Data Governance for Data Sharing: Why Is It So Hard?

Richard Howey, DBA
University of Minnesota
howe0156@umn.edu

Abstract

Efficient firm-wide allocation of data resources is a key goal of data governance. One way enterprise assets are often allocated is by an internal market wherein the internal organizational units inside the firm sell resources to each other. However, not all resources are efficiently allocated through free markets. Computerized data possess economic characteristics that may make an internal market for data fail. This research uses a literature review to hypothesize a structural cause/effect model of how this market failure may occur and then analyzes the validity and quantitative implications of that model using exploratory partial least squares structural equation modeling. The research concludes that the market failure is occurring in practice and that enterprise management and data governance are not effectively recognizing or dealing with the market failure. The paper concludes with recommendations for improving data governance practices and for additional research.

Keywords: internal market, data sharing, market failure, rivalrous, excludable

1. Introduction

One of the major responsibilities of enterprise management is to manage and allocate resources within the business enterprise or firm. In fact, it has been hypothesized that the reason we have firms or business enterprises in the first place is that management can allocate resources more efficiently within the firm than they could be allocated if the firm had to acquire resources externally through a market mechanism because the transaction costs of participating in a market would be minimized or eliminated (Coase, 1937). While Coase's theory of the firm depends on an entrepreneur who can personally manage the entire enterprise, modern firms are often so large and complicated that this would be exceedingly difficult or impossible (Ackoff, 1993). Thus, many theorists, especially those who subscribe to the systems theory of management, recommend using an internal market mechanism to allocate resources (Gharajedaghi, 2011). While this might at first seem to be inconsistent with Coase's theory of the firm, it is logical to conclude that it is consistent if the transaction costs of such an internal market are less than the transaction costs of the external market from which the firm would otherwise have to obtain resources.

Thus, it is logical to conclude that many modern firms may use an internal market mechanism to allocate resources across the internal organizational structures that comprise the business enterprise. Clearly, computerized data is an important enterprise-level resource in the modern firm. In fact, one of the major dimensions of the business models of modern firms is the degree to which data must be shared between the organizational units within that firm (Ross, Weill and Robertson, 2006). Thus, data are a resource that must be allocated within the firm by enterprise management. That must be a primary goal of enterprise data governance. Therefore, it is logical to conclude that at least some modern firms may use an internal market mechanism to do that allocation.

Accordingly, information technology (IT) has developed techniques to help share data across a business enterprise. One example is the data warehouse (DW) that integrates data from multiple sources across an enterprise to facilitate analytical or decision-making business processes (Inmon, 1996). Another example is the operational data store (ODS) that is similar to the data warehouse but serves current business operational purposes rather than strategic or analytical purposes (Inmon, 1999). A third example is master data management (MDM) that integrates and shares data related to entities such as customers, suppliers and products that participate in transactions across a business enterprise (Liyakasa, 2012). Yet another example is data virtualization that makes data that may be stored in many physical databases and technologies across an enterprise appear to be stored in a single integrated data asset (Denodo, 2014). One more example is big data that uses advanced technology such as data lakes and Hadoop to cost-effectively capture and analyze extreme volumes of data such as social media data that may be important to many organizational units inside a business enterprise (SAS, n.d.). As a final example, Data as a Service (DaaS) uses advanced networking and cloud computing capabilities to provide access to data across the enterprise through standardized interfaces while hiding its physical implementation in a single or many databases (Delphix, 2011).

URI: https://hdl.handle.net/10125/107167
978-0-9981331-7-1

Unfortunately, the success rate of initiatives for implementing many technologies that share data across organizational boundaries, e.g., divisions or business units, inside a single business enterprise, such as DW and MDM, is low. For instance, it is estimated that only 24 percent of MDM programs are fully successful (Epperson, 2013). DW fares a little better with a 42 percent success rate (Ambler, 2014). If the success of these initiatives is a goal of data governance, then clearly data governance must do better. (However, it should be noted that these practitioner studies typically do not formally define what they mean by "success." This is a topic that receives further analysis in this study.)

Of course, there are multiple theories of why these projects or initiatives fail so often along with advice to make them succeed (Epperson, 2013; Merrick, 2014). Yet, the failure rate remains high even with all the advice that is available on how to make these initiatives succeed. This research proposes a new theory of why these initiatives fail and then analyzes that theory quantitatively. That theory is based on the economic concept of a market failure.

Economists have long known that markets fail to efficiently supply certain goods and services. One category of goods and services that economists agree will experience a market failure is called a public good or service (Mitnick, 2008; Windsor, 2008). The reason that public goods or services lead to a market failure is that they are non-rivalrous and non-excludable meaning that many people can consume the good or service at the same time and nobody can be excluded from benefiting from the good or service (Mitnick, 2008; Samuelson, 1954; Windsor, 2008). This removes incentives to invest because people hope to benefit as a free rider from others' investments. In economics, this is known as an externality (Externality, 2008).

