

Contents lists available at ScienceDirect

Journal of Operations Management

journal homepage: www.elsevier.com/locate/jom

The impact of supply chain complexity on manufacturing plant performance

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ARTICLE INFO

Article history:

Received 13 January 2007

Received in revised form 17 July 2008

Accepted 31 July 2008

Available online 14 August 2008

Keywords:

Supply chain complexity

Supply chain management

Manufacturing strategy

Supply management

Empirical research methods

ABSTRACT

This paper puts forth a model of supply chain complexity and empirically tests it using plant-level data from 209 plants across seven countries. The results show that upstream complexity, internal manufacturing complexity, and downstream complexity all have a negative impact on manufacturing plant performance. Furthermore, supply chain characteristics that drive *dynamic* complexity are shown to have a greater impact on performance than those that drive only *detail* complexity. In addition to providing a definition and empirical test of supply chain complexity, the study serves to link the systems complexity literature to the prescriptions found in the flexibility and lean production literatures. Finally, this research establishes a base from which to extend previous work linking operations strategy to organization design [Flynn, B.B., Flynn, E.J., 1999. Information-processing alternatives for coping with manufacturing environment complexity. *Decision Sciences* 30 (4), 1021–1052].

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1. Introduction

The last twenty years have seen a steady convergence of the traditionally distinct areas of operations management (OM), sourcing, and logistics into a single area commonly known as supply chain management (SCM). According to the SCM perspective, it is no longer adequate for businesses to run these areas as loosely linked pockets of excellence. They must also develop and manage the information flows, physical flows and relationships that link these areas together, and link these areas with upstream and downstream partners.

At the same time, the SCM perspective requires businesses to broaden the scope of business activities that

must be designed and managed, and the nature of these activities has become more challenging as product life cycles shorten, product variety and customization levels increase and supply chain partners become more geographically dispersed. Managing the supply chain, therefore, is clearly a challenging mission, and most observers would agree that a supply chain is a complicated system. In this paper, however, we employ some of the concepts and terminology of the systems science literature to formally define *supply chain complexity*, clarifying the aspects of supply chains that make them truly *complex* systems. While much attention has been paid to why it is necessary for companies to expand the scope and depth of their supply chain activities (e.g., Swafford et al., 2006), only recently have researchers and practitioners begun to consider the downside of this added complexity (Hoole, 2006).

In addition to defining supply chain complexity, we also empirically explore the impact of various sources of complexity—upstream in the supply chain, internal to the manufacturing plant, and downstream from the plant—on manufacturing plant performance. Our results allow us

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to identify the sources of complexity that have a statistically significant impact on plant performance across a large data set of manufacturing plants from various industries and geographic regions of the globe. Moreover, our results resonate with the existing lean production literature in terms of the importance of certain sources of complexity in explaining poor manufacturing performance. Our research also helps to illuminate important priorities for supply chain managers in focusing on certain lean principles over others.

The remainder of this paper is organized as follows. We first review the systems complexity literature, paying particular attention to the concepts of detail complexity and dynamic complexity. Out of this, we develop a definition of supply chain complexity, and discuss its three component parts: internal manufacturing complexity, downstream complexity, and upstream complexity. In the third part of the paper, we put forth a conceptual model of supply chain complexity, which we then test using data gathered from 209 manufacturing plants in seven countries. We end the paper by discussing the parallels and differences between our results and the prescriptions found in the lean production literature, implications for managers, and directions for future research.

2. Literature review

2.1. System complexity

Complexity has been discussed in a wide range of literatures, including philosophy, the physical sciences, engineering and management (e.g., Simon, 1962; Casti, 1979; Holland, 1995; Choi et al., 2001). Despite this attention, there remains a broad range of definitions regarding what constitutes a complex system. Much of this definitional work has been used in studying, predicting, and controlling “chaotic” systems (e.g., Stewart, 2002), and has been incorporated in the organizational theory literature (e.g., Stacey, 1996; Stacey et al., 2000). This stream has also extended to the supply chain management literature, where Choi et al. (2001) have laid the groundwork for research that uses some of these ideas to model supply chains as “complex adaptive systems,” along the lines of the systems-theoretic work summarized in Holland (1995).

More recently, Surana et al. (2005) and Pathak et al. (2007) have extended the theory-building work that applies complex adaptive system (CAS) concepts to SCM, the former by suggesting analytical frameworks for applying CAS principles in studying the management and performance improvement of supply chains, and the latter by providing an extensive review of CAS theory development and application in a wide array of fields. In this section, we first review some of these definitions, and then provide our own definition of supply chain complexity, which forms the basis of our conceptual model and empirical tests.

Simon (1962) offers the following, concise definition of system complexity: “Roughly, by a complex system I mean one made up of a large number of parts that interact in a

nonsimple way” (p. 468). This two-pronged view of complexity—numerousness and interactions—is also found in Casti’s (1979) definition, which holds that “complexity refers to two major aspects of a system: (a) the mathematical *structure of the irreducible component subsystems* of the process and (b) *the manner in which the components are connected* to form the system” (p. 41) [author’s italics].

Yates (1978) defines a complex system as one that exhibits one or more of the following five attributes: (1) significant interactions, (2) high number of component parts or interactions, (3) nonlinearity, (4) broken symmetry, and (5) nonholonomic constraints. It is these last three characteristics that, according to Flood and Carson (1988), are indicative of higher-order complexity since they make a system’s responses hard to predict over time. Nonlinearity arises when the response of the system to a given input is non-proportional. Highly complex systems often fail to exhibit the kind of one-to-one mapping of inputs to outputs that one might find in a simple system. Other manifestations arise when portions of the system are in some way not accessible from other portions of the system. This can be due to the asymmetry of the system, or the existence of nonholonomic constraints, which arise when one or more portions of the system are left outside the central control, allowing these portions of the system to, in the words of Flood and Carson (1988, p. 27), “go off and do their own thing.” An example would be a supply chain with multiple downstream demand points that independently place orders on a centralized supply point without regard to supply constraints or the needs of other demand points. In such a case, the same “input” (placing an order based on pre-established inventory policies) can have varying effects, depending on the state of the supply chain. It is these higher-order aspects of complexity that Waldrop (1992) highlights when he points out that what makes complex systems complex is “a kind of dynamism that makes them qualitatively different from static objects such as computer chips or snowflakes, which are merely complicated” (pp. 11–12).

Based on this literature, then, we define *detail complexity* as the distinct number of components or parts that make up a system, while we use the term *dynamic complexity* to refer to the unpredictability of a system’s response to a given set of inputs, driven in part by the interconnectedness of the many parts that make up the system. Perhaps the most accessible view of dynamic complexity and its distinction from detail complexity is offered by Senge (1990), who defines detail complexity as being driven by the *number* of variables embedded in a system. In contrast, Senge indicates that dynamic complexity involves “situations where cause and effect are subtle, and where the effects over time of interventions are not obvious” (p. 71). Consistent with the various definitions we present above, Senge points out further that dynamic complexity is present “when an action has one set of consequences locally and a very different set of consequences in another part of the system . . . [or] when obvious interventions produce nonobvious consequences” (p. 71).

