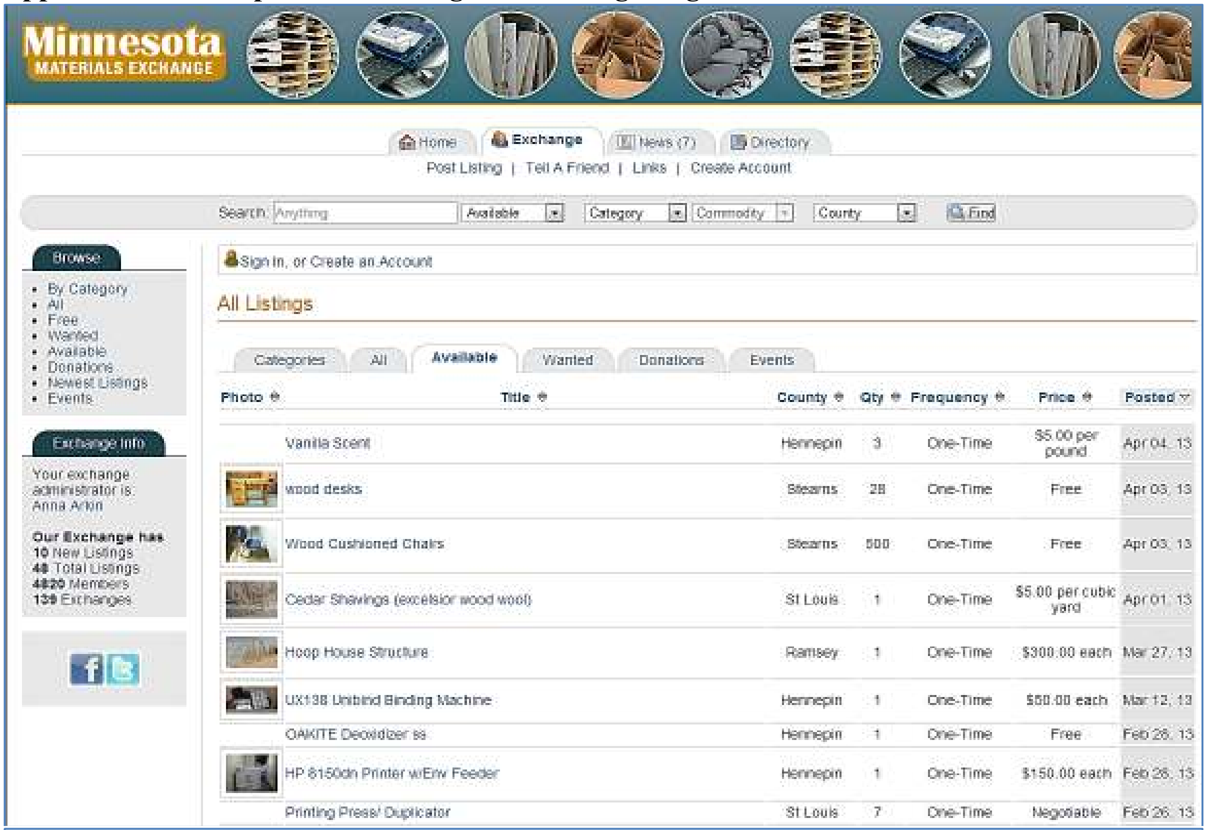
Classified as Senior Manager	**Classified as Employee/Mid-Level Manager**		
CEO	Assistant	Technician	Process Support Specialist
Facility Manager	Boiler engineer	Housekeeping	Project Engineer
General Manager	Chief Engineer	Human Resources/Safety	Quality Systems Manager
Manager of Manufacturing	Corporate Communications	Lab Coordinator	Quality and Environmental Manager
Manager, Product Utilization	EH & S Coordinator	Sales Manager	R & D Engineer
Manufacturing Manager	EHS Manager	Maintenance	Research Project Manager
Plant Manager	EHS Specialist	Maintenance Engineer	Safety Coordinator
President	Energy Manager	Maintenance Manager	Safety Officer
VP of Operations	Environmental Engineer	Maintenance Mechanic	Section Manager - Project
Vice President	EHS Supervisor	Maintenance Supervisor	Section Manager Maintenance
Vice President, Facility Operations	Environmental Manager	Nutrition Services	Site Utilities Coordinator
Owner	Environmental Program Manager	Office Manager	Surgical Services
Production Manager	Facilities Planning Assistant	Operating Room	Trades Manager
Operations Manager	Facility Coordinator	Paint Operations	Volunteer Coordinator
Director of Environmental Service	Facility Maintenance Manager	Pharmacist	Waste Water Superintendent
Physical Plant Director	Head Maintenance Supervisor	Pharmacy Director	Lean effort manager
	Process Engineer	Pharmacy Tech	Plant Maintenance Engineer