Data in a computerized database is clearly non-rivalrous. Because security can be implemented on a computer system that will prevent individuals from accessing the data, data in a computer system is clearly excludable. But sharing data across internal organizational boundaries is clearly important in at least some if not all business enterprises (Ross, Weill and Robertson, 2006). In fact, some consider that the more data or information are reused, the more valuable they become (Kubiszewski, Farley and Costanza, 2010). Thus, to maximize its business value, data should be considered both non-rivalrous and non-excludable, at least within the boundaries of a single business enterprise or firm.

As previously discussed, many management experts recommend internal markets as an appropriate way to allocate goods, services, resources, etc. inside a business enterprise. Basically, business units, divisions, departments, etc. act as buyers and sellers of goods and services to each other. Data, as a good, could be bought and sold in such a market. However, if data has the characteristics of a public good within the business enterprise, then an internal market for data could fail. Researchers have previously noted that allocation of public goods or services can be problematic in business enterprises because management behavior displays symptoms that are characteristic of a market failure (Olson, 1971).

Data is naturally non-rivalrous. Data sharing initiatives sponsored by enterprise data governance imply that data should not be excluded from anyone within the enterprise who has a legitimate business need for it. Yet, if intra-organizational relationships are based on a market mechanism, the executives who buy and sell data will be tempted to impose excludability on data to at least make a market functional. While enterprise data governance and enterprise executives want non-excludability of data, business unit executives try to impose excludability. This implies a direct conflict in the wishes and desires, and most importantly, in the behaviors of enterprise-level and business unit-level executives. The result is a chaotic and failed market.

Thus, the primary purpose of this research is to explore how an internal market culture for allocating enterprise resource across a business enterprise relates to management behavior and data sharing success or failure through the specific mechanism of an economic failure of the internal market for data.

While there has been considerable research into the success of information systems (IS) in general, e.g. (Petter, DeLone and McLean, 2008) and data sharing initiatives such as data warehouses, e.g. (Adamala and Cidrin, 2011; Alhyasat and Al-Dalameh, 2013; Chenowith, Corral and Demirkan, 2006; Laney, 2000; Sujitparapitaya, Janz and Gillenson, 2003), no existing research appears to have considered economic market failure as a specific cause of data sharing failure. Thus, this research makes a unique contribution to the literature.

2. Literature Review

An extensive literature review was undertaken. An important finding was that the only existing measurement structure that relates to this research that could be found was a model of IS success defined by Petter, DeLone and McLean (2008). No other existing measurement structures were found for the existence of a market culture or the process of the market failure

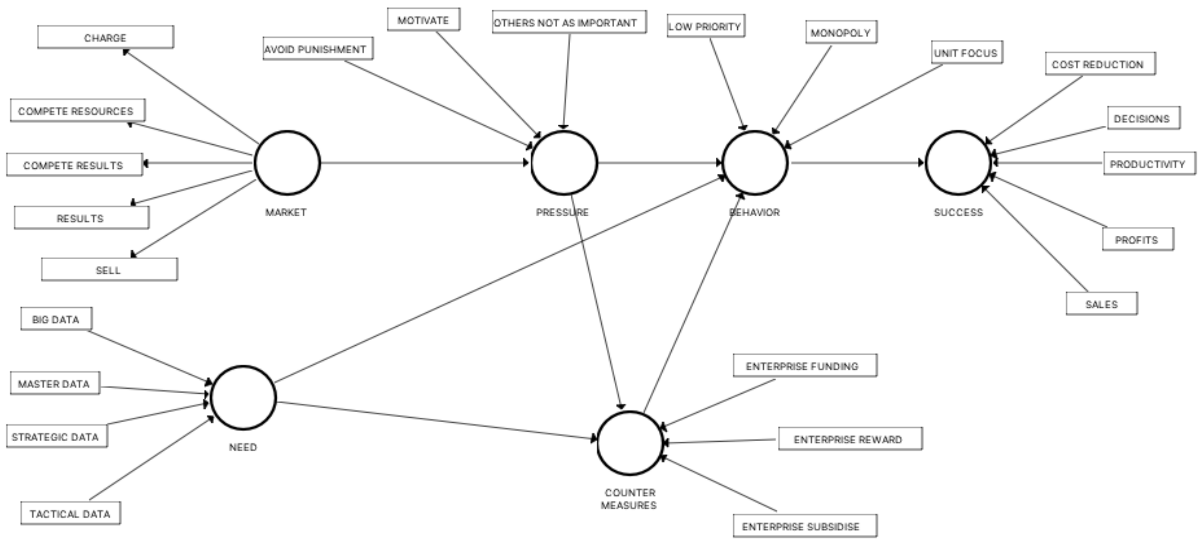

Figure 1. Initial Theoretical PLS/SEM Path Model

Therefore, the main result of the review was to develop a hypothetical structural equation modeling (SEM) path model to describe relationships between an internal market culture and its effect on data sharing behavior and data sharing success where success is defined as in Petter, DeLone and McLean (2008). The resulting SEM path model is illustrated in Figure 1.
.

