Decision Support Systems 93 (2017) 42–50

Contents lists available at ScienceDirect

Decision Support Systems

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

An empirical investigation on the impact of XBRL adoption on information asymmetry: Evidence from Europe

Chunhui Liu [a], Xin (Robert) Luo [b,*], Fu Lee Wang [a]

[a] Caritas Institute of Higher Education, 18 Chui Ling Road, Tseung Kwan O, New Territories, Hong Kong, China
[b] Anderson School of Management, The University of New Mexico, Albuquerque, NM 87131, USA

ARTICLE INFO

Article history:
Received 4 December 2015
Received in revised form 31 August 2016
Accepted 9 September 2016
Available online 20 September 2016

Keywords:
XBRL (eXtensible Business Reporting Language)
Information technology
Information asymmetry
Liquidity
Firm size
Technology intensity

ABSTRACT

Given the high cost of developing and implementing data standards such as eXtensible Business Reporting Language (XBRL), it is critical to assess their influences before they are adopted on a large scale. The European Parliament has voted for the new Transparency Directive that calls for the mandatory preparation of annual business performance reports in a single electronic reporting from January 1, 2020 based on a cost–benefit analysis by European Securities and Markets Authority (ESMA), with due reference to current and future technological options such as XBRL. Regulators in many other jurisdictions such as Canadian Securities Administrators are also assessing the costs and benefits from XBRL adoption. This paper informs such analysis by examining whether the expected benefit of information asymmetry reduction is realized through XBRL adoption in a European context. XBRL adoption among European non-financial firms is found to significantly increase market liquidity and thus reduce information asymmetry. The association is stronger for larger firms that have sufficient resources and expertise to properly implement the technology. The empirical findings also suggest that the association is stronger for non-high-technology firms whose financial statements affected by XBRL are more reliant upon by investors. Based on these findings, XBRL evidences a viable option as an electronic reporting format with effective implementation for businesses.

1. Introduction

With the advent of new forms of information technology (IT) such as eXtensible Business Reporting Language (XBRL), practitioners and academics face renewed challenges in measuring the impact and business value of IT [61]. In essence, XBRL is an IT data standard that provides an identifying tag for financial facts, such as total sales, to create an unambiguous way to identify and compare business performance of one company to another [33]. Ranked as one of top ten technologies for business professionals by the American Institute of Certified Public Accountants [55], XBRL has piqued mounting attention of a variety of regulators [65]. Many XBRL jurisdictions such as Belgium, Chile, China, Denmark, India, Israel, Japan, Luxembourg, Singapore, South Korea, and Spain have mandated its adoption [46]. In 2009, for instance, the U.S. Securities and Exchange Commission mandated the adoption of XBRL and contended that the technology has the potential to reduce information asymmetry [11]. In 2013, the European Parliament voted for the new European Union (EU) Transparency Directive on the harmonization of transparency requirements in relation to information about issuers whose securities are admitted to trading on a regulated market. The Directive calls for a harmonized electronic format for reporting to facilitate accessibility, analysis and comparability of annual financial reports by 2020 after a cost–benefit analysis has been undertaken by European Securities and Markets Authority (ESMA) with due reference to current and future technological options, such as XBRL. Furthermore, regulators in many other jurisdictions such as Canadian Securities Administrators are also assessing the costs and benefits from XBRL adoption [46]. Given the high cost of developing and implementing data standards such as XBRL and their significant impact [70], it is critical to assess their influences before they are adopted on a large scale.

Empirical studies of XBRL adoption impact have revealed mixed findings. Though [69] finds a significant negative association between XBRL adoption and information asymmetry in the Korean stock market, some research [11,15,68] shows a significant positive relation between XBRL adoption and information asymmetry as reflected by higher abnormal bid-ask spread after XBRL mandate in the U.S. While [49] reveals that the mandatory XBRL adoption among firms listed in the U.S. has led to increased analyst following and forecast accuracy, [47,50] disclose that the uncertainty related to XBRL, such as information errors, has decreased analysts' forecast accuracy and increased cost of capital among Chinese firms in an economy with relatively weak public information on listed firms. Departing from the Asian and

* Corresponding author.
E-mail addresses: mliu@cihe.edu.hk (C. Liu), xinluo@unm.edu (X.(R.) Luo), pwang@cihe.edu.hk (F.L. Wang).

http://dx.doi.org/10.1016/j.dss.2016.09.004
0167-9236/

American context, there is a paucity of further fathoming the potential impact of XBRL vis-à-vis information asymmetry from a European perspective. Since accounting information systems and technologies are an important part of the fabric of organizational life and thereby need to be evaluated in a wider environmental context [13], findings from samples outside the EU spectrum may not accurately inform potential impact of XBRL among EU members.

In a bid to further advance this line of research, this study investigates whether the adoption of XBRL has reduced the information asymmetry with European evidence from the Belgian stock market. Belgium is one of the leading EU countries that have mandated XBRL for financial reporting. The filing of non-financial registered companies' annual reports in XBRL format has been mandatory from April 2007 as per the National Bank of Belgium. A KPMG study [20] reveals that filing fees for companies using XBRL have been reduced by 35% for small medium Belgian companies and that the total yearly administrative burden reduction for these companies comes to 17.3 million EUR. However, how the adoption has affected the stock market is yet unknown. Studying the impact of XBRL mandate on Belgian companies reveals the potential impact of XBRL mandate on other European markets operating under similar institutional and economic conditions.

Extending prior studies on the influence of XBRL on information asymmetry, this research uses multiple liquidity measurements as proxies for information asymmetry instead of using one liquidity measurement as no liquidity proxy is known to work best for all markets. The empirical investigation is accomplished with Belgian non-financial firms with empirical data between 2005 and 2010. The research compares the influence of XBRL on high-technology firms and non-high-technology firms for the first time. XBRL adoption in Belgium is found to significantly increase market liquidity and thus reduce information asymmetry in general. In addition, as predicted by resource-based-view and organizational capability theories, the improvement is found to be stronger for larger firms that have ample resources and expertise to implement the technology. Investors have greater reliance on analyst forecasts to decipher and supplement financial statements of high-technology firms that have larger proportion of intangible assets. The influence of XBRL is found to be particularly apparent for non-high-technology firms whose financial statements are more reliant upon in investor decisions.

This study contributes to literature in at least six aspects. First, the research contributes to the IT business value literature by illustrating a positive association between IT (e.g. XBRL) adoption and business value (e.g. information asymmetry reduction and increased liquidity). Secondly, the research confirms the importance of resource-based view and contingency theory in understanding the value realization process of an IT artifact because the findings reveal that larger firms with ample resources can harvest more business value from XBRL adoption. Thirdly, the research reveals that XBRL implementation is particularly beneficial to non-high-technology firms whose financial statements are key sources of information to investors. Fourthly, the research provides empirical support for low frequency liquidity measurements such as Amivest ratio, trading volume, turnover, Zeros, and Zeros2 because they lead to similar research findings when these liquidity measurements are used as proxies for information asymmetry. One potential benefit from using low-frequency liquidity proxies is an enormous savings in computational time in comparison with using intraday data to calculate high-frequency liquidity proxies. In addition, we further extend and modify the model by [69] to add control for firm-specific, industry-specific, and year-specific effects. Last but not the least, the research contributes to XBRL literature by illustrating its impact in an EU market and thus may more efficiently and effectively inform EU regulators such as ESMA in their decision making about implementing XBRL among EU members.

This rest of this article is organized as follows. The next section presents relevant literature and develops hypotheses for the study. It is followed by a section describing data collection and outlining models. After main results are presented and discussed, the paper is concluded with implication and caveat disclosure as well as future research directions.