Appendix A3-1. Correlation Table

Variables	VIFs		1	2	3	4	5	6	7	8	9	10
Exchange		1										
Total Hits on Listing	1.37	-0.1144*	1									
Total Hits on Listing2	1.1	0.1433*	-0.0276*	1								
Time Listed	1.91	-0.0062	0.3904*	0.1595*	1							
Hazardous	1.03	0.0037	-0.1017*	0.0191*	-0.0173*	1						
Recurring	1.39	-0.0307*	0.3082*	0.0202*	0.4845*	0.0006	1					
Free Listing	1.22	-0.0133*	0.1385*	-0.0384*	-0.2588*	0.0344*	-0.1022*	1				
OMWE Users in Seller's County	2.29	-0.0078*	-0.0091*	-0.1233*	-0.2736*	0.0058	-0.0483*	0.1416*	1			
OMWE Users in Buyer's County	1.12	-0.0087*	0.0220*	-0.0822*	-0.2179*	-0.0003	-0.0680*	0.1978*	0.2075*	1		
Seller's Access to Disposal	1.34	-0.0043	0.1008*	0.0104*	0.1078*	-0.0380*	0.1420*	0.0212*	0.2350*	-0.0244*	1	
Seller's Access to Repurposing	2.07	0.0155*	-0.0093*	-0.0124*	-0.1295*	-0.0041	-0.0447*	0.0280*	0.6845*	0.0768*	0.2249*	1
Seller's Access to other OMWEs	1.43	0.0023	-0.0552*	-0.0489*	-0.1953*	0.0157*	-0.0322*	0.0291*	0.3548*	0.1026*	0.2817*	0.2671*
Buyer's Access to other OMWEs	1.04	-0.0042	0.0114*	-0.0215*	-0.0386*	-0.0120*	-0.0008	0.0410*	0.0466*	0.0501*	0.0201*	0.0252*
Repurposing/Disposal in Seller's County	1.12	-0.0091*	-0.0235*	-0.1399*	-0.0542*	0.0109*	0.0163*	0.0601*	-0.0979*	0.0526*	-0.2005*	-0.1638*
Textual Description Length	1.04	0.0080*	-0.0570*	0.0120*	-0.1270*	0.0200*	-0.0856*	0.0361*	0.0361*	0.0553*	-0.0199*	-0.0025
Visual Description Content	1.04	-0.002	-0.0415*	-0.0400*	-0.1597*	-0.0104*	-0.1071*	0.0472*	0.0743*	0.0691*	-0.0386*	0.0215*
Seller Size	1.1	0.0185*	-0.0081*	0.0098*	-0.0713*	0.1070*	-0.0267*	0.1389*	0.0784*	0.0592*	-0.1061*	0.0335*
Buyer Size	1.08	-0.0027	-0.0384*	0.0009	-0.0307*	0.0191*	-0.0329*	-0.0418*	-0.0418*	0.0035	-0.1295*	-0.0498*
Geographical Distance	1.17	-0.0208*	0.0401*	0.0134*	0.1450*	0.0079*	0.0530*	-0.0835*	-0.2651*	-0.0835*	-0.0279*	-0.3117*
Past Buyer-Seller Familiarity	1.05	0.0147*	0.0028	0.0032	-0.1406*	-0.0161*	-0.0487*	0.0921*	0.1549*	0.1006*	-0.0102*	0.0891*
Buyer's Experience as Seller	1.02	0.0301*	-0.0545*	-0.0043	-0.0434*	0.0059	-0.0143*	0.0045	0.0224*	0.0196*	-0.0038	0.0159*
Seller's Experience as Buyer	1.21	0.005	-0.1202*	-0.0042	-0.1809*	0.0157*	-0.0132*	-0.0118*	0.0855*	0.0985*	-0.1787*	-0.0076