Tables 1-8 summarize how the constructs, relationships and measurement models were developed from the literature. A full understanding of what was included in the model and later found to be valid or invalid is critical to an understanding of this paper.

Table 1. *Constructs in Initial Structural Model*

Construct Name	Description	Theoretical Justification
MARKET	There is a perception that there is an internal market culture in the enterprise where organizational units in the enterprise sell goods and/or services to other organizational units	Internal markets are effective mechanisms for allocating firm-level resources (Ackoff, 1993)
NEED	There is a perception that there is a business need to share data across organizational unit boundaries in the enterprise	Many business organizations need to share data across organizational boundaries (Ross, Weill and Robertson, 2006)
PRESSURE	There is a perception that there is pressure on managers/executives to withhold data from other organizational units within the enterprise to make an internal market for data functional	Markets for non-exclusive non-rivalrous goods can be made more efficient by implementing exclusivity (Kosmopoulou, 2001)
BEHAVIOR	There is a perception that managers/executives engage in behavior to withhold data from other organizational units within the firm	Individuals will take actions that they perceive are to their own benefit (Ellison and Ferrere, 2013)
COUNTER MEASURES	There is a perception that enterprise managers/executives, e.g. enterprise data governance, implement countermeasures to data withholding behavior from organizational unit managers/executives to encourage sharing of data across organizational unit boundaries	Principals will take action to incent agents to act in the principal's interest (Ross, 1973)

Construct Name	Description	Theoretical Justification
SUCCESS	There is a perception that information systems that share data across organizational unit boundaries are successful in providing net benefits to the business	Net benefits dimension of D&M model of success (Petter, DeLone and McLean 2008)

Table 2. *Construct Relationships in Initial Structural Model*

Relationship	Theoretical Justification
MARKET → PRESSURE	Markets for non-exclusive collective goods can be made more efficient by implementing exclusivity (Kosmopoulou, 2001)
PRESSURE → BEHAVIOR	Individuals will take actions that they perceive are to their own benefit, not necessarily those that are of most benefit to the enterprise (Ellison and Ferrere, 2013)
BEHAVIOR → SUCCESS	Primary conjecture that is being tested by this research – does data withholding behavior as motivated/de-motivated by the other constructs materially affect data sharing success? Justified by continued low data sharing success rates (Epperson, 2013; Ambler, 2014) in spite of all the data sharing technology that has been implemented
NEED → BEHAVIOR	At least in some organizations, particularly smaller ones, the need to supply a collective good may overcome other forces that may conspire to not supply it (Olson, 1971)
NEED → COUNTER MEASURES	Many business organizations need to share data across organizational boundaries (Ross, Weill and Robertson, 2006) Value of data is increased the more it is used (Kubiszewski, Farley and Costanza, 2010) If corporate executives perceive an agency conflict of interest on the part of business unit management, they will implement actions to counter it (Ellison and Ferrere, 2013) Only centralized interaction will correct a market failure (Samuelson, 1954)
PRESSURE → COUNTER MEASURES	If corporate executives perceive an agency conflict of interest on the part of business unit management, they will implement actions to counter it (Ellison and Ferrere, 2013) Only centralized interaction will correct a market failure (Samuelson, 1954) Behavior based on an emotional reaction can be logically modified or mediated (Ford-Martin and Lerner, 2012)
COUNTER MEASURES → BEHAVIOR	If corporate executives perceive an agency conflict of interest on the part of business unit management, they will implement actions to counter it (Ellison and Ferrere, 2013) Behavior based on an emotional reaction can be logically modified or mediated (Ford-Martin and Lerner, 2012)

Table 3. *Reflective Measurement Model for MARKET*

Indicator Name	Description	Theoretical Justification
SELL	Organizational units sell goods and/or services to other organizational units in the business enterprise	Definition of market (Kling, 2005)
CHARGE	Organizational units charge other organizational units in the business enterprise for goods and/or services that they provide to each other.	Definition of market (Kling, 2005)
COMPETE RESOURCES	There is competition for resources between organizational units within the business enterprise	Competitive cultures are likely to implement internal markets (Cameron and Quinn, 2011)