2. Theoretical foundation and hypotheses development

2.1. Information technology and firm performance

In the Information Systems literature, much research has examined the relation between IT and firm performance or business value. One stream of production economics theorists considers a firms' IT capital as a production factor that makes a positive contribution to a firm's value [38]. Recent studies have documented positive impact of IT on firm value [3]. On the other hand, prior research has identified a weak link between IT and its business value as an 'IT productivity paradox' [50]. One theory explaining the IT productivity paradox is that IT investments take time to realize their business value as time is needed to fine tune a new technology, to properly learn the technology, and to readjust it in an organization [57]. Organizational-capability theorists and resource-based-view theorists believe that innovations such as new IT artifacts are adopted when they help the organization to utilize its unique capabilities and resources to realize value [48]. Contingency theory predicts that value realization of a technology depends on the fit between technology integration and contingent factors in business [47]. Therefore, the value realization from IT adoption is reliant on a firm's capabilities and resources [46]. This study follows these streams of literature to explore the relation between an IT artifact such as XBRL and its realized value and to analyze the role of firm resources in realizing the value from IT adoption.

2.2. XBRL technology and its value realization

XBRL is an XML-based data standard for business reporting that uses taxonomies to provide meta-data for the semantics of the elements, such as total sales, to create an unambiguous way to identify and compare business performance of one company to another [26,33]. Self-describing mark-ups or tags provide notations to contents of a document and thus allow the search and extraction of desired information by purpose-built computer programs without downloading an entire document [63]. XBRL tags are defined and organized using a systematic classification scheme called a taxonomy that defines financial reporting concepts and their relationships as per specific legislation or standards [43,54]. By separating content from format, XBRL benefits all members of the financial information supply chain by making information exchangeable between different applications and systems and easy to extract, search, and reuse by users [37]. The American Institute of Certified Public Accountants has ranked XBRL as one of top ten technologies for business professionals [55].

Besides improving efficiency of financial disclosures, XBRL is expected to improve digital financial information quality [14,22,59] which is a key factor for decision performance [19]. In essence, [10] indicates that XBRL can improve internal control as XBRL eliminates manual intervention such as rekeying of data or manipulation via a spreadsheet with associated labor costs and possibility for error. In addition, uniquely identifying each line item on the financial statement and tagging the method of accounting used, XBRL standardizes current financial reporting data to resolve comparability issues resulted from different naming conventions, accounting policies, or account aggregation levels [63]. Such improved information quality is expected to lead to higher information transparency and lower information asymmetry [69].

Despite the high expectations of XBRL, empirical studies of its actual impact reveal mixed findings. Though [69] finds a significant negative association between XBRL adoption and information asymmetry in the Korean stock market, others [11] show a significant positive relation between XBRL adoption and information asymmetry as reflected by higher abnormal bid-ask spread after XBRL mandate in the U.S. While

[49] reveals that the mandatory XBRL adoption among firms listed in the U.S. has led to a significant improvement to both the quantity and quality of information, as measured by analyst following and forecast accuracy, [47,50] disclose that the uncertainty related to XBRL, such as information errors, has decreased analysts' forecast accuracy and increased cost of capital among Chinese firms in an economy with relatively weak public information on listed firms. Findings from samples outside the EU spectrum may not accurately inform potential impact of XBRL among EU members as per the contingency theory. This study extends this line of study by investigating whether the adoption of XBRL has reduced the information asymmetry in the European stock market.

2.3. Hypotheses development

Information asymmetry entails that someone possesses private information which other parties do not [66]. Information asymmetry promotes an unwillingness to trade and increases the cost of capital because investors "price protect" themselves against potential losses from trading with the better informed [9,64]. Theoretical and empirical studies in corporate disclosure and market microstructure literature show that high quality public disclosures reduce information asymmetry and increase liquidity in stock markets [28,31,44,64].

XBRL is expected to improve digital financial information quality and to increase efficiency in the search for information [22,59]. XBRL usage is found to associate with an increased level of reporting transparency and accuracy [49,56]. Uniquely identifying each line item on the financial statement and tagging the method of accounting used, XBRL standardizes current financial reporting data to resolve comparability issues [63]. Also, [32] finds that XBRL helps nonprofessional financial statement users to acquire and integrate related financial statement and footnote information in making investment decisions. Such improved information quality and information searching capability are expected to lead to higher information transparency and lower information asymmetry [69]. Prior studies [e.g. 51] reveal that information quality improvement from standard changes is bigger for adopters with poorer disclosure quality before the change. As per [44], the disclosure index of Belgium was 61, similar to that of South Korea (62), but much lower than that of U.S. (71) before XBRL adoption. The poorer disclosure quality of Belgium and South Korea in comparison to U.S. before XBRL adoption was also reflected in their higher aggregate earnings management score with 26.8 for South Korea, 19.5 for Belgium, but 2.0 for U.S. as per [44]. Because Belgium's disclosure quality is similar to that of South Korea before XBRL adoption, we expect XBRL's impact on information asymmetry in Belgium to be similar to that in South Korea [69]. Therefore, we hypothesize:

H1. The XBRL adoption among Belgium firms is associated with lower information asymmetry (i.e. a negative association between XBRL adoption and information asymmetry).

On the other hand, the adoption of a new technology like XBRL introduces uncertainty. IT productivity paradox literature reveals that IT investments take time to realize their business value as time is needed to fine tune a new technology, to properly learn the technology, and to readjust it in an organization [50,57]. Lack of expertise and resources can inhibit a firm's readiness to realize value from XBRL adoption because of the risk of errors in creating XBRL documents [6,18]. As per organizational-capability theories and resource-based-view theory, value can be best realized when the organization's unique capabilities and resources match the implementation requirement of a technology [48]. In the literature, [12] reveals significant variations of quality across financial statements and industries among U.S. firms using year 2000 version of XBRL taxonomy. The mixed findings of prior XBRL empirical studies [11,47,49,50,69] reveal that XBRL adoption may not influence information quality and information asymmetry uniformly as predicted by contingency theory [35,46,51,67].

Organizational capability and resources behave both as a source of competitive advantage and as a constraint of changes [48]. The U.S. SEC estimates that the direct costs to a company submitting its first interactive data financial statements with XBRL with block-text footnotes and schedules could average $40,510 with an upper bound of $82,220 while the costs for subsequent block-text filings could average $13,450 with an upper bound of $21,340 [60]. Besides financial resources, knowledge and expertise in XBRL are necessary in XBRL implementation [36]. Large firms may be in a better position to achieve superior firm performance due to their ability to garner efficiencies of scale [62]. In addition, large firms can develop higher-order capabilities to a greater extent due to the extra resources at their command [7,39,58]. Much research evidence points to the existence of a direct relation between firm size and the adoption of information technologies. [52], for example, confirms that larger firms often have superior financial and human resource capacity required to invest in high information capabilities. Thus, we hypothesize:

H2. Firm size increases the negative association between the XBRL adoption and information asymmetry among Belgium firms.

Financial statements like those reported in XBRL instance documents are not the only information source that affects information asymmetry and market liquidity. Analysts' forecasts augment the information contained in reported accounting earnings due to analysts' ability to use their individual private knowledge to produce forecasts that contain new analyst-specific information or interpretations [4]. Investors' demand for analyst reports is strongest for high-technology firms due to their substantial intangible assets that have uncertain realizations and lead to a higher incidence and/or larger magnitude of mismatched revenues and expenses being reported [4]. In particular, [5] finds that analyst coverage to be significantly greater for high-technology industries with larger research and development expenses and more intangible assets. If the change in information asymmetry identified is a result of XBRL adoption, the change should be the stronger among firms whose financial statements affected by XBRL implementation are more heavily used by investors. Since investors have lower reliance on financial statements for high-technology industries because of the supplement information provided by analysts, we hypothesize that.