Variables	VIFs	11	12	13	14	15	16	17	18	19	20
Exchange											
Total Hits on Listing	1.37										
Total Hits on Listing2	1.1										
Time Listed	1.91										
Hazardous	1.03										
Recurring	1.39										
Free Listing	1.22										
OMWE Users in Seller's County	2.29										
OMWE Users in Buyer's County	1.12										
Seller's Access to Disposal	1.34										
Seller's Access to Repurposing	2.07										
Seller's Access to other OMWEs	1.43	1									
Buyer's Access to other OMWEs	1.04	0.0467*	1								
Repurposing/Disposal in Seller's County	1.12	-0.1898*	0.0099*	1							
Textual Description Length	1.04	0.0785*	0.0084*	-0.0136*	1						
Visual Description Content	1.04	0.0557*	0.0121*	0.0451*	0.0161*	1					
Seller Size	1.1	0.1582*	0.0116*	-0.0021	0.0839*	0.0216*	1				
Buyer Size	1.08	0.1230*	-0.1136*	-0.0225*	0.0340*	0.0162*	0.0951*	1			
Geographical Distance	1.17	-0.1051*	-0.1300*	0.0352*	-0.0228*	-0.0303*	-0.0475*	-0.0457*	1		
Past Buyer-Seller Familiarity	1.05	0.0960*	0.0219*	0.0125*	0.0146*	0.0617*	0.0563*	-0.0191*	-0.0878*	1	
Buyer's Experience as Seller	1.02	0.0171*	0.0684*	-0.0045	0.0140*	0.0075	0.0232*	0.0177*	-0.1197*	0.0315*	1
Seller's Experience as Buyer	1.21	0.2506*	0.0122*	-0.0162*	0.1189*	0.0661*	0.1513*	0.1224*	-0.0536*	0.0860*	0.0330*

Appendix A3-2. Snapshot of Existing MNExchange.Org interface



Minnesota MATERIALS EXCHANGE

Home | Exchange | News (7) | Directory

Post Listing | Tell A Friend | Links | Create Account

Search: Anything | Available | Category | Commodity | County | Find

Browse

- By Category
- All
- Free
- Wanted
- Available
- Donations
- Newest Listings
- Events

Exchange Info

Your exchange administrator is: Anna Arkin

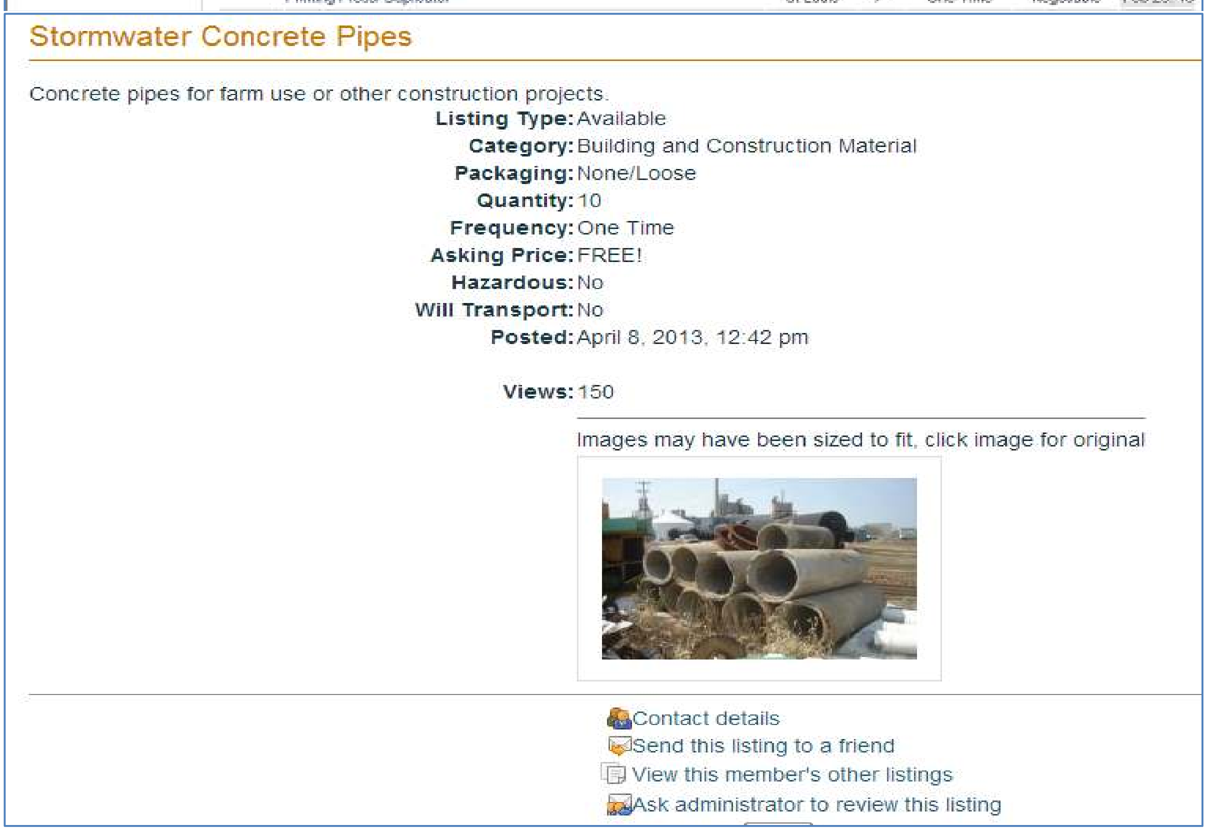
Our Exchange has
10 New Listings
48 Total Listings
4820 Members
139 Exchanges

