



# FinTech revolution: the impact of management information systems upon relative firm value and risk

Sovan Mitra<sup>1</sup> · Andreas Karathanasopoulos<sup>2</sup>

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## Abstract

The FinTech or ‘financial technology’ revolution has been gaining increasing interest as technologies are fundamentally changing the business of financial services. Consequently, financial technology is playing an increasingly important role in providing relative performance growth to firms. It is also well known that such relative performance can be observed through pairs trading investment. Therefore pairs trading have implications for understanding financial technology performance, yet the relationships between relative firm value and financial technology are not well understood. In this paper we investigate the impact of financial technology upon relative firm value in the banking sector. Firstly, using pairs trade data we show that financial technologies reveal differences in relative operational performance of firms, providing insight on the value of financial technologies. Secondly, we find that contribution of relative firm value growth from financial technologies is dependent on the specific business characteristics of the technology, such as the business application and activity type. Finally, we show that financial technologies impact the operational risk of firms and so firms need to take into account both the value and risk benefits in implementing new technological innovations. This paper will be of interest to academics and industry professionals.

**Keywords** FinTech · Financial technology · Operational risk · Relative firm value · Firm value · Risk management · Pairs trading · Shareholder value

## 1 Introduction

The financial technology or ‘FinTech’ revolution has enabled financial services to fundamentally change their businesses [1], by allowing firms to offer new products, new business processes and business models, to name a few everyday examples of FinTech would include bitcoin, big data analytics and peer to peer lending. Such innovation has been embraced by the financial sector, as firms are constantly seeking opportunities to differentiate themselves from competitors and allow companies to increase their firm value (or equivalently share prices) relative to their competitors (see [2–5]).

A consequence of the increase in FinTech has been an increased dependence upon it. This is because, firstly, increasingly larger amounts of data need to be managed, across a range of business lines and eventualities. Secondly, FinTech is increasingly being required to manage fundamental financial operations, such as analysis, reporting and modelling, with an increasing drive towards automating all financial processes. Finally, operational and IT management are increasingly being regarded as a strategic resource for competitive advantage; see for instance [6–9].

The use of operational factors to give competitive advantages (and so relative firm value growth) has already been supported by researchers (e.g. [10–13]) and this has also occurred in the banking sector. For example, the Merrill Lynch Cash Management Account System [14] is cited as a case where Merrill Lynch were able to capture 90% of the investment account market within 1 year of operation of the system.

Although there is no overwhelming consensus of opinion on the contribution of FinTech to firm value or relative firm value (see for instance [15–17]), it is well recognised that

✉ Sovan Mitra  
s.mitra@westminster.ac.uk

<sup>1</sup> School of Finance and Accounting, University of Westminster, 4–12 Little Titchfield Street, London W1W 7BY, UK

<sup>2</sup> University of Dubai, Academic city, Emirates road, Dubai, United Arab Emirates

investors profit from relative firm performances by engaging in pairs trades of firms' shares. Pairs trading is a trading strategy where an investor takes a 'long' and 'short' position in two different stocks [18], with the intention to benefit from relative share price growth (or equivalently the relative firm value growth) between the two firms. Moreover, using a standard model of operational risk (hereon OR) in the financial sector [19] it can be shown that pairs trading returns provide a measure on the difference in OR between the two financial firms (to be explained in more detail in the proceeding sections).

Consequently pairs trade (hereon PT) returns (which are equivalent to relative firm value growth) enable us to understand the contribution of FinTech and OR. Despite this, there is a lack of literature on relative firm value. This is particularly unusual, given that operational management has been studied as a source of firm value creation; for example see [20] and [21] to name a few articles.

The lack of literature can be explained by, firstly, financial technology research tending to address a specific characteristic, rather than investigating a broad range of characteristics (for example see [22, 23]). Consequently, our understanding of different FinTech issues impacting firm value, OR, etc. is limited. Secondly, FinTech research relating to firm value tends to be concerned with the firm's absolute value or its growth independent of other firms (for example see [24]). Consequently, we do not understand the contribution of financial technology to firm value relative to its competitors. Finally, PT literature tends to be concerned with investment strategies (e.g. [25, 26]), which focus on extracting empirical relationships on price data.

The scarce research literature upon FinTech, OR and relative firm value has meant that these interrelated areas are not fully understood. For example, are there specific financial technologies, designed for a particular business line, that could impact relative firm value more than other business lines? Are there particular financial technologies that increase OR more than other financial technologies? If so, does this impact a bank's FinTech strategy in any way?

In this paper we investigate financial technologies and their relation to relative firm value growth (or equivalently PT returns) and OR. Using operational event data and over 11,000 pairs trades data, we investigate PT returns, OR and the relation to financial technologies. This paper makes a number of contributions. Firstly, using pairs trade data we show that financial technologies reveal differences in relative operational performance of firms. Using market data we are able to provide a more realistic assessment of the contribution of financial technology to firms.