H3. Industry technology intensity decreases the negative association between the XBRL adoption and information asymmetry among Belgium firms.

3. Research method

Belgian non-financial firms are used as the sample mainly because Belgium is one of the leading EU countries that have mandated XBRL for financial reporting. The filing of non-financial registered companies' annual reports in XBRL format has been mandatory from April 2007 as per the National Bank of Belgium. Studying the impact of XBRL mandate on Belgian companies reveals the potential impact of XBRL mandate on other European markets operating under similar institutional and economic conditions. General implications from a study on Belgium are possible also because gross domestic spending of Belgium on research and development as a percentage of total GDP has been similar to the median of such spending among EU members as per Organisation for Economic Co-operation and Development (OECD) statistics. OECD data also show that the difference between the Information and Communication Technology sector gross output and intermediate consumption in Belgium is similar to the median of such a difference among EU members. Non-financial firms are studied as financial firms follow different rules and regulations. For instance, credit institutions are required to use consolidated financial reporting framework (FINREP) with XBRL since January 2006.

Data are collected for 2005–2010 period because the EU adopted an IAS Regulation requiring European companies listed in an EU securities market to prepare their consolidated financial statements in accordance with International Financial Reporting Standards starting with financial statements for year 2005 onwards. Information on Belgian stocks is obtained from the Compustat Global-Security Daily. There are 51,264 observations. 16,353 observations of financial firms are removed as they follow different regulations. 6200 observations with missing variable values are removed to result in 28,711 observations. The sample includes observations from different industries: 61% manufacturing industrials, 19% retail, 10% transportation and warehousing, 5% public administration and 5% construction.

Extant studies [e.g. 64] suggest that observable measures of market liquidity can be used to identify the perceived level of information asymmetry. Liquidity in the firm's stock increases if investors can be relatively confident that any stock transactions occur at a "fair price" when information asymmetry is low [28]. Also, [31] shows that information quality improves stock liquidity by increasing the ability of equity traders to effectively execute stock trades at reasonable costs. In addition, [27,64] reveal that stock liquidity increases with increases in analyst disclosure ratings. Prior studies [e.g. 11,69] use a high-frequency liquidity proxy, bid-ask spread to assess the association between XBRL adoption and information asymmetry. This study extends this stream of literature by assessing the association between XBRL adoption and information asymmetry through multiple low-frequency liquidity proxies such as Amivest ratio that divides the dollar volume on day *t* by the absolute return on day *t* as a measure of liquidity in many studies [e.g. 2,8,16], Turnover that divides trading volume over shares outstanding as used in many studies [e.g. 21,41]; Zeros that divides the number of days with zero returns by the total number of trading days in a year [42], and Zeros2 that divides the number of positive volume days with zero returns by the total number of trading days [25]. Zeros is used as a proxy for liquidity as proposed by [42] because stocks with lower liquidity are more likely to have zero-volume days. The effectiveness of Zeros and Zeros2 has been supported by much research [e.g. 34,41]. Since Amivest ratios are very large, we scale them down by dividing them over 10^9.

The following model further extends and modifies the model by [69] to test H1 by identifying the impact of XBRL adoption on liquidity while controlling variables previously found to influence liquidity:

$$\begin{aligned}\text{Liquidity}_{it} = {} & \alpha_0 + \alpha_1 * \text{XBRL}_{it} + \alpha_2 * \text{Size}_{it} + \alpha_3 * \text{Volatility}_{it} \\ & + \alpha_4 * \text{StockPrice}_{it} + \alpha_5 * \text{Industry}_{it} + \alpha_6 * \text{Firm}_{it} \\ & + \alpha_7 * \text{Year}_{it} + \varepsilon \end{aligned} \tag{1}$$

where *i* denotes firm and *t* denotes day. XBRL denotes either pre-adoption period (0) or post-adoption period (1). Size is the natural log of a firm's market value of equity at *t*. Volatility is the annualized historical volatility as the product of square root of total number of trading days in a year and standard deviation of inter-day return. Inter-day return is the natural log of the ratio of the sum of closing price$_t$ and dividend$_t$ over closing price$_{t-1}$. StockPrice is the closing price on *t*. Unlike [69], Turnover (trading volume over shares outstanding) is not included as a control variable because many consider it to be a proxy for liquidity [e.g. 17,21]. In addition, we add Firm as identified by Gvkey, Industry as denoted by NAICS code, and Year to control for the specific effects of a firm, a firm's industry, and year effect like prior studies [1,23,24]. Doing so reduces the chance that the association between liquidity and XBRL adoption is driven by omitted variables specific to a firm, an industry, or a year. Liquidity is measured with Amivest ratio, Turnover, Zeros, or Zeros2 separately. If H1 is true, α_1 is expected to be significantly positive when Turnover and Amivest ratio are proxies because higher ratios reflect higher liquidity [8,21] while α_1 is expected to be significantly negative when Zeros and Zeros2 are proxies because their lower values reflect higher liquidity [25,42].

To test H2, model (1) is modified to test the interaction of large firm Size and XBRL adoption:

$$\begin{aligned}\text{Liquidity}_{it} = {} & \alpha_0 + \alpha_1 * \text{XBRL}_{it} + \alpha_2 * \text{Large}_{it} + \alpha_3 * \text{Large}_{it} * \text{XBRL} \\ & + \alpha_4 * \text{Volatility}_{it} + \alpha_5 * \text{StockPrice}_{it} + \alpha_6 * \text{Industry}_{it} \\ & + \alpha_7 * \text{Firm}_{it} + \alpha_8 * \text{Year}_{it} + \varepsilon \end{aligned} \tag{2}$$

where Large denotes either a Size higher than sample average (1) or a Size no more than sample average (0). If H22 is true, α_3 is expected to be significant and in the direction that reflects higher liquidity. α_1 reflects the association between XBRL and Liquidity for smaller firms.

To test H3, model (1) is modified to test the interaction of high-technology and XBRL adoption:

$$\begin{aligned}\text{Liquidity}_{it} = {} & \alpha_0 + \alpha_1 * \text{XBRL}_{it} + \alpha 2 * \text{High-tech}_{it} + \alpha_3 * \text{High-tech}_{it} \\ & * \text{ XBRL} + \alpha_4 * \text{Size}_{it} + \alpha_5 * \text{Volatility}_{it} + \alpha_6 * \text{StockPrice}_{it} \\ & + \alpha_7 * \text{Industry}_{it} + \alpha_8 * \text{Firm}_{it} + \alpha_9 * \text{Year}_{it} + \varepsilon \end{aligned} \tag{3}$$

where High-tech is set to 3 for Level I high-technology firms that come from industries that technology-oriented occupations account for the highest proportion of that industry's total employment, 2 for Level II high-technology firms with lower proportion of technology-oriented employment, 1 for Level III high-technology firms with lowest proportion of technology-oriented employment among high-technology industries, and 0 for non-technology firms as per [29]. An industry is considered high-tech if employment in technology-oriented occupations accounted for a proportion of that industry's total employment that was at least twice the 4.9% average for all industries [29]. For example, firms from industries like aerospace product and parts manufacturing, communication equipment manufacturing, and pharmaceutical and medicine manufacturing industries are Level I high-technology firms. Firms from industries like basic chemical manufacturing, resin manufacturing, commercial, industrial, or service machinery manufacturing are Level II high-technology firms. Firms from industries like pesticide, fertilizer, and other agricultural chemical manufacturing are Level III high-technology firms. α_1 reflects the association between XBRL and Liquidity for less technology intensive firms. If H3 is true, α_3 is expected to be significant and in the direction that reflects lower liquidity.