We can illustrate detail and dynamic complexity with examples from inventory management and manufacturing planning and control. Consider, for example, an independent-demand inventory system (such as a distribution center) in which all items have deterministic demand and are supplied by a perfectly reliable supplier with a constant replenishment lead time. In this case, the only systemic source of complexity is detail complexity, driven by the number of stock-keeping units that must be managed. In contrast, a dependent-demand environment, such as a manufacturing planning and control (MPC) system that utilizes material requirements planning (MRP), provides a textbook illustration of dynamic complexity: changes to the master schedule quantities can have unpredictable, non-linear impacts on the individual material plans due to differences in planning lead times, lot-sizing rules, and inventory levels for lower level components. Even if the demand for the finished items is deterministic, the connectedness, and possible nonholonomic constraints (e.g., various decision makers for component parts who might not necessarily be under the restrictions of centralized control in their ordering decisions) could lead to a wide variety of outcomes over time.

Finally, it is important to note that a firm's supply chain linkages are also sources of dynamic complexity. For instance, when demand levels and supplier lead times are stochastic, the same independent inventory policies that lead to adequate inventory levels at one point in time may result in stockouts in another. Clearly, a more general supply chain – comprised of suppliers of various components, a manufacturer subject to uncertainty in both supply and demand, and the many customers of the finished goods that the manufacturer produces from those components – has the potential to exhibit both detail and dynamic complexity.

2.2. Supply chain complexity

We define supply chain complexity, then, as the level of detail complexity and dynamic complexity exhibited by the products, processes and relationships that make up a supply chain. The earliest mention of supply chain complexity in the academic literature appears to be by Wilding (1998), who proposed a supply chain complexity triangle, comprised of what he calls deterministic chaos, parallel interactions and amplifications. At first blush, the notion of “deterministic chaos” seems oxymoronic. In the precise language of systems science, however, “chaos occurs when a deterministic (that is, non-random) system behaves in an apparently random manner” (Stewart, 2002, p. vii).

Vachon and Klassen (2002) provide a multi-dimensional definition of supply chain complexity and some early empirical analysis to link the construct to delivery performance. The authors first present complexity as a three-dimensional construct, comprising numerosness, interconnectivity and systems unpredictability. They then boil these three dimensions down to two, the levels of complicatedness and uncertainty, and then overlay those two dimensions in a two-by-two matrix with “structure technology” (i.e., product/process structure) and “infra-

structure technology,” ultimately presenting a four-dimensional definition of supply chain complexity. Vachon and Klassen extracted measures for this four-dimensional construct from the Global Manufacturing Research Group (GMRG) database (Whybark and Vastag, 1993) and measured the relationships between these complexity components and delivery performance. Their regression models demonstrated some support for the hypotheses that complicatedness and uncertainty have a negative impact on delivery performance. Interestingly, larger firms—which Vachon and Klassen argue to be a “generic indicator of organizational complexity” (p. 227)—demonstrated lower levels of delivery performance.

Choi et al. (2001) offer a different perspective on supply chain complexity. Using the idea of a “complex adaptive system” (CAS), developed in the systems science literature (cf. Holland, 1995), Choi et al. conceptualize extensive supply networks as CAS's. Consistent with the idea of dynamic complexity, they argue that this type of complexity naturally stems from the extensive interconnectedness of supply networks, where most suppliers are connected to numerous supply chains that ultimately generate diverse products serving diverse, and often hard-to-predict, sets of consumers.

There are several levels at which one could examine supply chain complexity, including by industry, geographic region or business unit. In this paper, we empirically examine supply chain complexity at the manufacturing plant level. At this level of analysis, supply chain complexity can arise from within the plant (what we call internal manufacturing complexity), or via the plant's connections with downstream and upstream partners (downstream and upstream complexity).

2.2.1. Internal manufacturing complexity

Internal manufacturing complexity is defined as the level of detail and dynamic complexity found within the manufacturing facility's products, processes, and planning and control systems. Potential drivers of internal manufacturing complexity include the number of supported parts and products, the types of manufacturing processes, and the stability of manufacturing schedules from one period to the next (Flynn and Flynn, 1999).

Consistent with our earlier definitions, detail complexity within the manufacturing environment increases as the number of supported products and parts increases. Practitioners and academics have long recognized the negative impact of product proliferation on manufacturing performance (Salvador et al., 2002). For example, among practitioners, one of the main tenets of Efficient Consumer Response (ECR) and Collaborative Planning Forecasting and Replenishment (CPFR) is to control product proliferation by maintaining an efficient selection of products and avoiding unnecessary new product introductions (VICS, 2004). “Efficient” selection assumes an “optimum” number of products, after which the additional costs of supporting the products outweigh the increased revenues. Analytical research in the area has focused primarily on the impact of product proliferation on setup costs and/or replenishment lead times (e.g., Yano and Dobson, 1998). More recent research has extended

this to look at supply chain costs as well. For example, Thonemann and Bradley (2002), seeking to quantify the trade-offs involved when setup times are present, put forth an analytical model of a single manufacturer serving multiple retailers. They show that, as process changeover times increase, high levels of product variety lead to longer manufacturing lead times, as well as higher expected cost for the retailers.

The number of unique parts also drives detail complexity in the manufacturing environment, thereby negatively affecting performance (Fisher et al., 1999; Krishnan and Gupta, 2001; Ramdas and Sawhney, 2001). Researchers have examined how manufacturers can employ parts commonality and shared product platforms, in particular, to reduce internal manufacturing complexity, while still meeting diverse market requirements (Meyer and Lehnerd, 1997; Robertson and Ulrich, 1998). In a recent paper, Huang et al. (2005) specifically note that “increased commonality generally encourages the risk pooling effect and then further improves material availability and reduces system complexity” (p. 270). The authors go on to develop a mathematical decision model that analyzes the impact of product platform commonality on the optimal supply chain configuration of products, processes and suppliers, and illustrate their model using data from a notebook computer manufacturer. From a broader perspective, Closs et al. (2008) use a multi-case study approach to motivate prescriptions for utilizing socio-technical systems design principles to mitigate the potential negative impacts of product portfolio complexity on business unit profitability, and they present a framework for these relationships that can be tested explicitly in future research.

The level of detail and dynamic complexity inherent in the manufacturing processes themselves will contribute to internal manufacturing complexity. Manufacturing processes have typically been modeled on a spectrum, ranging from job shops that produce customized, one-of-a-kind (or very low volume) products, to repetitive/flow processes that produce high volumes of standardized products (Hayes and Wheelwright, 1979; Hill, 1994; Safizadeh et al., 1996; Duray et al., 2000). Manufacturing environments characterized by lower volume production processes will generally experience higher levels of detail and dynamic complexity. First, the number of unique jobs that must be managed will be higher in such environments (detail complexity). At the same time, the manufacturing task is more likely to vary from one job to the next, requiring more complex interactions between different areas of the plant and higher levels of decentralized decision making (dynamic complexity) (Hill, 1994).

Finally, unstable production schedules will force manufacturers to either put in place planning and control systems that are capable of dealing with the complex interactions required to link production plans and execution activities, or experience unpredictable, non-linear impacts on lower-level production and material plans. Therefore, unstable production schedules drive dynamic complexity in the manufacturing environment (Vollmann et al., 2005).

2.2.2. Downstream complexity

We define downstream complexity as the level of detail and dynamic complexity originating in a manufacturing facility’s downstream markets. Potential drivers of downstream complexity include the number of customers, the heterogeneity of customer needs, the average length of the product life cycle, and the variability of demand.