Sign In, or Create an Account

All Listings

Categories | All | **Available** | Wanted | Donations | Events

Photo	Title	County	Qty	Frequency	Price	Posted
	Vanilla Scent	Hennepin	3	One-Time	$5.00 per pound	Apr 04, 13
	wood desks	Stearns	28	One-Time	Free	Apr 03, 13
	Wood Cushioned Chairs	Stearns	500	One-Time	Free	Apr 03, 13
	Cedar Shavings (excelsior wood wool)	St Louis	1	One-Time	$5.00 per cubic yard	Apr 01, 13
	Hoop House Structure	Ramsey	1	One-Time	$300.00 each	Mar 27, 13
	UX138 Unibind Binding Machine	Hennepin	1	One-Time	$50.00 each	Mar 12, 13
	OAKITE Deoxidizer ss	Hennepin	1	One-Time	Free	Feb 28, 13
	HP 8150dn Printer w/Env Feeder	Hennepin	1	One-Time	$150.00 each	Feb 28, 13
	Printing Press/ Duplicator	St Louis	7	One-Time	Negotiable	Feb 26, 13



Stormwater Concrete Pipes

Concrete pipes for farm use or other construction projects.

Listing Type: Available
Category: Building and Construction Material
Packaging: None/Loose
Quantity: 10
Frequency: One Time
Asking Price: FREE!
Hazardous: No
Will Transport: No
Posted: April 8, 2013, 12:42 pm

Views: 150

Images may have been sized to fit, click image for original

Contact details
Send this listing to a friend
View this member's other listings
Ask administrator to review this listing

Appendix A3-3. Details about Discussions with staff from MNExchange.Org and other OMWEs