4. Empirical analysis

4.1. Descriptive statistics

Table 1 summarizes the descriptive statistics about the sample. When non-nominal variables are compared between the pre-adoption and the post-adoption periods, significant differences are revealed for all listed variables by the Mann–Whitney test. The significant increase to Turnover and significant decrease to Zeros and Zeros2 in the post-adoption period support H1.

4.2. Model testing

Table 2 reports spearman correlations between variables. Amivest and Turnover are positively correlated as expected because both proxies positively associate with liquidity [8,21] while these ratios correlate negatively with Zeros and Zeros2 that are expected to negatively associate with liquidity [25,42]. Zeros and Zeros2 are highly correlated positively as Zeros2 is a variation of Zeros. Most of correlations between an independent variable and a dependent variable is below 0.80. On the other hand, the correlation between Year and XBRL is above 0.80. However, tests of tolerance (minimum tolerance = 0.30 for model

Table 1
Descriptive statistics for non-nominal variables.

Complete sample					
Variable	Mean	Median	Std Dev	Skewness	Kurtosis
Amivest	1.653	0.098	9.898	21.768	678.291
Size	20.243	20.586	2.218	-0.699	0.273
StockPrice	83.230	49.005	104.753	2.370	5.842
Turnover	0.002	0.001	0.003	5.473	85.895
Volatility	0.451	0.297	0.639	7.362	75.192
Zeros	0.100	0.039	0.134	2.316	6.535
Zeros2	0.036	0.016	0.047	2.284	7.808

	Pre-adoption period			Post-adoption period		
	Mean	Std	Median	Mean	Std	Median
Amivest	1.707	9.850	0.114	1.616	9.932	0.088***
Size	20.490	2.230	20.668	20.075	2.194	20.466***
StockPrice	95.241	118.533	59.000	75.066	93.368	43.45***
Turnover	0.002	0.002	0.001	0.002	0.003	0.002***
Volatility	0.357	0.812	0.223	0.515	0.478	0.389***
Zeros	0.095	0.111	0.046	0.104	0.148	0.023***
Zeros2	0.040	0.052	0.020	0.033	0.044	0.012***

*** Indicates difference significant at $p < 0.01$ as per Mann–Whitney test.
Amivest divides the dollar volume on day t by the absolute return on day t;
Size is the natural log of a firm's market value of equity at t;
StockPrice is the closing price on t;
Turnover divides trading volume over shares outstanding;
Volatility is the product of square root of total number of trading days in a year and standard deviation of inter-day return;
Zeros divides the number of days with zero returns by the total number of trading days in a year;
Zeros2 divides the number of positive volume days with zero returns by the total number of trading days.

(1); 0.22 for model (2); 0.27 for model (3)) and variance inflation factor (maximum VIF = 3.35 for model (1), 4.57 for model (2), and 3.72 for model (3)) are conducted to confirm low risk of multicollinearity in regression models. The correlations between XBRL and dependent variables support the findings of Table 1 in that XBRL adoption is positively associated with Turnover but negatively associated with Zeros and Zeros as proposed in H1. On the other hand, Amivest is shown to negatively associate with XBRL when no control variables are considered. In agreement with [69], Volatility negatively associates with Size but positively associates with Turnover with significance. We also find StockPrice to positively associate with Size and negatively associate with Volatility with significance.

Since the sample period 2005–2010 covers the 2008–2009 period of the Great Recession that influenced the world including the Europe, model (1) is tested using data for the whole period (Panel A in Table 3) as well as with data not affected by the recession period (Panel B in Table 3) to assure robustness of findings. Table 3 shows empirical evidence in support of H1. As predicted by H1, XBRL positively associates with Amivest (α_1 is 0.848 for 2005 ~ 2010 but 1.125 when recession period is removed) and Turnover ratios (α_1 is 0.001 for both cases) at $p < 0.01$ while it negatively associates with Zeros (α_1 is -0.040 for 2005–2010 but -0.021 when recession period is removed) and Zeros2 (α_1 is -0.006 for 2005–2010 but -0.002 when recession period is removed) at $p < 0.01$ to reveal an increase in liquidity after XBRL adoption among Belgium firms. In agreement with prior findings [69], Size is positively associated with liquidity proxies that increase with liquidity while being negatively associated with liquidity proxies that decrease with liquidity. Like [69], StockPrice is generally found to positively associate with liquidity proxies that decrease with liquidity while being negatively associated with liquidity proxies that increase with liquidity. In addition, the findings reveal that firm-specific characteristics, industry-specific characteristics, and year-specific elements all significantly influence liquidity, thus they should be included in the model to account for the impact of these characteristics on liquidity.

In general, Table 4 shows empirical evidence in support of H2. When data from the recession period are removed as shown in Panel B, Large*XBRL negatively associates with Zeros ($\alpha_3 = -0.080$) and Zeros2 ($\alpha_3 = -0.016$) but positively associates with Amivest ($\alpha_3 = 0.645$) and Turnover ($\alpha_3 = 0.001$) with significance at least at $p < 0.05$ in support of H2 that large firm size strengthens the increase to liquidity after XBRL adoption. This finding is in agreement with the findings by [69]. Even though Amivest ($\alpha_1 = 0.548$) increases significantly for smaller firms, indicating higher liquidity, Zeros ($\alpha_1 = 0.035$) and Zeros2 ($\alpha_1 = 0.011$) seem to have increased also for such firms after XBRL adoption. When the complete data set is analyzed as shown in Panel A, the expected relation between Large*XBRL and liquidity proxies are all significant and in the expected direction except for Amivest. Even though Amivest is positively associated with Large*XBRL as expected by H2, the coefficient is not significant. For smaller firms with no more than average Size, both Amivest ($\alpha_1 = 0.460$) and Turnover ($\alpha_1 = 0.000$) have also increased with XBRL adoption, but changes to Zeros ($\alpha_1 = 0.000$) and Zeros2 ($\alpha_1 = 0.001$) for such firms are not significant. Possible explanations for such differences between larger firms and smaller firms lie in differences in IT resources and expertise available to different firms. The risk of errors in creating XBRL documents is higher for smaller firms with insufficient resources and expertise. Errors decrease information transparency and efficiency of information search and thus decrease liquidity. Such a finding is in agreement with [12] that reveal significant variations of quality in XBRL documents among U.S. firms and provides a possible explanation for the mixed findings of prior XBRL empirical studies.

In general, Table 5 shows empirical evidence in support of H3. Regardless of whether recession years are included, the interaction term of High-tech*XBRL (α_3) is in the projected direction of lower liquidity. The coefficient is significant for all liquidity proxies except for Amivest that is significant at $p < 0.10$ for the full sample where $\alpha_3 = -0.216$ and not significant when the recession years are removed

Table 2
Spearman correlation coefficients.