Downstream complexity increases as both the number of customers and the heterogeneity of their needs increase. As the number of customers increases, the magnitude of the customer relationship management tasks, demand management tasks and order management tasks all increase, driving detail complexity (Vollmann et al., 2005). Different types of customers are also more likely to vary with regard to order winners and qualifiers, creating the potential for conflicting manufacturing tasks, lower levels of manufacturing performance (Hill, 1994; Bozarth and Edwards, 1997; Bozarth and McCreery, 2001), and potential misalignment between manufacturing capabilities and customer needs (Bozarth and Berry, 1997; da Silveira, 2005).

Shorter product life cycles affect downstream complexity in two ways. First, shorter product life cycles will necessarily increase the number of parts and products that must be supported over a given time frame, thereby increasing detail complexity (Fisher et al., 1999; Krishnan and Gupta, 2001; Ramdas and Sawhney, 2001). Second, customers’ demands for newer products expose a manufacturing plant to greater levels of dynamic complexity as people and systems adjust to ever-changing product requirements.

Demand variability is a significant source of dynamic complexity in the supply chain. This is because the same supply chain actions (e.g., reordering to a fixed stocking level) can have different outcomes (e.g., positive inventory or stockout), depending on the level of demand. The classic example is the bullwhip effect, which demonstrates how a lack of coordination in ordering policies at different points in the supply chain can lead to wide fluctuations in upstream ordering patterns as downstream demand varies only slightly over time (Forrester, 1961; Lee et al., 1997; Chen et al., 2000).

2.2.3. Upstream complexity

Upstream complexity is characterized by the level of detail and dynamic complexity originating in a manufacturing facility’s supply base. Potential drivers of upstream complexity include the number of supplier relationships that must be managed, the delivery lead time and reliability of suppliers, and the extent of global sourcing.

Taking these issues one at a time, we first note that adding suppliers necessarily increases detail complexity, due to the increased number of information flows, physical flows and relationships that must be managed. Second, just as customer heterogeneity and demand variability determine the level of downstream complexity, supplier lead time performance can be viewed as a key driver of upstream complexity. Long and/or unreliable supplier lead times can force manufacturers to adopt planning and material management processes characterized by longer planning horizons and greater levels of detail (Vollmann et al., 2005),

Table 1
Drivers of supply chain complexity

Driver	Complexity type	Supporting literature
Downstream complexity		
Number of customers	Detail	Vollmann et al. (2005)
Heterogeneity in customer needs	Detail and dynamic	Hill (1994), Bozarth and Edwards (1997), da Silveira (2005)
Shorter product life cycles	Detail and dynamic	Fisher et al. (1999), Krishnan and Gupta (2001), Ramdas and Sawhney (2001)
Demand variability	Dynamic	Forrester (1961), Lee et al. (1997), Chen et al. (2000)
Internal manufacturing complexity		
Number of products	Detail	Salvador et al. (2002), Yano and Dobson (1998), Thonemann and Bradley (2002), Closs et al. (2008)
Number of parts	Detail	Fisher et al. (1999), Krishnan and Gupta (2001), Ramdas and Sawhney (2001), Huang et al. (2005)
One-of-a-kind/low volume batch production	Detail and dynamic	Hayes and Wheelwright (1979), Hill (1994), Safizadeh et al. (1996), Duray et al. (2000)
Manufacturing schedule instability	Dynamic	Vollmann et al. (2005)
Upstream complexity		
Number of suppliers	Detail and dynamic	Choi et al. (2001), Wu and Choi (2005), Goffin et al. (2006)
Long and/or unreliable supplier lead times	Detail and dynamic	Vollmann et al. (2005), Chen et al. (2000)
Globalization of the supply base	Dynamic	Cho and Kang (2001), Nellore et al. (2001)

while longer supplier lead times can increase the level of dynamic complexity in the supply chain. For example, [Chen et al. \(2000\)](#) showed that, under certain demand conditions, the magnitude of the bullwhip effect is driven by the replenishment lead time, and can in fact be expressed as an explicit, super-linear function of the lead time.

Finally, upstream complexity is posited to increase as the supply base extends globally. These global linkages potentially expose manufacturers to a wide range of complicating factors—including import/export laws, fluctuations in currency valuations, cultural differences, and longer and more uncertain lead times ([Cho and Kang, 2001](#))—and can force manufacturers to look beyond just price when making purchasing decisions ([Nellore et al., 2001](#)). Hence, we would expect higher levels of global sourcing to increase the levels of dynamic complexity found within the supplier base.

[Table 1](#) summarizes the various individual drivers of internal manufacturing, downstream and upstream complexity described in this section, as well as the supporting literature.

3. Conceptual model and hypotheses

In this section, we present a conceptual model that formally states the relationship between supply chain complexity and plant performance. The model, shown in [Fig. 1](#), defines supply chain complexity as consisting of three parts: downstream complexity, internal manufacturing complexity, and upstream complexity.

[Hypotheses 1–3](#) consider the impact of upstream, internal manufacturing, and downstream complexity on two key operational measures, schedule attainment and unit manufacturing cost performance. Building on the previous discussion, drivers of detail complexity, such as the number of products or suppliers, increase the numerosness of planning activities and level of resources required. The result is an increase in manufacturing costs. At the same time, drivers of dynamic complexity will make planning activities more expensive and less effective due

to non-linear interactions and nonholonomic constraints. This reduced planning effectiveness will force plants to increase buffer capacities, which drives up costs, or risk experiencing unanticipated disruptions in plant activities, which negatively impacts production schedules.

With regard to upstream complexity, a larger supply base will increase the size of the plant's purchasing and materials management activities, thereby driving up costs. Imported goods are subject to additional costs (such as tariffs and documentation fees) and often have longer physical supply chains than domestic goods. If manufacturers are not careful in selecting foreign sources, the result can be higher costs and difficulty adhering to production schedules. Regardless of where the source is located, longer and more uncertain supplier lead times will force manufacturers to lengthen their planning horizons and hold higher levels of safety stock to maintain the same service level. Stated formally:

Hypothesis 1. Higher levels of upstream complexity will negatively impact plant schedule attainment and manufacturing costs.

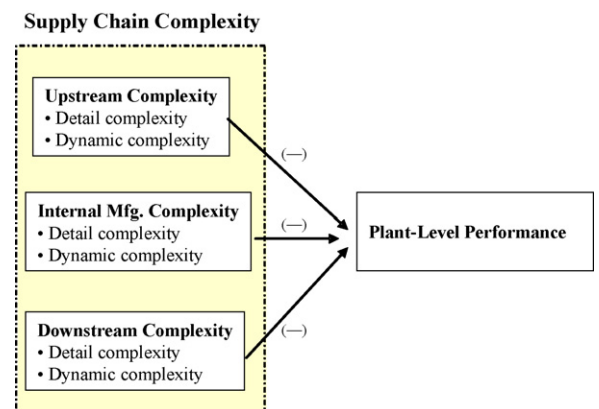


Fig. 1. Conceptual model: The impact of supply chain complexity on plant performance.

Higher levels of internal manufacturing complexity are also hypothesized to have a negative impact on plant schedule attainment and manufacturing costs. At the manufacturing planning level, greater numbers of products and parts, and higher levels of customization will increase the size and scope of the plant's manufacturing task, thereby driving up planning costs. An unstable MPS will also make it more difficult for plants to effectively balance demands against capacity and identify feasible production schedules.

At the execution level, manufacturing costs will tend to increase as the number of supported parts or products increases and production volumes are spread across more distinct items. An unstable MPS is more likely to result in unanticipated capacity conflicts that manifest themselves during execution, resulting in expediting costs or missed due dates (Vollmann et al., 2005).