Indicator Name	Description	Theoretical Justification
COMPETE OUTCOMES	There is competition for business outcomes between organizational units within the business enterprise	Competitive cultures are likely to implement internal markets (Cameron and Quinn, 2011)
RESULTS	There is an emphasis on business results at the organizational unit level	Results oriented cultures are likely to implement internal markets (Choo, 2013)

Table 4. *Formative Measurement Model for NEED*

Indicator Name	Description	Theoretical Justification
STRATEGIC DATA	There is a business need to share data across organizational units for strategic analysis purposes	Definition of data warehouse (Inmon, 1996)
TACTICAL DATA	There is a business need to share data across organizational units for tactical reporting purposes	Definition of operational data store (Inmon, 1999)
MASTER DATA	There is a business need to share data that provide context for transactions across organizational units	Definition of master data management (Liyakasa, 2012)
BIG DATA	There is a business need to share big data across organizational units	Definition of big data (SAS, N.D.)
NEEDG (Global Reflective Indicator)	There is a general business need to share data across organizational units	Many business organizations need to share data across organizational boundaries (Ross, Weill and Robertson, 2006)

Table 5. *Formative Measurement Model for PRESSURE*

Indicator Name	Description	Theoretical Justification
MOTIVATE	Motivations are primarily directed towards achieving the goals of the organizational unit	Success in the internal market would be a major factor in the success of a manager or executive (Ackoff, 1993)
AVOID PUNISHMENT	Organization unit managers/executives fear punishment for contributing too much to enterprise-level collective goods	Individuals who contribute too much to a collective good can feel punished (Ertan, Page and Putterman, 2009)
OTHERS NOT AS IMPORTANT	Organizational unit managers/executive fear punishment for not meeting unit-level goals even if the reason was that they allocated resources to achieving more important enterprise or firm level goals	Individuals who contribute too much to a collective good can feel punished (Ertan, Page and Putterman, 2009) Results oriented cultures are likely to implement internal markets (Choo, 2013)
PRESSUREG (Global Reflective Indicator)	Organizational unit manager/executives feel pressure to not share data with other organizational units that might need that data	Individuals will take actions that they perceive are to their own benefit, not necessarily those that are of most benefit to the enterprise (Ellison and Ferrere, 2013)

Table 6. *Formative Measurement Model for BEHAVIOR*

Indicator Name	Description	Theoretical Justification
LOW PRIORITY	Organizational unit managers/executives give low priority to sharing data with other organizational units	Individuals will take actions that they perceive are to their own benefit, not necessarily those that are of most
MONOPOLY	Organization unit managers/executives charge monopolistic prices for sharing data with other organizational units	
UNIT FOCUS	Organizational unit managers/executives sponsor and fund data sharing initiatives that are limited to data sharing within their own organizational unit only	

Indicator Name	Description	Theoretical Justification
BEHAVIORG (Global Reflective Indicator)	Organizational unit manager/executives withhold data from other organizational units within the firm	benefit to the enterprise (Ellison and Ferrere, 2013)

Table 7. *Formative Measurement Model for COUNTER MEASURES*

Indicator Name	Description	Theoretical Justification
ENTERPRISE FUNDING	Enterprise management funds data sharing initiatives from an enterprise budget	Principals will take action to incent agents to act in the principal's interest (Ross, 1973) Only centralized intervention will correct market failures (Samuelson, 1954).
ENTERPRISE SUBSIDISE	Enterprise budgets subsidize organizational units that support data sharing initiatives	
ENTERPRISE REWARD	Organizational unit managers/executives who sponsor and fund data sharing initiatives with other organizational units are financially or otherwise rewarded by enterprise management	
COUNTER MEASURESG (Global Reflective Indicator)	Enterprise management undertakes actions to encourage organizational unit managers/executives to share data with other organizational units	

Table 8. *Formative Measurement Model for SUCCESS*

Indicator Name	Description	Theoretical Justification
DECISIONS	IS that shares data across organizational unit boundaries contributes to improved decision-making	Improved decision-making, productivity, sales, cost reductions and profits are all examples of net benefits at the firm level (Petter, DeLone and McLean 2008)
PRODUCTIVITY	IS that shares data across organizational unit boundaries contributes to improved productivity	
SALES	IS that shares data across organizational unit boundaries contributes to increased sales	
COST REDUCTION	IS that shares data across organizational unit boundaries contributes to cost reductions	
PROFITS	IS that shares data across organizational unit boundaries contributes to improved profits	
SUCCESSG (Global Reflective Indicator)	IS that shares data across organizational unit boundaries contributes to net business results	Net benefits dimension of D&M model of success (Petter, DeLone and McLean 2008)

3. Methodology

Exploratory Partial Least Squares Structural Equation Modeling (PLS-SEM) as defined by Hair, Hult, Ringle and Sarstedt (2014). was chosen as the appropriate analytical technique to use for this research.