<table>
<tr><th>Discussant</th><th>Understanding OMWEs</th><th>Data Collection</th><th>Hypotheses Development</th><th>Data Analysis</th><th>Writing & Implications</th></tr>
<tr><td>Current Director
Role: Strategic Planning, Inform Environmental Policy, Manage other environmental services offered</td><td>2 Unstructured Interviews
Discussed functioning, OMWE funding, challenges and goals, potential for data collection</td><td></td><td>3 Semi-Structured Interviews
Discussed policy challenges and drivers of transactions on OMWEs. Practice-focused hypotheses</td><td></td><td>3 Semi-Structured Interviews
Discussed policy implications and steps to be taken in future. Discussed practitioner dissemination</td></tr>
<tr><td>Online Admin
Role: Plan and Implement technical improvements for MnExchange.Org, Participate in policy discussions</td><td>2 Unstructured Interviews
Discussed operational challenges, benchmarks and statistics. OMWE technicalities and online platform</td><td>3 Semi-Structured Interviews
Discussions around terminology used. Potential biases in data and possible solutions</td><td>3 Semi-Structured Interviews
Discussed operational challenges and drivers. Past examples of failed and successful transactions</td><td>4 Semi-Structured Interviews
Monthly meetings to verify and interpret new results. First point of contact for trouble shooting</td><td>3 Semi-Structured Interviews
Discussed operational strategies and implemented several changes. Addressed limitations of study</td></tr>
<tr><td>Past Director
Role: Director of MnExchange.Org until 2009. Currently serves as a faculty at a large public university</td><td>2 Unstructured Interviews
Discussed historical developments, changes to policies and key drivers of exchanges OMWEs</td><td></td><td>1 Semi-Structured Interview
Verified preliminary list of factors potentially driving transactions. Outsider's perspective of OMWEs</td><td></td><td>1 Semi-Structured Interviews
Presented final findings and discussed applicability to policy. Discussion section developed</td></tr>
<tr><td>Past Online Admin
Role: Online Admin until 2005. Currently serves as Environmental Consultant</td><td>2 Unstructured Interviews
Discussed historical challenges and OMWE functioning and policy implications</td><td></td><td></td><td>1 Semi-Structured Interview
Discussed accuracy of archival data and interpretability of findings. Clarified potential biases in data</td><td></td></tr>
<tr><td>Other MNExchange.Org Staff
Roles: Providing variety of Environmental services to firms in the state of Minnesota</td><td>5×1 Unstructured Interviews
Confirmatory Interviews to verify details and roles played in OMWE. Past experience with firms</td><td rowspan="2">3×1 Semi-Structured Interviews
Verified data collection and accuracy. Potential hypotheses, measures and tests</td><td></td><td rowspan="2">1 Presentation of Findings
Presented results at monthly meeting to get feedback on results. Post-hoc analysis added based on suggestions</td><td>1 Presentation of Findings
Presented results at monthly meeting to discuss implications. Discussion section developed further</td></tr>
<tr><td>Other OMWEs in US
Roles: Directors/Admins for 5 other OMWE platforms in New York, Alabama and Northeast US</td><td></td><td></td><td>1 Webinar
Presented results to the Materials Exchange Managers' Network. Discussion section developed further</td></tr>
</table>

Unstructured and Semi-structured Interviews were conducted face-to-face. Additional ad-hoc telephonic conversations were also conducted. Online Admin was replaced after Data collection stage. Total time span for study was 2 years.

Appendix A3-4 Additional Robustness Checks (See Table on next page)

Listing-level Robustness Analysis: Column 1 is a *listing level* analysis which transforms *Textual Information Length* into an ordinal variable. This was created based on each 25th percentile of number of characters (32, 56, 92, 150 characters etc.). This approach actually makes our findings weaker due to loss of information, as can be expected when a continuous variable is transformed into a categorical variable. Column 2 is a *listing level* analysis based the concern was that *Recycling/Disposal in Seller's County* is endogenous since it might be simultaneously affecting (and being affected by) likelihood of exchange. We therefore ran a 2-stage least squares model, where *Recycling/Disposal in Seller's County* was instrumented using county-level fertility rate (based on demographic data) per year as the instrument. The instrument is correlated with *Recycling/Disposal in Seller's County* but is highly unlikely to have any relationship with the structural error terms (or the outcome variable "Exchange_Listing"), thereby satisfying the criteria for good instrument (Wooldridge 2002). This approach actually strengthened the impact of *Recycling/Disposal in Seller's County* on likelihood of an exchange, but did not affect our findings qualitatively.

Interaction-level Robustness Analysis: Column 3 shows *interaction level* analysis based on re-estimation of *Past Buyer-Seller Familiarity* using cumulative experience. Instead of using a binary indicator variable for *Past Buyer-Seller Familiarity* (1 if buyer-seller pair had interacted before; 0 otherwise), we use a continuous variable based on the number of previous interactions between the same buyer-seller pair. Column 4 shows *interaction level* analysis based on re-estimation of the three *Experience* variables (*Past Buyer-Seller Familiarity, Buyer's Experience as Seller* and *Seller's Experience as* Buyer) based on a two-year time window. Hence, only buyer-seller interactions occurring over the last 2 years were considered to measure "experience". This approach does not qualitatively change our findings, although the coefficient values were affected to some extent. In the model considered under Column 5, we only retained the 'final' interactions for each buyer-seller pair in circumstances where a buyer-seller pair had multiple interactions for the *same* item listing. Notice the drop in observations. This approach did not change our findings significantly.