Hypothesis 2. Higher levels of internal manufacturing complexity will negatively impact plant schedule attainment and manufacturing costs.

As noted earlier, larger numbers of customers, greater customer heterogeneity, and greater levels of demand variability will increase the size and scope of a plant's demand management and order management activities, thereby increasing costs. Furthermore, in contrast to more stable environments, high levels of demand variability will make it difficult for manufacturers to establish and adhere to an effective production schedule.

Hypothesis 3. Higher levels of downstream complexity will negatively impact plant schedule attainment and manufacturing costs.

Hypotheses 1–3 examine the impacts of supply chain complexity on two relatively narrow, *operations-based* measures of plant performance. For broader, *market-based measures*, such as customer satisfaction and plant competitive performance, the relationship between complexity and performance will likely not be as straightforward. This is because what constitutes "good" market-based performance will depend, at least in part, on what customers need and what they are willing to pay for it. For example, markets made up of customers who only require a standard product at the lowest possible cost are less likely to benefit from the added complexity of a broad product line, while markets made up of customers who require more choice in product offerings or greater levels of customization will experience greater satisfaction from increased product line breadth, even if the trade-off is higher product costs and/or less reliable delivery times. Therefore, while we will examine the relationships between supply chain complexity and customer satisfaction and plant competitive performance as part of the larger study, we do not present formal hypotheses for these dependent variables, and our results should be interpreted only within the context of the current plant sample.

Last, we propose that manufacturing plants will have greater difficulty dealing with dynamic complexity than with detail complexity in their supply chain interactions

and internal manufacturing systems. This argument is rooted in the earlier discussion of Yates' (1978) model of system complexity. Detail complexity accounts for only one of the five dimensions ("high number of component parts or interactions"), while dynamic complexity accounts for the others, including nonlinearity, broken symmetry, and nonholonomic constraints. It is these latter system characteristics that directly account for system unpredictability, increasing the challenge of managing them effectively and, as a result, making them more likely to impact performance negatively. Although it would be challenging to test for this effect formally as a statistical hypothesis, we can still utilize the study results to assess the comparative impact of dynamic and detail complexity factors on manufacturing performance. Thus, we state our premise in the form of a proposition:

Proposition 1. Drivers of dynamic complexity will have a greater impact on manufacturing plant performance than drivers of detail complexity.

4. Methodology

4.1. Sample

This study uses data from the third round of the High Performance Manufacturing (HPM) project data set (Schroeder and Flynn, 2001) to test the hypotheses and research proposition. The data were collected during the 2005–2007 timeframe, updating the on-going work of the HPM project, and includes responses from manufacturing plants in seven countries: U.S., Japan, South Korea, Germany, Austria, Finland, and Sweden. These countries were included because they contain a mix of high performing and traditional manufacturing plants in the selected industries, while providing diversity of national cultural and economic characteristics. In each country, data were collected from plants in three industries: machinery, electronics, and transportation components. These industries were selected to include a mix of stable and rapidly changing competitive environments.

The plants in the HPM study were randomly selected from a master list of manufacturing plants in each of the countries. The study administrators sent requests for data to an approximately equal number of plants in each of the three industries. All plants within a given country were from different parent corporations, and each had at least 100 employees. A local member of the research team contacted the plant manager of each plant to solicit participation in the HPM study. In exchange for participation, the plants received a profile that compared their performance on a variety of measures to high performing and traditional plants in their industry, both in their country and in the other countries surveyed.

4.2. Instrument

Participating plants were sent a battery of 23 separate questionnaires, targeted at the respondents who were the

Table 2
Distribution of questionnaires at each sample plant

Respondents	Number of respondents per plant
Plant accounting manager (AC)	1
Direct labor (DL)	10
Human resources manager (HR)	1
Information systems manager (IS)	1
Production control manager (PC)	1
Inventory manager (IM)	1
Member of product development team (PD)	1
Process engineer (PE)	1
Plant manager (PM)	1
Quality manager (QM)	1
Supervisor (SP)	3
Plant superintendent (PS)	1
Total respondents per plant	23

best informed about the topic of the specific questionnaire. The questionnaires, originally developed in English, were translated into the local language by a local member of the research team. They were then back-translated into English by a different local team member to assure accuracy in translation. The questionnaires were sent to a research coordinator at each plant who was responsible for distributing them and collecting the completed questionnaires, as well as serving as a liaison with the research team for resolving data collection issues. The respondents returned their completed questionnaires to the research coordinator in a sealed envelope.

The survey items were divided between the questionnaires in order to obtain information from the respondents who were most knowledgeable. For example,

the production control managers and inventory managers were asked questions related to planning and control systems and supplier delivery performance, while the HR managers were questioned about cross-training efforts in the plants. A mix of item types and some reversed scales were used to minimize the possibility of common methods variance (Crampton and Wagner, 1994). Table 2 provides a list of target recipients of the 23 questionnaires distributed to each plant. Not all plants returned the complete set of questionnaires. Where a particular plant was missing responses that were required for a regression model (as described in Section 5), it was excluded from that particular analysis. Table 3 reports summary statistics for the plants, by industry and by country.

4.3. Measurement development

A subset of the HPM questionnaire items was used in this study. Where there were multiple respondents within a plant for an item, an average was taken to obtain a single value for each plant. We also controlled for industry and country effects by standardizing the individual items. The result was that a particular plant's scores were scaled relative to other respondents in the same industry/country group. While we recognize that industry and country differences could have an impact on complexity levels, the present research goal is to define and measure supply chain complexity at the plant level and determine whether, all other things being equal, it has an effect on manufacturing plant performance. Future research could be directed at determining how the relationships posited in Fig. 1 might differ across industries and countries.

Table 3
Demographics for sample plants

	Frequency count by industry and country						
	Austria (n = 20)	Finland (n = 30)	Japan (n = 34)	Germany (n = 41)	Sweden (n = 24)	United States (n = 29)	South Korea (n = 31)
Electronics	9	14	10	9	10	9	10
Machinery	7	6	11	13	7	11	10
Transportation Components	4	10	13	19	7	9	11
Comparative statistics	Non-standardized mean results, by country						
	Austria (n = 20)	Finland (n = 30)	Japan (n = 34)	Germany (n = 41)	Sweden (n = 24)	United States (n = 29)	South Korea (n = 31)
Annual sales volume, plant (×1000 US\$)	64,475	47,705	1,066,049	173,623	584,371	284,181	2,266,962
Percentage of sales exported (%)	77.99	64.47	32.89	51.51	46.84	23.84	37.62
Percentage of sales, products introduced in last 5 years (%)	51.56	63.65	48.08	60.20	53.19	64.83	72.50
Percentage of materials imported (%)	51.56	35.78	8.67	22.43	39.17	16.93	32.82
Number of hourly personnel	196.24	266.13	975.03	433.96	5.77	326.10	1737.75
Number of salaried personnel	124.12	87.13	462.06	161.80	348.70	153.81	1220.70
Comparative statistics	Non-standardized mean results, by industry						
	Electronics (n = 68)		Machinery (n = 68)		Transportation Components (n = 73)		
Annual sales volume for plant (×1000 US\$)	316,774		438,240		1,063,288		
Percentage of sales exported (%)	51.28		50.01		39.78		
Percentage of sales, products introduced last 5 years (%)	67.40		44.13		63.67		
Percentage of materials imported (%)	39.84		23.31		23.82		
Number of hourly personnel	329.06		526.66		662.92		
Number of salaried personnel	299.78		314.30		364.05		

4.3.1. Supply chain complexity measures

The study incorporated twelve measures of supply chain complexity, consistent with the literature review summarized in Table 1. Appendix A reports detailed information for the measures and underlying survey items. Seven of the supply chain complexity measures consisted of objective data, including (1) the average product life cycle, (2) number of customers, (3) number of active parts, (4) number of products produced, (5) percentage of production volume accounted for by one-of-a-kind or low volume production, (6) number of suppliers to the plant, and (7) percentage of purchases made in the home country.