While the desired unit of analysis would be the firm or business enterprise, that would present a daunting data collection problem. Therefore, the unit of analysis was taken to be the perceptions of individual people related to some business enterprise. While this was not as desirable as more objective data at the firm level, it did make an anonymous survey a practical data collection method. Thus, data was collected using such a survey where each of the indicator variables was structured as a statement to which the respondent could indicate his or her level of agreement in the context of a firm with which the respondent was familiar using a 7-point Likert scale. The survey also included demographic variables to categorize the respondent and the firm.

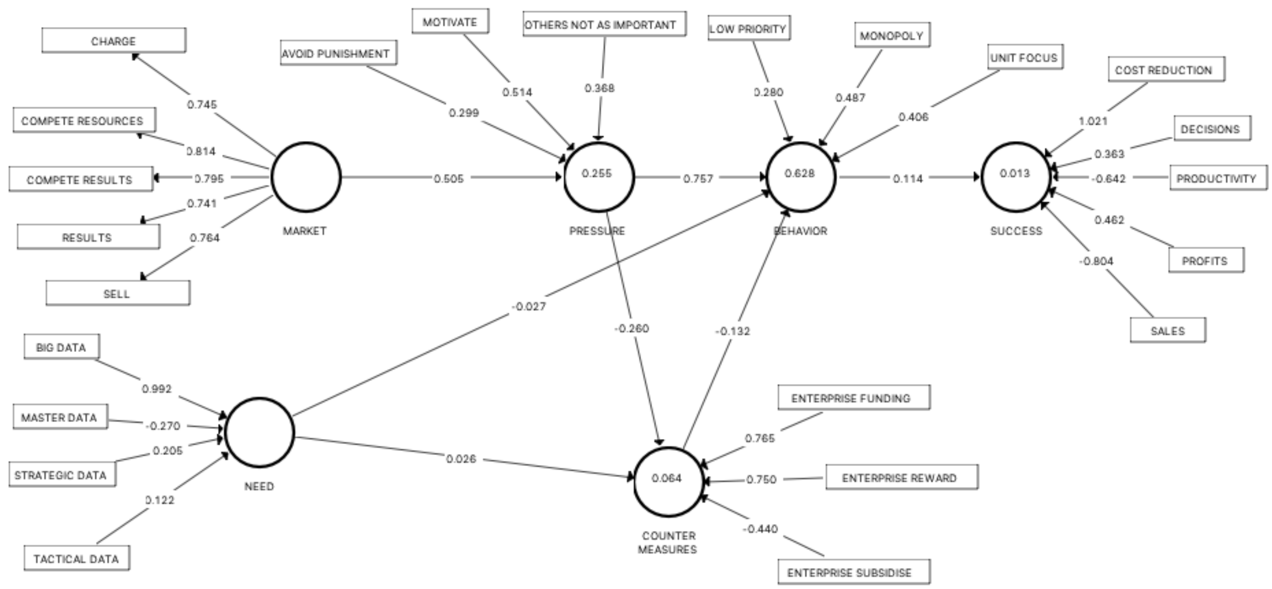

Figure 2. Initial PLS-SEM Results

The exploratory PLS-SEM analysis used the SmartPLS 3 software package (Ringle, Wende and Becker, 2015). In this approach, the measurement models for the constructs are first examined for several types of validity/reliability. Reflectively measured constructs are assessed for internal consistency, convergent validity/indicator reliability and discriminant validity. Formatively measured constructs are assessed for convergent validity, indicator collinearity and indicator significance/relevance. All assessments and thresholds used in this analysis were based on Hair, Hult, Ringle and Sarsted (2014). As necessary, the constructs' measurement models were modified to ensure validity. Once the measurement models have been validated, the structural model is assessed for construct collinearity, relationship significance/relevance and predictive relevance using measures such as R^2, f^2, Q^2 and q^2. Insignificant relationships were dropped from the model. Finally, results were interpreted and conclusions were drawn.

4. Results

4.1. Data Collection Results

A total of 122 usable responses were received to the survey which included purchased responses from a panel of senior business and IT executives as well as a convenience sample of data management professionals related to the author on LinkedIn. Missing data were processed using mean substitution. To ensure that mean substitution would not bias the results, all surveys that did not answer two or more of the Likert-scale questions for the indicator variables in the measurement model were discarded. According to a power sensitivity analysis for linear multiple regression random model using G*Power 3.1 software, the level of R^2 that should be detected with 80% power and 0.05 significance with this sample is 0.108. Thus, the collected data have a reasonable degree of statistical power to detect the phenomena being studied.