	1	2	3	4	5	6	7	8	9	10	11
Dependent variables											
1 Amivest	1										
2 Turnover	0.727***	1									
3 Zeros	−0.747***	−0.649***	1								
4 Zeros2	−0.654***	−0.546***	0.898***	1							
Independent variables											
5 XBRL	−0.027***	0.080***	−0.150***	−0.144***	1						
6 Size	0.776***	0.446***	−0.733***	−0.755***	−0.084***	1					
7 Volatility	−0.218***	0.102***	0.000	0.045***	0.541***	−0.391***	1				
8 StockPrice	0.355***	0.055***	−0.310***	−0.385***	−0.109***	0.556***	−0.415***	1			
9 Industry	0.026***	0.092***	−0.078***	−0.030***	0.009	−0.069***	0.247***	−0.149***	1		
10 Firm	−0.324***	−0.276***	0.361***	0.325***	0.005	−0.325***	0.117***	0.045***	0.239***	1	
11 Year	−0.047***	0.040***	−0.086***	−0.140***	0.842***	−0.090***	0.508***	−0.138***	0.005	0.013**	1

*** Indicates difference significant at $p < 0.01$; ** Indicates difference significant at $p < 0.05$.

Table 3
Model (1) test results for non-financial Belgian firms.

$$\text{Liquidity}_{it} = \alpha_0 + \alpha_1 {}^*\text{XBRL}_{it} + \alpha_2 {}^*\text{Size}_{it} + \alpha_3 {}^*\text{Volatility}_{it} + \alpha_4 {}^*\text{StockPrice}_{it} + \alpha_5 {}^*\text{Industry}_{it} + \alpha_6 {}^*\text{Firm}_{it} + \alpha_7 {}^*\text{Year}_{it} + \varepsilon$$

	Panel A: Sample data covering 2005–2010 28711 observations				Panel B: 2005–2010 excluding 2008–2009 19926 observations			
	Amivest	Zeros	Zeros2	Turnover	Amivest	Zeros	Zeros2	Turnover
Intercept	455.276***	−20.235***	6.597***	0.310***	534.723***	−15.315***	6.991***	0.244***
	(122.018)	(1.043)	(0.313)	(0.029)	(127.663)	(1.011)	(0.335)	(0.029)
XBRL	0.848***	−0.040***	−0.006***	0.001***	1.125***	−0.021***	−0.002***	0.001***
	(0.213)	(0.002)	(0.001)	(0.000)	(0.238)	(0.002)	(0.001)	(0.000)
Size	0.820***	−0.065***	−0.017***	0.001***	0.851***	−0.050***	−0.018***	0.000***
	(0.031)	(0.000)	(0.000)	(0.000)	(0.038)	(0.000)	(0.000)	(0.000)
Volatility	0.504***	0.011***	0.014***	0.000***	0.550***	0.011***	0.015***	0.000***
	(0.099)	(0.001)	(0.000)	(0.000)	(0.104)	(0.001)	(0.000)	(0.000)
StockPrice	−0.001**	0.000***	0.000***	−0.000***	−0.002**	0.000***	0.000***	−0.000***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Industry	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year	−0.235***	0.011***	−0.003***	−0.000***	−0.275***	0.008***	−0.003***	−0.000***
	(0.061)	(0.000)	(0.000)	(0.000)	(0.064)	(0.001)	(0.000)	(0.000)

*** Indicates difference significant at $p < 0.01$; ** Indicates difference significant at $p < 0.05$.

from analysis. Regardless of whether recession data are incorporated in the analysis and despite the choice of liquidity proxy, the coefficient for XBRL (α_1) is all significant in the direction of higher liquidity, implying that XBRL adoption has led to higher liquidity for non-high-technology firms. Such a finding confirms our projection that the improvement to information asymmetry and market liquidity is particularly evident for non-high-technology firms whose financial statements play a bigger role in investors' decision making.

4.3. Additional robustness tests

To make sure that differences identified are not due to differences in sample firms between the pre-adoption period and post-adoption period, we test the models again after removing firms that only have data in one of the two periods. H1, H2 are both fully supported with significance at $p < 0.01$ no matter what liquidity proxy is used. H3 is fully supported with significance at $p < 0.01$ for all proxies except for Amivest whose inverse relation with High-tech*XBRL is found to be significant at $p < 0.05$.

Since Table 1 reveals that variables under study are not normally distributed, we transform all non-categorical variables by using natural log in all models as per [40]. For model (1), the coefficient for XBRL is significant and positive when liquidity is measured by LnTurnover (0.299, $p < 0.01$) or LnAmivest (0.103, $p < 0.01$) as expected by H1. The coefficient for XBRL is significant and negative when liquidity is measured by LnZeros (−0.669, $p < 0.01$) or LnZeros2 (−0.205, $p < 0.01$) as expected by H1. For model (2), Large*XBRL is positively associated with LnTurnover (0.778, $p < 0.01$) and LnAmivest (1.417, $p < 0.01$) with significance as predicted by H2. Large*XBRL is negatively associated with LnZeros (−0.868, $p < 0.01$) and LnZeros2

Table 4
Model (2) test results for non-financial Belgian firms.

$$\text{Liquidity}_{it} = \alpha_0 + \alpha_1 {}^*\text{XBRL}_{it} + \alpha_2 {}^*\text{Large}_{it} + \alpha_3 {}^*\text{Large}_{it} {}^*\text{XBRL} + \alpha_4 {}^*\text{Volatility}_{it} + \alpha_5 {}^*\text{StockPrice}_{it} + \alpha_6 {}^*\text{Industry}_{it} + \alpha_7 {}^*\text{Firm}_{it} + \alpha_8 {}^*\text{Year}_{it} + \varepsilon$$

	Panel A: Sample data covering 2005–2010 28711 observations: 14098 Large = 1 vs. 14613 Large = 0				Panel B: 2005–2010 excluding 2008–2009 19926 observations 10065 Large = 1 vs. 9861 Large = 0			
	Amivest	Zeros	Zeros2	Turnover	Amivest	Zeros	Zeros2	Turnover
Intercept	369.706***	−15.255***	7.834***	0.232***	413.575***	−7.228***	9.213***	0.160***
	(122.705)	(1.293)	(0.412)	(0.029)	(128.836)	(1.281)	(0.441)	(0.029)
XBRL	0.460*	0.000	0.001	0.000***	0.548*	0.035***	0.011***	0.000
	(0.251)	(0.003)	(0.001)	(0.000)	(0.288)	(0.003)	(0.001)	(0.000)
Large	2.842***	−0.108***	−0.045***	0.002***	2.824***	−0.109***	−0.044***	0.001***
	(0.197)	(0.002)	(0.001)	(0.000)	(0.199)	(0.002)	(0.001)	(0.000)
Large*XBRL	0.388	−0.057***	−0.008***	0.001a***	0.645**	−0.080***	−0.016***	0.001***
	(0.240)	(0.003)	(0.001)	(0.000)	(0.284)	(0.003)	(0.001)	(0.000)
Volatility	−0.283***	0.062***	0.031***	−0.000	−0.244**	0.061***	0.032***	−0.000***
	(0.093)	(0.001)	(0.000)	(0.000)	(0.096)	(0.001)	(0.000)	(0.000)
StockPrice	−0.000	0.000***	−0.000***	−0.000***	0.000	0.000**	−0.000***	−0.000***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Industry	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year	−0.185***	0.011***	−0.004***	−0.000***	−0.207***	0.004***	−0.005***	−0.000***
	(0.061)	(0.000)	(0.000)	(0.000)	(0.064)	(0.001)	(0.000)	(0.000)

*** Indicates difference significant at $p < 0.01$; ** Indicates difference significant at $p < 0.05$; * Indicates difference significant at $p < 0.10$.

Table 5
Model (3) test results for non-financial Belgian firms.