Five of the supply chain complexity measures were developed from Likert-scaled items, with values ranging from 1 (“Strongly Disagree”) to 7 (“Strongly Agree.”). In three cases, the measure consisted of a single perceptual item (Appendix A). While multi-item perceptual measures have been the norm, Bergkvist and Rossiter (2007, p. 176) argue in a recent *Journal of Marketing Research* article that single-item measures are acceptable when “(1) the object of the construct is ‘concrete singular,’ meaning that it consists of one object that is easily and uniformly imagined, and (2) the attribute of the construct is ‘concrete,’ again meaning it is easily and uniformly imagined.” In this study, the construct object for each item was unambiguous (i.e., the respondent’s plant). To evaluate attribute concreteness, we calculated the inter-class correlations (ICCs) for the three single-item measures. ICC scores ranged from 0.779 to 0.843, indicating a high level of agreement across inter-plant respondents (Garson, 2008). Last, we tested for unidimensionality of the twelve supply chain complexity measures by performing a factor analysis (varimax rotation) on the complete set of items used to construct the upstream, internal manufacturing and downstream complexity measures (Appendix A). The results indicated that each item loaded heavily (0.812 or higher) onto a single factor consistent with the underlying measures, and with minimal cross-loadings. These results suggest that the final measures of supply chain complexity have convergent and discriminant validity.

4.3.2. Plant performance measures

Four measures of plant performance were used in this study (Appendix B). Two of these measures were operational, schedule attainment and unit manufacturing cost performance, and were used in testing Hypotheses 1–3. Schedule attainment was captured via a multi-item scale derived from responses provided by a production control manager, an inventory manager, and a supervisor at each plant (Cronbach’s alpha = 0.92). For unit manufacturing cost performance, the plant manager was asked to rate plant performance on a Likert scale from 1 (“Poor, low end of industry”) to 5 (“Superior”).

Two of the plant performance measures were market-based: plant-level competitive performance and plant-level customer satisfaction. Consistent with Rossetti and Choi (in press) and Flynn and Flynn (2004), we used a formative measure of plant-level competitive performance. Specifically, each plant manager was asked to rate

how well his or her plant compared to the competition across twelve key areas (1 = “poor” to 5 = “superior”). The plant manager, process engineer, and plant superintendent then independently rated how important superior performance in each of these areas was to meeting the firm’s manufacturing goals (1 = “least important” to 5 = “absolutely critical”). The average individual performance ratings were then multiplied by their respective average importance scores and summed to derive the final measure. Note that the plant manager’s assessment of unit manufacturing cost performance is also used separately and without the performance ranking as a measure of operational performance. Nevertheless, the remaining 23 of the 24 scales used in calculating competitive performance are unique to this measure. Last, customer satisfaction was measured using five perceptual items reflecting customer satisfaction with the plant’s responsiveness, quality levels, and ability to satisfy or exceed customers’ requirements (Cronbach’s alpha = 0.90). Note that, of the four performance measures, only unit manufacturing cost performance and plant-level competitive performance were anchored relative to the respondent plant’s industry or competitors. Table 4 contains the correlation matrix, as well as means and standard deviations, for the final measures.

5. Analysis

The analysis was divided into two stages. First, multiple regression modeling was used to separately test the effects of downstream, internal manufacturing and upstream supply chain complexity on each of the four measures of manufacturing performance. Because the independent and dependent variables were standardized by industry and country, all results are interpreted relative to other plants within the same industry/country group. In the second stage of the analysis, we used the regression results to examine the proposition that drivers of dynamic complexity exhibit greater influence in explaining plant performance than drivers of detail complexity (Proposition 1).

Table 5 contains the entire set of regression results. The first two columns contain results for schedule attainment and unit manufacturing cost performance, and provide the tests for Hypotheses 1–3. The last two columns contain results for the two market-based measures, customer satisfaction and plant competitive performance and are included here for discussion purposes. Collinearity diagnostics were used to test for potential multicollinearity effects (SPSS, Version 16.1). Resulting tolerance (>0.20) and condition indices (<30) indicated no significant multicollinearity effects for any of the models (Garson, 2008). In related previous studies, some researchers have included plant size to control for complexity (number of products, customers, etc.) or economies of scale differences (e.g., Shah and Ward, 2003) while others have not (Swafford et al., 2006). Plant size was not included in this study since the measures of downstream, internal manufacturing and upstream complexity already explicitly capture the complexity dimensions of interest.

Table 4
Correlation matrix

		(Mean, S.D.)	Pearson correlation coefficients, significance levels, and sample sizes (listed top to bottom in each cell)																
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	
1	Short product life cycles	(0.00,0.94)	1.000																
			157																
2	Heterogeneity of customer demands	(0.00,0.95)	-0.090	1.000															
			0.261																
			157	205															
3	Number of customers	(0.00,0.94)	-0.178*	-0.055	1.000														
			0.038	0.475															
			137	169	171														
4	Demand variability	(0.00,0.95)	-0.065	-0.197**	0.011	1.000													
			0.416	0.005	0.884														
			157	205	171	209													
5	Number of active parts	(0.00,0.93)	-0.105	-0.192*	0.049	0.149	1.000												
			0.239	0.016	0.573	0.062													
			128	156	137	157	157												
6	Number of products	(0.00,0.94)	0.046	0.039	0.055	0.144	0.234**	1.000											
			0.604	0.625	0.521	0.067	0.007												
			130	163	139	163	132	163											
7	Un-level MPS	(0.00,0.95)	-0.174*	0.041	0.061	0.407**	0.241**	0.179*	1.000										
			0.030	0.559	0.427	0.000	0.002	0.023											
			157	205	171	209	157	163	209										
8	% one-of-a-kind/ low volume batch production	(0.00,0.94)	-0.058	-0.023	0.078	0.234**	0.249**	0.020	0.195*	1.000									
			0.504	0.763	0.348	0.002	0.004	0.818	0.010										
			134	171	147	171	133	140	171	171									
9	Number of suppliers	(0.00,0.93)	-0.128	-0.212**	0.119	0.186*	0.417**	0.132	0.172*	0.217*	1.000								
			0.150	0.008	0.165	0.020	0.000	0.138	0.031	0.011									
			128	155	137	157	132	127	157	136	157								
10	Long supplier lead times	(0.00,0.95)	-0.033	0.123	-0.045	0.127	-0.078	0.100	0.178**	0.044	-0.114	1.000							
			0.679	0.080	0.556	0.066	0.330	0.206	0.010	0.564	0.154								
			157	205	171	209	157	163	209	171	157	209							
11	Unreliable supplier delivery	(0.00,0.95)	-0.135	0.074	-0.068	0.277**	0.190*	0.102	0.300**	0.201**	0.233**	0.403**	1.000						
			0.091	0.289	0.376	0.000	0.017	0.194	0.000	0.008	0.003	0.000							
			157	205	171	209	157	163	209	171	157	209	209						
12	% purchases imported	(0.00,0.94)	0.066	-0.087	-0.006	-0.043	-0.205*	-0.137	-0.139	-0.047	-0.065	-0.026	-0.007	1.000					
			0.432	0.248	0.940	0.568	0.012	0.098	0.062	0.566	0.448	0.726	0.921						
			144	179	153	181	150	146	181	153	139	181	181	181					
13	Schedule attainment	(0.00,0.95)	0.102	0.054	0.166*	-0.336**	-0.099	-0.122	-0.251**	-0.110	-0.118	-0.470**	-0.507**	0.100	1.000				
			0.250	0.501	0.049	0.000	0.263	0.160	0.001	0.195	0.187	0.000	0.000	0.240					
			128	158	141	160	129	135	160	140	127	160	141	160	141	160			
14	Unit mfg. cost performance	(0.00,0.94)	-0.026	-0.078	0.090	-0.112	-0.066	-0.064	-0.293**	-0.242**	-0.013	-0.222**	-0.123	-0.004	0.236**	1.000			
			0.761	0.294	0.251	0.128	0.431	0.435	0.000	0.002	0.877	0.002	0.095	0.957	0.004				
			143	184	165	187	143	151	187	158	141	187	164	148	187				
15	Customer satisfaction	(0.00,0.95)	0.046	-0.060	0.098	-0.289**	0.013	-0.075	-0.151*	-0.131	0.075	-0.349**	-0.225**	0.006	0.463**	0.159*	1.000		
			0.566	0.392	0.201	0.000	0.873	0.345	0.029	0.089	0.350	0.000	0.001	0.937	0.000	0.030			
			157	205	171	209	157	163	209	171	157	209	209	181	160	187	209		
16	Competitive performance	(0.00,0.95)	-0.067	-0.010	0.139	-0.135	0.019	-0.060	-0.175*	-0.127	0.052	-0.385**	-0.196**	0.030	0.265**	0.593**	0.263**	1.000	
			0.435	0.898	0.084	0.075	0.827	0.475	0.020	0.126	0.552	0.000	0.009	0.712	0.002	0.000	0.000		
			137	173	155	176	135	142	176	147	134	176	176	154	138	176	176	176	