4.2. PLS SEM Results

The initial PLS SEM Results are illustrated in Figure 2. The numbers on the arrows are regression coefficients. The numbers in the constructs are R^2.

Several constructs and measurement models were found to be invalid. The COUNTER MEASURES construct failed tests for convergent reliability. Thus, it was replaced with three independent single-indicator constructs based on its three original indicator variables.

Next, the indicator variables for the SUCCESS construct except COST REDUCTION failed indicator significance validation. This means that SUCCESS as defined in this model really means only COST REDUCTION. While this is an important element of success, it is very limited in the context of data sharing. However, a general question about success was also asked in the survey allowed the survey respondents to

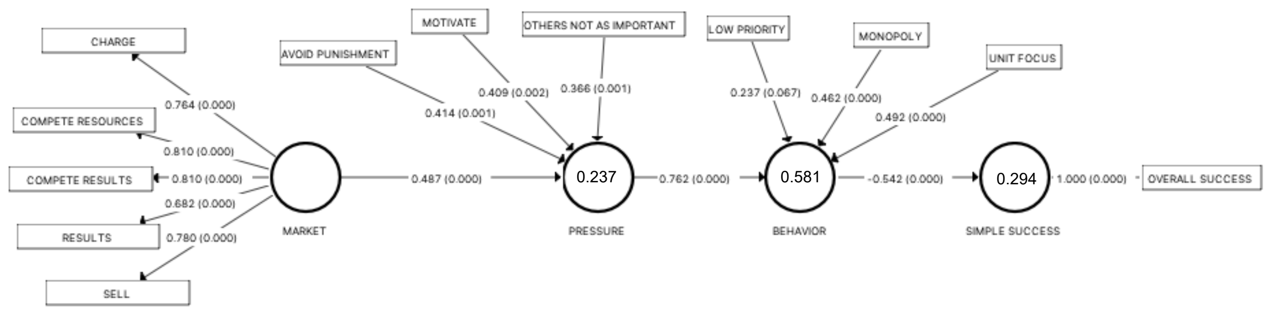

Figure 3. Final PLS-SEM Model Results

use their own interpretation. Therefore, SUCCESS was replaced with a single-indicator construct called SIMPLE SUCCESS based on this question.

Finally, many of the relationships were proven to be insignificant or did not exhibit predictive relevance. These were removed from the model resulting in the final model illustrated in Figure 3. P-values are shown in parenthesis.

5. Discussion

5.1. Market Failure Is a Cause of Data Withholding

The fact that the paths MARKET -> PRESSURE -> BEHAVIOR -> SIMPLE SUCCESS are all statistically significant in the final path model and have the signs that one would expect is evidence that the market failure that was theorized actually occurs. Further, the market failure is a cause of pressure on organizational unit managers to withhold data and that withholding behavior has a negative impact on the perceived success of data sharing IT initiatives, at least when the definition of success is left up to the respondent to determine. However, strength of a MARKET culture only has a moderate influence on PRESSURE.

5.2. There Are Additional Causes for Data Withholding

The fact that MARKET accounts for only a moderate amount of the variance in PRESSURE indicates that other forces besides a market-based culture are at work that place pressure on organizational unit managers to withhold data from other organizational units.

An unanswered question is what that additional cause, or causes, might be. It could be a fruitful area for future research to explore what other phenomena besides the market failure could be at work and whether at least some of those phenomena are more focused on the individual person and his or her perception than they are focused on the firm.

Another potential is data privacy or security concerns. Data breaches are often publicized in the news media and many industries are subject to stringent privacy or security regulations. Thus, the possibility of privacy or security breaches may be top-of-mind for many business managers and could make them reluctant to allow others not under their direct management control access to their data. It would be interesting to see if future research could specifically include this in a data withholding theoretical model.

Yet another potential is that managers/executives simply behave in their own perceived best interests rather than in the interests of the firm even in firms that do not have a strong internal market culture. This would likely be more a result of a narcissistic personality than it would be of any external forces influencing behavior. Future research should also address this potential issue.

5.3. Success Is Affected But It Is Not Clear How Success Is Perceived

The facts that BEHAVIOR -> SIMPLE SUCCESS is significant, its path coefficient has the proper sign and that the model accounts for 29.4% of the variance of SIMPLE SUCCESS is evidence that there is at least a moderate impact on success. In addition, the failure to validate the original SUCCESS construct has important implications. This construct was based on the net business benefits dimension of one of the most accepted models of IS success (Petter, DeLone, and McLean, 2008). Its invalidity is evidence that net business benefits is not a major component of what the survey respondents consider to be the success of data sharing initiatives. Exploring other possibilities for what success really means could be another fruitful area for further research.