$Liquidity_{it} = \alpha_0 + \alpha_1 * XBRL_{it} + \alpha_2 * High\text{-}tech_{it} + \alpha_3 * High\text{-}tech_{it} * XBRL + \alpha_4 * Size_{it} + \alpha_5 * Volatility_{it} + \alpha_6 * StockPrice_{it} + \alpha_7 * Industry_{it} + \alpha_8 * Firm_{it} + \alpha_9 * Year_{it} + \varepsilon$

	Panel A: Sample data covering 2005–2010 28711 observations: 15309 High-tech = 1 vs. 13402 High-tech = 0				Panel B: 2005–2010 excluding 2008–2009 19926 observations 10516 High-tech = 1 vs. 9410 High-tech = 0			
	Amivest	Zeros	Zeros2	Turnover	Amivest	Zeros	Zeros2	Turnover
Intercept	451.221***	−20.992***	6.439***	0.319***	528.454***	−15.897***	6.917***	0.249***
	(122.033)	(1.016)	(0.309)	(0.029)	(127.664)	(0.991)	(0.334)	(0.029)
XBRL	0.995***	−0.056***	−0.010***	0.001***	1.216***	−0.037***	−0.005***	0.001***
	(0.226)	(0.002)	(0.001)	(0.000)	(0.254)	(0.002)	(0.001)	(0.000)
High-tech	0.256***	−0.001	−0.001***	0.000*	0.291***	0.000	−0.001***	0.000
	(0.090)	(0.001)	(0.001)	(0.000)	(0.090)	(0.000)	(0.000)	(0.000)
High-tech*XBRL	−0.216*	0.025***	0.006***	−0.000***	−0.140	0.023***	0.004***	−0.000***
	(0.111)	(0.001)	(0.000)	(0.000)	(0.131)	(0.001)	(0.000)	(0.000)
Size	0.833***	−0.047***	−0.016***	0.001***	0.876***	−0.048***	−0.017***	0.000***
	(0.032)	(0.000)	(0.000)	(0.000)	(0.039)	(0.000)	(0.000)	(0.000)
Volatility	0.545***	0.016***	0.015***	0.000***	0.617***	0.014***	0.015***	0.000***
	(0.101)	(0.001)	(0.000)	(0.000)	(0.106)	(0.001)	(0.000)	(0.000)
StockPrice	−0.001*	0.000***	0.000***	−0.000***	−0.001**	0.000**	0.000***	−0.000***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Industry	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year	−0.234***	0.011***	−0.003***	−0.000***	−0.273***	0.008***	−0.003***	−0.000***
	(0.061)	(0.001)	(0.000)	(0.000)	(0.064)	(0.000)	(0.000)	(0.000)

*** Indicates difference significant at $p < 0.01$; ** Indicates difference significant at $p < 0.05$; * Indicates difference significant at $p < 0.10$.

(−0.503, $p < 0.01$) with significance as predicted by H2. For model (3), High-tech*XBRL is negatively associated with LnTurnover (−0.221, $p < 0.01$) and LnAmivest (−0.261, $p < 0.01$) with significance as predicted by H2. High-tech*XBRL is positively associated with LnZeros (0.287, $p < 0.01$) and LnZeros2 (0.211, $p < 0.01$) with significance as predicted by H3.

The model used by [69] does not control Firm, Industry, or Year. Besides, Year is highly correlated with XBRL. Therefore, we retest the models by removing these control variables. Findings are similar to those achieved with these variables controlled in the models. The coefficient for XBRL is significant for Turnover, Zeros, and Zeros2 in the expected direction at $p < 0.01$ in support of H1 while it is positive but not significant for Amivest. The coefficient for Large*XBRL is significant for Turnover, Zeros, and Zeros2 in the expected direction at $p < 0.01$ while it is significant and positive for Amivest at $p < 0.10$ in support of H2. The coefficient for High-tech*XBRL is significant for Turnover, Zeros, and Zeros2 in the expected direction at $p < 0.01$ while it is negative for Amivest as predicted by H3 but not significant.

Trading volume can also serve as a proxy for liquidity because higher liquidity often associates with higher trading volume [44]. We test our models with trading volume as the liquidity proxy to find XBRL to positively associate with trading volume at $p < 0.01$ regardless of whether natural log or original trading volume is used or whether Firm, Industry, and Year are controlled in model (1) or whether recession period data are excluded in support of H1. When model (2) is tested with trading volume, it is revealed that not only the coefficient for Large*XBRL is always positive and significant with trading volume or Lntrading volume, the coefficient XBRL is also always positive and significant, indicating that the adoption of XBRL has led to significant increase to trading volume for both smaller firms and larger firms but that increase is more significant to larger firms as predicted by H2. When model (3) is tested with trading volume, the coefficient for High-tech*XBRL is negative with significance ($p < 0.01$) as predicted after transforming it with natural log.

When we group data by Large and retest model (3), we find the coefficient for High-tech*XBRL in the expected direction at $p < 0.01$ for both larger firms with above average size and smaller firms for all liquidity proxies except for Amivest that is negatively associated with High-tech*XBRL at $p < 0.01$ only for larger firms but negatively associate with it without significance for smaller firms.

High-technology industries can be identified with different methods [29,30,53]. We reclassify the industries by SIC code as per [30] or by the level of R&D intensity as per [53] to finding similar conclusions for H3. When SIC code is used as per [30], High-tech*XBRL is significant in the expected direction for Turnover, Zeros, and Zeros2 at $p < 0.01$ and for Amivest at $p < 0.10$. When [53] is followed in classifying high-technology industries, High-tech*XBRL is significant in the expected direction for Turnover, Zeros, and Zeros2 at $p < 0.01$. For Amivest, the coefficient for High-tech*XBRL is not significant but negative as expected.

5. Discussion and conclusions

XBRL as a recent technology is expected to improve business information transparency due to a streamline reporting process, improved information quality, improved search and analysis by business information users, and improved business-to-government reporting process. Significant relation has been identified between XBRL adoption and information asymmetry with rather contradictory findings likely due to different contextual factors in different samples under this study. Our literature review shows that researchers have not yet explored this relation in the European context. Therefore, in this study we set out to (1) study the association between XBRL adoption and information asymmetry in Belgium, (2) investigate the moderating role of firm size, and (3) probe the moderating role of technology intensity.

The results clearly indicate that the XBRL adoption among Belgian firms associates with significantly increased liquidity and reduced information asymmetry. As expected, the similar disclosure quality of Belgium and South Korean before XBRL adoption is in line with similar XBRL's impact on information asymmetry [69]. It thus seems that differences in disclosure quality before XBRL adoption can be among the factors explaining mixed findings on the impact of XBRL. Much of the increase to liquidity is achieved by larger firms due to the availability of more abundant IT resources and by non-high-technology firms whose financial statements play a bigger role in investors' decision making. We show that firm size and technology intensity can help to better predict the association between XBRL adoption and information asymmetry change.

The findings have significant implications to regulars such as ESMA that are assessing costs and benefits of XBRL mandate. Financial reports in XBRL format associates with information asymmetry improvement. This association is evident in an European context. Future research may examine the association with samples from other nations of different disclosure quality and environment. In addition, the improvement to information asymmetry is found to be particularly apparent when financial reports play a bigger role in investment decisions. Such a finding supports U.S. SEC contention that the technology has the potential to reduce information asymmetry [11]. The improvement is more apparent for larger firms due to the availability of more abundant IT resources. To allow smaller firms to benefit more from such a technology, technical support to these firms plays an indispensable role. This study also provides empirical support for low frequency liquidity measurements that can offer enormous savings in computational time in comparison with high-frequency liquidity proxies. Future research may also benefit from using such measurements.