* Significant at the $p = 0.05$ level.

** Significant at the $p = 0.01$ level.

Table 5
Regression results, Hypotheses 1–3

Upstream complexity measures	Plant-level performance measures											
	Schedule attainment			Unit manufacturing cost performance			Customer satisfaction			Competitive performance		
	$R^2 = 0.37$, $F = 16.30$ (0.000)			$R^2 = 0.07$, $F = 2.13$ (0.081)			$R^2 = 0.12$, $F = 4.38$ (0.002)			$R^2 = 0.12$, $F = 4.10$ (0.004)		
	Standard β	t	Significance	Standard β	t	Significance	Standard β	t	Significance	Standard β	t	Significance
Number of suppliers	-0.11	-1.28	0.2	-0.05	-0.49	0.63	0.08	-0.94	0.35	0.04	0.38	0.7
Long supplier lead times	-0.42^b	-5.02	0.0	-0.22^a	-2.24	0.03	-0.25^b	-2.69	0.01	-0.26^b	-2.63	0.01
Unreliable supplier delivery	-0.29^b	-3.18	0.0	-0.06	-0.61	0.55	-0.15	-1.50	0.14	-0.15	-1.41	0.16
% purchases imported	0.16	2.03	0.05	0.01	0.10	0.92	0.04	0.52	0.61	0.11	1.21	0.23
Internal manufacturing complexity measures	$R^2 = 0.13$, $F = 3.59$ (0.009)			$R^2 = 0.12$, $F = 3.41$ (0.012)			$R^2 = 0.09$, $F = 2.65$ (0.037)			$R^2 = 0.12$, $F = 3.23$ (0.016)		
	Standard β	t	Significance	Standard β	t	Significance	Standard β	t	Significance	Standard β	t	Significance
Number of active parts	0.02	0.17	0.87	0.01	0.05	0.96	0.17	1.63	0.11	0.04	0.34	0.74
Number of products	0.01	0.05	0.96	0.09	0.92	0.36	-0.02	-0.23	0.82	0.06	0.55	0.58
Un-level MPS	-0.36^b	-3.61	0.00	-0.25^b	-2.55	0.01	-0.27^b	-2.79	0.01	-0.33^b	-3.24	0.0
% one-of-a-kind/low volume batch production	-0.03	-0.25	0.80	-0.20^a	-2.00	0.05	-0.11	-1.18	0.24	-0.09	-0.93	0.35
Downstream complexity measures	$R^2 = 0.14$, $F = 4.42$ (0.002)			$R^2 = 0.06$, $F = 1.85$ (0.123)			$R^2 = 0.08$, $F = 2.85$ (0.026)			$R^2 = 0.04$, $F = 1.38$ (0.244)		
	Standard β	t	Significance	Standard β	t	Significance	Standard β	t	Significance	Standard β	t	Significance
Short product life cycles	0.06	0.69	0.49	-0.04	-0.46	0.65	0.04	0.42	0.68	-0.11	-1.16	0.25
Heterogeneity of customer demands	-0.05	-0.49	0.63	-0.18^a	1.96	0.05	-0.15	-1.63	0.11	-0.11	-1.19	0.24
Number of customers	0.15	1.60	0.11	0.09	0.99	0.33	0.10	1.18	0.24	0.13	1.40	0.17
Demand variability	-0.35^b	-3.71	0.0	-0.18^a	-1.95	0.05	-0.26^b	-2.93	0.0	-0.06	-0.68	0.50

^a $p < 0.05$, one-tailed test.

^b $p < 0.01$, one-tailed test.

5.1. Upstream complexity results (*Hypothesis 1*)

Hypothesis 1 holds that higher levels of upstream complexity will have a negative impact on plant schedule attainment and unit manufacturing cost performance. The results in [Table 5](#) provide support for this hypothesis. The results are particularly strong for schedule attainment, with the drivers of upstream complexity explaining 37% of the variance in schedule attainment scores.

Examining the individual model results yields some additional insights. The number of suppliers, a driver of detail complexity, has no significant impact on any of the plant performance measures. In contrast, long supplier lead times has a significant, negative impact across all four performance measures, while unreliable supplier delivery has a significant, negative impact on schedule attainment. In effect, within a particular industry/country group, it is the dynamic complexity embedded in the supply base, more so than its detail complexity, which appears to have the greatest impact on plant-level performance. The results for the percent of purchases imported are particularly interesting. While we expected this variable to have a significant negative impact on schedule attainment and unit manufacturing cost performance, the results suggest otherwise. One possible explanation is the overriding performance impact of short, reliable supplier lead times. Put simply, it is the suppliers' delivery performance, more so than their geographic location or nationality, which impacts operations-based plant performance relative to other plants in the same industry/country group.

5.2. Internal manufacturing complexity results (*Hypothesis 2*)

Hypothesis 2 argues that higher levels of internal manufacturing complexity will have a negative impact on schedule attainment and unit manufacturing cost performance. The results in [Table 5](#) fully support this hypothesis. The regression results for these two performance measures (as well as customer satisfaction and competitive performance) are significant at the $p = 0.05$ level or better, with one independent variable, instability of the master production schedule, having a significant, negative performance impact across all four models.

As with the upstream complexity results, the individual regression models yield some interesting insights. Experts have long argued that instability at the MPS level can have unpredictable, non-linear impacts on lower level planning and control activities ([Vollmann et al., 2005](#)). The breadth and strength of our results provide empirical support for these arguments.