Table A3-4. Additional Analysis

	Listing Level Models		Interaction Level Models		
Variables (Hypotheses Tested)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Total Hits on Listing	-0.74**	-0.26*	-1.83***	-1.84***	-1.79***
	(0.37)	(0.16)	(0.07)	(0.07)	(0.07)
Total Hits on Listing^2	0.12**	0.05	0.16***	0.16***	0.16***
	(0.06)	(0.04)	(0.01)	(0.01)	(0.01)
Time Listed	0.27***	0.24**	0.22***	0.22***	0.22***
	(0.07)	(0.10)	(0.04)	(0.04)	(0.04)
Hazardous	-0.38*	-0.31	-0.30	-0.30	-0.29
	(0.20)	(0.25)	(0.22)	(0.22)	(0.22)
Recurring	-0.42***	-0.29**	-0.21**	-0.21**	-0.23***
	(0.12)	(0.13)	(0.09)	(0.09)	(0.09)
Free Listing	0.69***	0.62**	0.66***	0.66***	0.65***
	(0.26)	(0.31)	(0.09)	(0.09)	(0.09)
MNExchange.Org Users in Seller's County	0.04	0.06	0.02	0.02	0.00
	(0.05)	(0.12)	(0.05)	(0.05)	(0.05)
MNExchange.Org Users in Buyer's County			0.03	0.04	0.03
			(0.03)	(0.03)	(0.03)
Seller's Access to other OMWEs	0.02	0.03	-0.32***	0.01	0.01
	(0.13)	(0.13)	(0.12)	(0.12)	(0.12)
Buyer's Access to other OMWEs			0.19***	0.17**	0.17**
			(0.07)	(0.07)	(0.07)
Seller's Access to Disposal	-0.32***		0.01	-0.32***	-0.29**
	(0.11)		(0.12)	(0.12)	(0.12)
Seller's Access to Repurposing	0.23***		0.16**	0.18***	0.18***
	(0.07)		(0.07)	(0.07)	(0.07)
Repurposing/Disposal in Seller's County	0.47**		0.43*	0.43*	0.52**
	(0.22)		(0.22)	(0.22)	(0.23)
Repurposing/Disposal in Seller's County (Instrumented)		2.53*			
		(1.49)			
Textual Information Length			0.12***	0.05**	0.14***
			(0.04)	(0.03)	(0.04)
Textual Information Length (Ordinal)	-0.02	0.02			
	(0.03)	(0.02)			
Visual Information Content	0.12*	0.13***	0.14	0.12	0.12
	(0.07)	(0.05)	(0.11)	(0.11)	(0.11)
Seller Size	0.27**	0.31**	0.27***	0.28***	0.30***
	(0.13)	(0.14)	(0.06)	(0.06)	(0.06)
Buyer Size			-0.38***	-0.35***	-0.39***
			(0.10)	(0.10)	(0.10)
Geographical Distance			-0.06***	-0.08***	-0.06***
			(0.02)	(0.02)	(0.02)
Past Buyer-Seller Familiarity			0.23***		
			(0.05)		
Past Buyer-Seller Familiarity (Cumulative)			0.48***		0.78***
			(0.08)		(0.07)
Buyer's Experience as Seller			-0.00		0.49***
			(0.08)		(0.08)
Seller's Experience as Buyer					-0.06
					(0.08)
Past Buyer-Seller Familiarity (2 years)				0.36***	
				(0.07)	
Buyer's Experience as Seller (2 years)				0.21*	
				(0.12)	
Seller's Experience as Buyer (2 years)				0.00	
				(0.08)	
Observations	4330	4330	100625	100625	78876
Log Likelihood	-1921.68	-1469.75	-4876.72	-4891.34	-4678.34

*Cluster Robust Standard Errors; *p<.10, **p<0.05, ***p<0.01; Material Codes for 14 Categories; Year dummies for 2000-2008; Controls for 6 Buyer and Seller Types included (Commercial, Education, Manufacturing, Government, Non-Profit and Other);*