5.4. Enterprise Management & Data Governance Do Not Effectively Incentivize Data Sharing

The hypothesized mitigating effects in the original path models were based on enterprise management, especially data governance leaders, understanding their role in mitigating market failures inside the enterprise. There is strong theoretical justification for expecting those effects, The facts that these effects did not possess predictive relevance is evidence that enterprise management/data governance is not taking effective mitigating action to prevent data withholding when it is warranted. But the current research cannot identify whether they would be effective if they were systematically applied or if they are ineffective because they are not systematically applied,

5.5. A Known Business Need to Share Data is Not Enough to Encourage Data Sharing

Because the path NEED -> BEHAVIOR proved to be insignificant, we cannot rely on organizational unit managers or executives to share data with other organizational units even when they know it is in the best interests of the business enterprise.

6. Conclusion

6.1. Limitations of this Research

As was stated previously, a limitation based on the research design is that the research is based on personal opinions of individuals rather than more objective measurements by a third party of the phenomena at work. However, some researchers such as Cecez-Kecmanovic, Kauts and Abrahal (2014) conclude that IS success, this research's ultimate dependent variable, is not objectively measurable. Only individual's perceptions of success are measurable. This research supports that conclusion.

In addition, several multi-indicator measurement models of the constructs proved to be invalid and were replaced by single indicator constructs. Single indicator constructs, while allowed in PLS-SEM, have a disadvantage compared to multi-indicator constructs in that they do not account for potential measurement errors in the individual indicator variables. Thus, future research should attempt to find new ways to develop multi-indicator measurement models for those constructs.

The current NEED construct is rather limited and is based more on technical than business considerations. It may be fruitful to expand it to more of a true business need construct in the future.

Finally, because the dependent and independent variables were obtained from the same sources, there is a possibility of common method bias. This was an unavoidable limitation of an anonymous survey.

6.2. Implications for Future Research

A more rigorous SEM model than the current one could possibly be developed through an interpretive methodology such as grounded theory rather than the literature review approach used in this research.

Other IT goods and services that are non-rivalrous such as metadata, enterprise architecture and reusable services in a service-oriented architecture (SOA) may also be affected by market failure. Expanding this research for such goods and services that should be shared at an enterprise level might be fruitful.

Another possibility is to incorporate the Data Management Maturity Model from Carnegie Melon into the research to see how the market failure relates to levels of data management maturity.

Finally, it might be fruitful to extend this research beyond intra-enterprise data sharing to sharing beyond the borders of a single enterprise. Healthcare information exchanges (HIEs) and the European Union's Data Act may bear a relationship to this research.

6.3. Recommendations for Data Governance

The final recommendation of this study is for enterprise executive management and especially data governance professionals to become more educated and aware of the potential for market failure. They need to be able to recognize when and if the market failure exists and to act to mitigate its effects. They need to understand that it is only enterprise-level intervention that can solve the problem – it cannot be solved at the organizational unit level. Nor can it be solved by individual IS projects such as a DW or MDM implementation project because they have no control over the market culture. Balancing the tradeoff between the benefits of an internal market culture and the benefits of being able to share data across organizational units should be a major responsibility of Chief Data Officers (CDOs) and enterprise data governance professionals.

7. References

Ackoff, R. (1993). Corporate perestroika: The internal market economy. In W. Halal, A. Geranmayeh & J. Pourdehnad (Eds.), Internal Markets: The Power of Free Enterprise Inside Your Organization (pp. 15-26). New York, NY: Wiley.

Adamala, S. and Cidrin, L. (2011). Key success factors in business intelligence. *Journal of Intelligence in Business Studies, 1,* 107-127.

Alhyasat, E. & Al-Dalahmeh. (2013). Data warehouse success and strategic oriented business intelligence: A theoretical framework. *Journal of Management Research, 5(3),* 169-184

Ambler, S. (2014). 2013 data warehouse (DW)/business intelligence (BI) survey results. Downloaded from Ambysoft website: http://www.ambysoft.com/surveys/datawarehousing2013.html

Cameron, K. & Quinn, R. (2011). Diagnosing and changing organizational culture. San Francisco, CA: Josey Bass [Amazon Kindle Edition].

Cecez-Kecmanovic, D., Kauts, K. & Abrahall, R. (2014). Reframing success and failure of information systems: A performative perspective. *MIS Quarterly, 38(2),* 561-588.