The following caveats limit generalization from the research findings. First, sample firms are from Belgium of Europe. Findings from these Belgian firms are only generalizable to firms operating with similar disclosure quality before XBRL adoption, similar financial reporting environment, and similar technological development context. In addition, not all available proxies of liquidity are tested in this study. However, at least four commonly-used proxies of liquidity are tested and have led to similar conclusions. Besides, future research can use information asymmetry proxies other than liquidity to assess the impact of XBRL on information asymmetry. The findings from the proposed methods should be compared with those using other methods in future research. Finally, XBRL is being continuously developed and improved [45]. Future research can investigate its influence with more recent data.

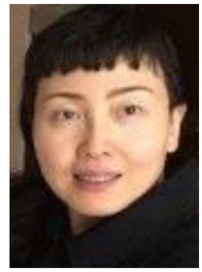
Acknowledgments

The authors would like to thank two anonymous referees and Editor-in-Chief for their insightful comments and suggestions that have improved the manuscript significantly.

References

[1] L.H. Amato, C.H. Amato, Retail philanthropy: firm size, industry, and business cycle, Journal of Business Ethics 107 (4) (2012) 435–448.
[2] Y. Amihud, Y. Mendelson, B. Lauterbach, Market microstructure and securities values: evidence from the Tel Aviv stock exchange, Journal of Financial Economics 45 (3) (1997) 365–390.
[3] R.D. Banker, H. Chang, Y.C. Kao, Evaluating cross–organizational impacts of information technology – an empirical analysis, European Journal of Information Systems 19 (2010) 153–167.
[4] O.E. Barron, D. Byard, C. Kile, High-technology intangibles and analysts' forecasts, Journal of Accounting Research 40 (2) (2002) 289–312.
[5] M.E. Barth, R. Kasznik, M.F. Mcnichols, Analyst coverage and intangible assets, Journal of Accounting Research 39 (1) (2001) 1–34.
[6] J. Bartley, A.Y.S. Chen, E.Z. Taylor, Avoiding common errors of XBRL implementation, Journal of Accountancy 209 (2) (2010) 46–51.
[7] J. Benitez–Amadol, R.M. Walczuch, Information technology, the organizational capability of proactive corporate environmental strategy and firm performance: a resource based analysis, European Journal of Information Systems 21 (2012) 664–679.
[8] H. Berkman, V. Eleswarapu, Short–term traders and liquidity: a test using Bombay stock exchange data, Journal of Financial Economics 47 (1998) 339–355.
[9] U. Bhattacharya, M. Spiegel, Insiders, outsiders, and market breakdowns, Review of Financial Studies 4 (2) (1991) 255–282.
[10] P.A. Bizarro, A. Garcia, XBRL – beyond the basics, CPA Journal 80 (5) (2010) 62–71.
[11] E. Blankespoor, B.P. Miller, H.D. White, Initial evidence on the market impact of the XBRL mandate, Review of Accounting Studies 19 (4) (2014) 1468–1503.
[12] M. Bovee, M. Ettredge, R. Srivastava, M. Vasarhelyi, Does the year 2000 XBRL taxonomy accommodate current business financial reporting practice? Journal of Information Systems 16 (2) (2002) 165–182.
[13] H.K. Cheung, J. Burn, Distributing global information systems resources in multinational companies, Journal of Global Information Management 2 (3) (1994) 14–27.
[14] R. Chowdhuri, V.Y. Yoon, R.T. Redmond, U.O. Etudo, Ontology based integration of XBRL filings for financial decision making, Decision Support Systems 68 (2014) 64–76.
[15] Y. Cong, J. Hao, L. Zou, The impact of XBRL reporting on market efficiency, Journal of Information Systems 28 (2) (2014) 181–207.
[16] K.S. Cooper, J.C. Groth, W.E. Avera, Liquidity, exchange listing and common stock performance, Journal of Economics and Business 37 (1985) 19–33.
[17] V.T. Datar, N.Y. Naik, R. Radcliffe, Liquidity and stock returns: an alternative test, Journal of Financial Markets 1 (2) (1998) 203–219.
[18] R. Debreceny, A. Chandra, J.J. Cheh, D.D. Guithues–Amrhein, N.J. Hannon, P.D. Hutchison, D. Janvrin, R.A. Jones, B. Lamberton, A. Lymer, M. Mascha, R. Nehmer, S. Roohani, R.P. Srivastava, S. Trabelsi, T. Tribunella, G. Trites, M. Vasarhelyi, Financial reporting in XBRL on the SECs EDGAR systems: a critique and evaluation, Journal of Information Systems 19 (2) (2005) 191.
[19] J. Du, L. Zhou, Improving financial data quality using ontologies, Decision Support Systems 54 (2012) 76–86.
[20] L. Dufresne, XBRL and the Belgian "building blocks" approach, XBRL Global 1 (2) (2010) 28–31.
[21] B.E. Eckbo, Ø. Norli, Liquidity risk, leverage, and long–run IPO returns, Journal of Corporate Finance 11 (1–2) (2005) 1–35.
[22] J. Efendi, J.D. Park, C. Subramaniam, Does the XBRL reporting format provide incremental information value? A study using XBRL disclosures during the voluntary filing program, Abacus 52 (2016) 259–285.
[23] M. Feng, J.D. Gramlich, S. Gupta, Special purpose vehicles: empirical evidence on determinants and earnings management, The Accounting Review 84 (6) (2009) 1833–1876.
[24] A. Gande, A. Saunders, Are banks still special when there is a secondary market for loans? The Journal of Finance 67 (5) (2012) 1649–1684.
[25] R. Goyenko, C. Holden, C. Trzcinka, Do liquidity measures measure liquidity? Journal of Financial Economics 92 (2009) 153–181.
[26] V. Guilloux, J. Locke, A. Lowe, Digital business reporting standards, European Journal of Information Systems 22 (2013) 257–277.
[27] P.M. Healy, A.P. Hutton, K.G. Palepu, Stock performance and intermediation changes surrounding sustained increases in disclosure, Contemporary Accounting Research 16 (3) (1999) 485–520.
[28] P.M. Healy, K. Palepu, A review of the empirical disclosure literature, Journal of Accounting and Economics 31 (1–3) (2001) 405–440.
[29] D.E. Hecker, High-technology employment: a NAICS-based update, Monthly Labor Review (July 2005) 57–72.
[30] D.E. Hecker, High-technology employment: a broader view, Monthly Labor Review (June 1999) 18–28.
[31] F. Heflin, K. Shaw, J. Wild, Disclosure quality and market liquidity: impact of depth quotes and order size, Contemporary Accounting Research 22 (4) (2005) 829–865.
[32] F.D. Hodge, J.J. Kennedy, L.A. Maines, Does search–facilitating technology improve the transparency of financial reporting? The Accounting Review 79 (3) (2004) 687–703.
[33] R. Hoitash, A. Kogan, M.A. Vasarhelyi, Peer–based approach for analytical procedures, Auditing: A Journal of Practice & Theory 25 (2) (2006) 53–84.
[34] C.W. Holden, New low-frequency spread measures, Journal of Financial Markets 12 (2009) 778–813.
[35] I. Ionascu, M. Ionascu, M. Minu, M. Sacarin, Local accounting culture facing globalization: the case of Romania's patrimoniality principle, International Journal of Accounting and Information Management 19 (2) (2011) 205–206.
[36] D. Janvrin, W.G. No, XBRL implementation: a field investigation to identify research opportunities, Journal of Information Systems 26 (1) (2012) 169–197.
[37] R.E. Jensen, J.Z. Xiao, Customized financial reporting, networked databases, and distributed file sharing, Accounting Horizons 15 (3) (2001) 209–222.
[38] S. Kudyba, R. Diwan, Research report: increasing returns to information technology, Information Systems Research 13 (1) (2002) 104–111.
[39] F. Lai, C.T. Hsieh, D. Li, J. Wang, Impact of industry type, ownership, and company size on Chinese firms' e-business strategy, International Journal of Intercultural Information Management 1 (2) (2009) 143–165.
[40] F. Lakhal, Stock market liquidity and information asymmetry around voluntary earnings disclosures, International Journal of Managerial Finance 4 (1) (2008) 60–75.
[41] D.A. Lesmond, Liquidity of emerging markets, Journal of Financial Economics 77 (2) (2005) 411–452.
[42] D. Lesmond, J. Ogden, C. Trzcinka, A new estimate of transaction costs, Review of Financial Studies 12 (1999) 1113–1141.
[43] W.F. Lester, XBRL: the new language of corporate financial reporting, Business Communication Quarterly 70 (2) (2007) 226–235.
[44] C. Leuz, R.E. Verrecchia, The economic consequences of increased disclosure, Journal of Accounting Research 38 (2000) 91–124.
[45] S. Li, E.T. Nwaeze, The association between extensions in XBRL disclosures and financial information environment, Journal of Information Systems 29 (3) (2015) 73–99.
[46] C. Liu, XBRL: a new global paradigm for business financial reporting, Journal of Global Information Management 21 (3) (2013) 60–80.
[47] C. Liu, X. Luo, C.L. Sia, G. O'Farrell, H.H. Teo, The impact of XBRL adoption in P. R. China, Decision Support Systems 59 (2014) 242–249.
[48] C. Liu, C.L. Sia, K.K. Wei, Adopting organizational virtualization in B2B firms: an empirical study in Singapore, Information Management 45 (2008) 429–437.
[49] C. Liu, D. Wang, L.J. Yao, An empirical study of XBRL's impact on analyst forecast behaviour, Journal of Accounting and Public Policy 33 (1) (2014) 69–82.