Not surprisingly, as the percent of production characterized by one-of-a-kind or low volume batch production increases, unit manufacturing cost performance suffers relative to other plants in the same industry/country group. In contrast, the results provide no evidence that the number of active parts or products has an impact on plant-level performance relative to

other plants in the same industry/country group. This is an important finding, because it suggests that efforts to reduce the amount of detail complexity within the plant's product lines are not as critical to plant performance as attacking sources of dynamic complexity.

5.3. Downstream complexity results (*Hypothesis 3*)

Hypothesis 3 holds that as downstream complexity increases, plant schedule attainment and unit manufacturing cost performance will decrease. The results in [Table 5](#) provide support for this hypothesis, albeit not as strongly as for [Hypotheses 1 and 2](#).

Demand variability is the only independent variable to show consistently strong results, with significant, negative impacts on schedule attainment and unit manufacturing cost performance relative to other plants in the same industry/country group. Only one other independent variable, heterogeneity of customers' demands, shows any impact on operations-based performance (unit manufacturing costs). As with the upstream and internal manufacturing complexity models, the pure measure of detail complexity (number of customers) shows no significant results across any of the regression models.

5.4. Dynamic complexity vs. detail complexity impacts (*Proposition 1*)

Proposition 1 states that drivers of dynamic complexity will have a stronger negative impact on plant-level performance than will drivers of detail complexity. To examine whether or not this was the case, we sorted the twelve independent variables into three categories, based on the literature summarized in [Table 1](#): (1) drivers of detail complexity alone, (2) drivers of both detail and dynamic complexity, and (3) drivers of dynamic complexity alone. We then used the regression results in [Table 5](#) to further divide each category into two groups: those variables that show a significant, negative impact on at least one measure of plant-level performance, and those that do not. [Table 6](#) highlights our findings.

The results strongly support [Proposition 1](#). The significant independent variables from our regressions are exclusively those that are sources of dynamic complexity alone, or sources of both dynamic and detail complexity. None of the four pure detail complexity measures (number of customers, parts, products, and suppliers) proved to be significant at the $p = 0.05$ level in any of the regression models, while six of the eight measures capturing at least some level of dynamic complexity had a significant, negative impact on one or more measures of plant performance. Furthermore, two of the three measures with the broadest impact on plant-level performance (i.e., those that are significant in all or almost all of the performance regressions)—unstable master production schedules and demand variability—represent pure measures of dynamic complexity.

Table 6
Summary results for Independent Variables

Type of complexity measure	Plant-level performance impact	
	Not significant at the $p = 0.05$ level across all regression models (Table 5)	Significant at the $p = 0.05$ level for one or more regression models (Table 5)
Detail complexity	<ul style="list-style-type: none"> • Number of suppliers • Number of active parts • Number of products • Number of customers 	
Detail and dynamic complexity	<ul style="list-style-type: none"> • Shorter product life cycles 	<ul style="list-style-type: none"> • Long supplier lead times^a • % one-of-a-kind and low volume batch production • Heterogeneity of customer needs
Dynamic complexity	<ul style="list-style-type: none"> • % Purchases imported 	<ul style="list-style-type: none"> • Unreliable supplier lead times • Unstable MPS^b • Demand variability^c

^a Most significant variable measuring upstream complexity.

^b Most significant variable measuring internal manufacturing complexity.

^c Most significant variable measuring downstream complexity.

While we had expected drivers of dynamic complexity to have a greater negative impact on a plant's performance, relative to industry/country peers, we were surprised by the lack of results for the pure detail complexity drivers. These results provide some of the first empirical evidence that contemporary manufacturers are doing a credible job of managing the impacts of detail complexity in the form of large numbers of customers, parts, products and suppliers on plant performance. Further research should explore the specific mechanisms underlying these results.

6. Discussion and directions for future research

6.1. Parallels to the lean production literature

Practitioners and academics are starting to recognize how supply chain complexity affects plant performance (Deloitte and Touche, 2003). More formally, our research presents a conceptual model that divides plant-level supply chain complexity into three distinct parts (downstream complexity, internal manufacturing complexity, and upstream complexity), and distinguishes between drivers of detail complexity and dynamic complexity.

levels of upstream, internal manufacturing, and downstream complexity will have a negative impact on plant performance. The empirical analysis, based on a sample of 209 plants from seven countries, supports these hypotheses. Three supply chain complexity drivers stand out in terms of their impact on plant performance: long supplier lead times, instability in the master production schedule, and variability in demand. Note that these findings parallel the prescriptions commonly advocated in the lean production literature, as captured in the comprehensive definition put forth by Shah and Ward (2007):

“Lean production is a socio-technical system whose main objective is to eliminate waste by concurrently reducing or minimizing supplier, customer and internal variability” (p. 791—our italics).

Our research does more than provide empirical support for lean prescriptions, though. It establishes a link between the lean production literature and the systems science literature that formally defines the characteristics of higher-order complexity systems. In doing so, our study provides an alternative view into why variability and unpredictability in supplier, customer, and internal inputs to the manufacturing process can be so detrimental to plant performance.

In at least one important way, our findings differ from traditional lean prescriptions. Controlling for industry and country effects, we did not see a significant relationship between plant performance and the supply chain characteristics that addressed *numerousness* in the system—number of suppliers, number of parts and products, and number of customers. One possible explanation is that manufacturers have become adept at managing such sources of detail complexity, either through product design efforts that limit true variability in product design, through marketing efforts that grow the number of customers without increasing heterogeneity, through the use of information technology, or through lean-based simplifications to the production system that allow it to accommodate more environmental uncertainty (an excellent example of the latter is the Aisin Mattress Factory described in Spear and Bowen, 1999, p. 102). It remains to be seen whether our findings represent an anomaly or an early indication that manufacturers have learned to effectively manage detail complexity.

6.2. Determining the appropriate level of supply chain complexity

Another interesting issue highlighted by the results is one that, in our view, is not discussed enough in the operations and supply chain management literature—the extent to which the firm *should* reduce or eliminate certain sources of supply chain complexity. Indeed, a firm might consciously decide to take on customers who, although their demands are less predictable, might

nevertheless purchase higher-margin products and services. Moreover, a firm might decide for strategic reasons to use suppliers whose piece prices are substantially lower, but whose delivery capabilities are deficient, or perhaps to hedge its bets between fast and expensive suppliers and slow and inexpensive suppliers by employing both, thereby injecting additional complexity in its supply management and internal planning systems.

Our argument, then, is *not* that all sources of supply chain complexity are bad things and therefore must be eliminated or reduced to the lowest possible levels. Rather, it is our contention that if manufacturers engage in activities and relationships that increase the complexity of their supply chains—something they might indeed need to do for competitive reasons—they need to understand the potential performance impacts of these choices, and, where necessary, take actions to offset or accommodate the higher levels of complexity that strategic imperatives might entail.

6.3. Accommodating supply chain complexity

Most of the trade and academic literature on lean production has focused predominantly on how to *reduce* supply chain complexity—see, e.g., the excellent literature reviews in Shah and Ward (2003, 2007). Yet the literature on flexibility (e.g., Swink et al., 2005; Sethi and Sethi, 1990 and Swafford et al., 2006) and operations strategy (from, e.g., Hayes and Wheelwright, 1979, to recent work like that of Closs et al., 2008) indicates that manufacturers must understand how to *accommodate* high levels of supply chain complexity when the business strategy requires it. Galbraith (1973, 1974, 1977), in his information processing view of the firm, posited that organizations have two basic strategies for accommodating environmental uncertainty: (1) put in place mechanisms that *absorb* the effects of uncertainty or (2) *enhance* the organization's ability to manage uncertainty. Flynn and Flynn (1999) studied the impacts of such strategies within the manufacturing plant, but to our knowledge, no one has examined how effective these strategies are at moderating the impacts of upstream and downstream complexity.