Chenowith, T., Corral, K. & Demirkan, H. (2006). Seven key interventions for data warehouse success. *Communications of the ACM, 49(1),* 115-119.

Choo, C. (2013). Information culture and organizational effectiveness. *International Journal of Information Management, 33,* 775-779.

Coase, R. (1937). The nature of the firm. *Economica*, 386-405.

Denodo. (2014). Technology solutions: Data virtualization. Retrieved from Denodo website: http://www.denodo.com/en/solutions/technology/data_virtualization.php

Elson, C. & Ferrere, C. (2013). Surplus, agency theory, and the Hobbesian corporation. *Wake Forest Law Review, 48,* 721-744.

Epperson, D. (2013). Why master data management (MDM) efforts fail. Retrieved from Sirius Solutions website: http://www.sirsol.com/blog/2013/11/Why-Master-Data-Management-Efforts-Fail

Ertan, A., Page, T. & Putterman, L. (2009). Who to punish? Individual decisions and majority rule in mitigating the free rider problem. European Economic Review, 53, 495-511.

Externality. (2008). In W. Darity, Jr (Ed.) International Encyclopedia of the Social Sciences (2nd ed., vol. 3). Detroit, MI: Macmillan, 70-71.

Ford-Martin, P., & Lerner, B. (2012). Cognitive-Behavioral Therapy. In K. Key (Ed.), *The Gale Encyclopedia of Mental Health* (3rd ed., Vol. 1). Detroit, MI: Gale, 354-358.

Gharajedaghi, J. (2011). Systems thinking: Managing chaos and complexity. Burlington, MA: Elsevier [Amazon Kindle Edition].

Hair, J., Hult, G., Ringle, C. & Sarstedt, M. (2014). A primer on partial least squares structural equation modeling (PLS-SEM). Thousand Oaks, CA: Sage [Amazon Kindle Edition].

Inmon, W. (1996). Building the data warehouse, second edition. New York, NY: Wiley.

Inmon, W. (1999). Building the operational data store, second edition. New York, NY: Wiley.

Kling, A., (2005). Market theory. In C. Mitcham (Ed.) Encyclopedia of Science, Technology and Ethics (vol. 3). Detroit, MI: Macmillan, 1160-1165.

Kosmopoulou, G. (2001). Efficient Bayesian mechanisms for collective goods: Is a deficit inevitable? *Journal of Public Economic Theory, 3,* 527-549.

Kubiszewski, I., Farley, J. & Costanza, R. (2010). The production and allocation of information as a good that is enhanced with increased use. *Ecological Economics, 69,* 1344-1354.

Laney, Douglas. (2000). Data warehouse factors to address for success. *HP Professional, 14(5),* 1-3.

Liyakasa, K. (2012). Solve the master data management equation. *Customer Relationship Management, 16,* 56-60.

Merrick, C. (2014). 9 reasons why data warehouse projects fail. Retrieved from RJMetrics website: https://blog.rjmetrics.com/2014/12/04/10-common-mistakes-when-building-a-data-warehouse/

Mitnick, B. (2008). Market failure. In R. Kolb (Ed.). Encyclopedia of Business Ethics and Society. Thousand Oaks, CA: SAGE Publications, 1329-1333.

Olson, M. (1971). The logic of collective action: Public goods and the theory of groups. Cambridge, MA: Harvard University Press [Amazon Kindle Edition].

Petter, S., DeLone, W. & McLean E. (2008). Measuring information systems success: Models, dimension, measures and interrelationships. *European Journal of Information Systems, 17,* 236-263.

Ringle, C., Wende, S., & Becker, J. (2015). SmartPLS 3. Retrieved from SmartPLS website: http://www.smartpls.de

Ross, J., Weill, P. & Robertson, D. (2006). Enterprise architecture as strategy: Creating a foundation for business execution. Cambridge, MA: Harvard Business School Press [Amazon Kindle Edition].

Ross, S. (1973). The economic theory of agency: The principal's problem. *American Economic Review, 63(2),* 133-139.

Samuelson, P. (1954). The pure theory of public expenditure. *The Review of Economics and Statistics, 4,* 387-389.

SAS. (n.d.). Big data what it is and why it matters. Retrieved from SAS web site: http://www.sas.com/en_us/insights/big-data/what-is-big-data.html

Sujitparapitaya S., Janz B. & Gillenson, M. (2003). The contribution of IT governance solutions to the implementation of data warehouse practice. *Journal of Database Management, 14(2)*, 52-69.

Windsor, D. (2008). Public good. In R. Kolb (Ed.). Encyclopedia of Business Ethics and Society. Thousand Oaks, CA: SAGE Publications, 1730-1735.