[50] C. Liu, L.J. Yao, C.L. Sia, K.K. Wei, The impact of early XBRL adoption on analysts' forecast accuracy: empirical evidence from China, Electronic Markets 24 (1) (2014) 47–55.
[51] C. Liu, L.J. Yao, N. Hu, L. Liu, The impact of IFRS on accounting quality in a regulated market: an empirical study of China, Journal of Accounting, Auditing, and Finance 26 (4) (2011) 659–676.
[52] D. Mani, A. Barua, A. Whinston, An empirical analysis of the impact of information capabilities design on business process outsourcing performance, MIS Quarterly 34 (1) (2010) 39–62.
[53] S. Montresor, A. Vezzani, The production function of top R&D investors: accounting for size and sector heterogeneity with quantile estimations, Research Policy 44 (2015) 381–393.
[54] R.C. Nickerson, U. Varshney, J. Muntermann, A method for taxonomy development and its application in information systems, European Journal of Information Systems 22 (2013) 336–359.
[55] J. Peng, C.J. Chang, Applying XBRL in an accounting information system design using the REA approach: an instructional case, Accounting Perspectives 9 (1) (2010) 55–78.
[56] R. Pinsker, S. Li, Costs and benefits of XBRL adoption: early evidence, Communications of the ACM 51 (3) (2008) 47–50.
[57] A. Rai, R. Patnayakuni, N. Patnayakuni, Technology investment and business performance, Communications of the ACM 40 (7) (1997) 89–97.
[58] M.V. Russo, P.A. Fouts, A resource–based perspective on corporate environmental performance and profitability, Academy of Management Journal 40 (3) (1997) 534–559.
[59] A. Seetharaman, R. Subramaniam, Y.S. Seow, Internet financial reporting: problems and prospects, Corporate Finance Review 10 (2) (2005) 23–34.
[60] E. Sledgianowski, R. Fondeder, N.S. Slavin, Implementing XBRL reporting, CPA Journal 80 (8) (2010) 68–72.
[61] P.P. Tallon, Do you see what I see? The search for consensus among executives' perceptions of IT business value, European Journal of Information Systems 23 (2014) 306–325.
[62] H. Tanriverdi, Information technology relatedness, knowledge management capability, and performance of multibusiness firms, MIS Quarterly 29 (2) (2005) 311–334.
[63] M.A. Vasarhelyi, D.Y. Chan, J.P. Krahel, Consequences of XBRL standardization on financial statement data, Journal of Information Systems 26 (1) (2012) 155–167.
[64] M. Welker, Disclosure policy, information asymmetry and liquidity in equity markets, Contemporary Accounting Research 11 (2) (1995) 801–823.
[65] M.R. Wenger, R. Elam, K. Williams, Global ledger: the next step for XBRL, CPA Journal 81 (9) (2011) 64–71.
[66] Z. Xiao, P.L. Powell, J.H. Dodgson, The impact of information technology on information asymmetry, European Journal of Information Systems 7 (1998) 77–89.
[67] L.J. Yao, C. Liu, S.H. Chan, The influence of firm specific context on realizing information technology business value in manufacturing industry, International Journal of Accounting Information Systems 11 (2010) 353–362.
[68] J.C. Yen, T. Wang, The association between XBRL adoption and market reactions to earnings surprises, Journal of Information Systems 29 (3) (2015) 51–71.
[69] H. Yoon, H. Zo, A.P. Ciganek, Does XBRL adoption reduce information asymmetry? Journal of Business Research 64 (2011) 157–163.
[70] H. Zhu, H. Wu, Assessing the quality of large–scale data standards: a case of XBRL GAAP taxonomy, Decision Support Systems 59 (2014) 351–360.



Dr. Chunhui Liu is a Professor at Caritas Institute of Higher Education. She received PhD from the National University of Singapore. Her research interests include accounting information systems, international accounting, and accounting ethics education. Her publications have appeared in journals like *Decision Support Systems*, *Information & Management*, *International Journal of Human Computer Studies*, *Journal of Accounting and Public Policy*, *Journal of Accounting, Auditing, and Finance*, *Electronic Markets*, and *Issues in Accounting Education*.

Dr. Xin (Robert) Luo is an Endowed Regent's Professor and Associate Professor of MIS and Information Assurance at the University of New Mexico, USA. He received his Ph.D. in Information Systems from Mississippi State University. He has published research papers in leading journals including *Decision Support Systems, Decision Sciences*, *European Journal of Information Systems, Journal of the AIS, Communications of the ACM, Computers & Security, Information Systems Journal, Information & Management*, and *Journal of Strategic Information Systems*, etc. His research interests center around information assurance, innovative technologies, and cross-cultural information systems management. He is an ad-hoc AE for *MIS Quarterly* and an Associate Editor *for Decision Sciences, European Journal of Information Systems, Electronic Commerce Research*, and *Journal of Electronic Commerce Research*. He is the Editor in Chief for *International Journal of Information and Computer Security* and co-Editor in Chief for *International Journal of Accounting and Information Management.*

Professor Fu Lee Wang is the Vice-President (Research and Advancement) at Caritas Institute of Higher Education. He received PhD from the Chinese University of Hong Kong. His research interests include electronic business, information retrieval, information systems and e-learning. He has published over 100 papers in international journal and conferences, including *Decision Support Systems, IEEE Intelligent Systems, IEEE MultiMedia, Information Processing and Management, Information Processing Letters, Journal of the American Society for Information Science and Technology, Neurocomputing*, and more. He is Past Chair of ACM Hong Kong Chapter and IEEE Hong Kong Section Computer Society Chapter.