While Flynn and Flynn focused on complexity in manufacturing, we extend the scope of analysis to study sources of complexity upstream and downstream from the plant. The nature of the study carried out by Flynn and Flynn, however, is broader in that it also studies the moderating effects of applying Galbraith's prescriptions for managing uncertainty. It would be useful, then, to extend our research to explore whether Galbraith's prescriptions are being employed in managing complex supply chains, and to the extent that they are, whether they moderate the negative effects of supply chain complexity on plant performance.

6.4. Study limitations and directions for future research

While this research makes a significant contribution to the academic literature and provides the potential to

positively influence managerial practice, there are nonetheless limitations that provide opportunities for further research. First, we did not explicitly explore the impact of industry and country differences on the complexity–performance relationships we found in our analysis. In some industries or countries, these relationships may differ due to differences in customer requirements and preferences, or differences in manufacturing or supply chain management practices. Moreover, the set of significant supply chain complexity drivers might vary across industries or countries. Second, our study has not explored the *source* of the differences in the complexity–performance relationships among firms, just that those relationships exist. A deeper question, then, is whether plant-level decision makers actually recognize these relationships and account for them in managing the supply chain. Finally, we have proposed what we believe would be an interesting study to extend previous work (Flynn and Flynn, 1999) regarding the moderating impact of organizational prescriptions for managing in an uncertain environment (Galbraith, 1973, 1974, 1977). The research presented in this paper serves as a natural base from which to explore similar effects in the broader supply chain.

Thus, we close the paper with a series of specific questions regarding those directions for future research:

- To the extent that the relationships posited in the conceptual model might differ across geographic regions or industries, how do these differences affect our more general findings regarding the effects of specific sources of complexity on plant performance?
- Are there other important sources of complexity in the supply chain not addressed in this study that might also explain performance differences among manufacturers? Moreover, do manufacturing industries that differ from those considered in this study exhibit different complexity drivers and performance effects? For example, do these complexity issues present themselves differently in “lighter” manufacturing industries (e.g., consumer electronics or medical devices) or in non-manufacturing portions of physical goods supply chains (e.g., retailing or distribution)? Could a study parallel to ours be undertaken on service supply chains?
- How well do plant-level decision makers understand supply chain complexity and its impacts? Do the better performers in our data set reflect proactive management or good instincts on the part of some plants, lack of awareness on the part of other plants, or something else?
- Building on the work of Galbraith (1973, 1974, 1977) and Flynn and Flynn (1999), what strategies are plants using to moderate the impacts of supply chain complexity? How effective are these strategies?
- Last, what frameworks can manufacturers use to identify and balance the positive, revenue-generating aspects of increased supply chain complexity versus their performance impacts? How can these frameworks be integrated into the supply chain strategy debate?

Appendix A. Supply chain complexity measures (see Table 2 for respondent key)**Downstream complexity**

Measure	Complexity type	Survey item
Number of customers	Detail	How many customers does this plant serve (approximately)? <i>Respondent: PM</i>
Customer heterogeneity	Dynamic	All of our customers desire essentially the same products. (reverse scored) <i>Respondents: PD, PE, PS, IM (ICC = 0.779)</i>
Short product life cycle	Detail and dynamic	What is the average life cycle of your products (years)? (inverse) <i>Respondents: PS, PE</i>
Demand variability	Dynamic	Average of the following standardized items: <ul style="list-style-type: none"> • Our total demand, across all products is relatively stable. (reverse scored) • Manufacturing demands are stable in our firm. (reverse scored) <i>Respondents: IM, SP, PS</i>

Internal manufacturing complexity

Measure	Complexity type	Survey item
Number of active parts	Detail	This plant's output requires approximately how many individual active part numbers of material items? <i>Respondents: IM, PC, PE</i>
Number of products	Detail	How many product models are manufactured at this plant? <i>Respondents: IM, PC, PE</i>
Manufacturing schedule instability	Dynamic	The master schedule is level-loaded in our plant, from day to day. (reverse scored) <i>Respondents: PC, IM, SP, PS (ICC = 0.843)</i>
% One-of-a-kind/low volume batch production	Dynamic	The production processes in this plant are best characterized as follows: 1) one of a kind, 2) small batch, 3) large batch, 4) repetitive/line low, and 5) continuous. (Respondents were asked to indicate the percent of production volume accounted for by each category, with all percentages adding to 100%. The sum of the first two categories was then calculated.) <i>Respondent: PE</i>

Upstream complexity

Measure	Complexity type	Survey item
Number of suppliers	Detail	How many suppliers does the plant have? <i>Respondent: QM</i>
Long supplier lead times	Detail and dynamic	Average of the following standardized items: <ul style="list-style-type: none"> • We seek short lead times in the design of our supply chains. (reverse scored) • Our company strives to shorten supplier lead time, in order to avoid inventory and stockouts. (reverse scored) <i>Respondents: IM, SP, PS</i>
Supplier delivery unreliability	Dynamic	We can depend upon on-time delivery from our suppliers. (reverse scored) <i>Respondents: PM, IM, SP (ICC = 0.816)</i>
Percentage of purchases imported	Dynamic	What percentage of purchases come from your home country? (reverse scored) <i>Respondent: IM</i>

Appendix B. Plant performance measures (see Table 2 for respondent key)

Measure	Survey item
Unit cost of manufacturing	Rated from 1 ("Poor, low end of industry") to 5 ("Superior") <i>Respondent: PM</i>
Schedule attainment	Average of the following items (Cronbach's alpha = 0.92): <ul style="list-style-type: none"> • We usually meet the production schedule each day. • Our daily schedule is reasonable to complete on time. • We cannot adhere to our schedule on a daily basis (reverse scored). • It seems like we are always behind schedule (reverse scored). <i>Respondents: PC, IM, SP</i>

Appendix B (Continued)

Measure	Survey item
Plant-level competitive performance	<p>Sum of (Plant performance compared to competition) × (Relative importance) across the following areas:</p> <ul style="list-style-type: none"> • Unit cost of manufacturing • Conformance to product specifications • On-time delivery performance • Fast delivery • Flexibility to change product mix • Flexibility to change volume • Inventory turnover • Cycle time (raw material to delivery) • Development lead time • Product capability and performance • Product innovativeness • Customer support and service <p>Where:</p> <ul style="list-style-type: none"> • “Plant performance compared to competition” is rated from 1 (“Poor”) to 5 (“Superior”) • “Relative importance” is rated from 1 (“Least important”) to 5 (“Absolutely critical”) <p>Respondents: PM, PE, PS</p>
Plant-level customer satisfaction	<p>Average of the following items (Cronbach's alpha = 0.90):</p> <ul style="list-style-type: none"> • Our organization satisfies or exceeds the requirements and expectations of our customers. • Customer standards are always met by our plant. • Our customers are pleased with the products and services we provide them. • Our customers seem happy with our responsiveness to their problems. • Our customers have always been well satisfied with the quality of our products over the past three years. <p>Respondents: DL, QM, SP</p>

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