The advantage of utilising empirical market data is that we are not reliant on a theoretical approach to examine operational issues. Consequently, such an approach can help resolve the widely cited 'productivity paradox' [27].

This paradox is related to the fact that productivity tends to decrease as increased investment is made in improving productivity (particularly in areas such as IT). The reasons relating to decreased productivity tend to be related to human and decision making factors, rather than pure electronic or technological causes, consequently the issues in the 'productivity paradox' [27] are relevant in the twenty-first century as they were in the twentieth century, as well as in developed or developing countries.

Secondly, we find that contribution of relative firm value growth from financial technologies is dependent on the specific business characteristics of the technology, such as the business application and activity type. Thus firms can improve relative firm value contribution by strategically re-allocating or concentrating on particular financial business lines and operational events. Finally, we find that financial technologies impact the operational risk of firms and so firms need to take into account both the value and risk benefits in implementing new technological innovations. New FinTech products and services (from hereon FPAS) should bear in mind such variations to maximise relative firm value and minimise OR.

The rest of the paper is organised as follows: in the next section we introduce PT, FinTech in the financial sector, OR and the motivation of our study. We then provide a literature review, we then discuss our research methodology and our data. We then discuss our results, analyse them and end with a conclusion.

## 2 Related literature and motivation of study

The financial technology or 'FinTech' revolution has arisen from a convergence in technology and finance that has provided a new means for financial services to fundamentally change their businesses, even in developing countries [28]. Financial technology has been defined [29] as the systems that model, value, and process financial products. Financial technology has allowed financial services to offer new business models (such as online wealth management to new customer segments), new products (such as digital wallets and bitcoin) and new business processes (such as big data analytics). As financial firms are increasingly pushing towards automating many processes (for the benefits of efficiency, effectiveness and cost), financial processes nowadays are almost entirely IT generated and managed.

The usage of financial technologies to give competitive advantages within the banking sector has been well documented by a number of researchers. A classic example is the case study of the Merrill Lynch Cash Management Account system [14]. The system is frequently cited as not only improving banking operations but also providing a competitive advantage on new products and banking performance.

The system enabled Merrill Lynch to capture 90% of the investment account market within the first year of operation [30]. Other examples include Fuster et al. [31] who examined FinTech improving the productivity of mortgage lending, in Monaco [32] high frequency trading and FinTech are discussed and their impact on market structures (such as trading volume and market orders).

To summarise, the role of FinTech or IT and technology investment in the banking sector in recent years has focussed on a number of different areas to improve productivity and competitiveness; in particular there has been a focus on peer to peer lending, cryptocurrencies and smart contracts. Such products and services will have fundamental impacts on standard financial intermediation services, they will also affect credit markets as deposits and capital raising can be executed in different formats. In fact, peer to peer lenders will be able to gain market share from traditional banks for saving and lending. Moreover, FinTech will also disrupt traditional payment systems, leading to different money market instruments and implications for monetary policy from central banks. We note that whilst ‘bottlenecks’ for implementation of FinTech may exist in developed or developing countries, it is still likely that FinTech will have a significant influence.

Pairs trading is a stock trading strategy that involves taking a ‘long’ position in one stock and a ‘short’ position in another stock [18]. The two firms are rival companies, that is they are firms that compete in similar market segments and industries, typically for the same group of customers. Consequently, rival firms tend to operate in the same industry, stock market, country etc., and PT is generally applied to rival firms only rather than any set of firms. In fact stocks involved in PT tend to exhibit high correlations, and such stocks have been used in many instance to create natural ‘hedges’, for instance one can create ‘market neutral’ trades to remove market risk by constructing appropriate PT strategies. The PT strategy also benefits from relative share price growth (or equivalently the relative firm value growth) between the two firms. The fact that the trading strategy relies on relative firm value growth to achieve a profit is reflected by the fact the PT method is often called a ‘relative value’ trading strategy [33].

Operational risk, the risk arising from business operations within a firm [34], has been gaining increasing interest in literature (see for instance [35, 36]). A consequence of the increasing emphasis on financial technologies has been a greater sophistication and dependence on financial technologies and this has substantially affected OR [37, 38]. For example, [39] claim that data breaches lead to severe financial losses, IT infrastructure attacks are estimated to cost as much as \$2.4 million [40], firms are now investing in cyberinsurance [41] and unauthorised trading in Allied Irish Bank caused a \$750 million loss [42].

In Ref. [19] a standard model of OR in financial firms is modelled by the following equation:

$$R(A) = R_M(A) + R_C(A) + R_{OR}(A), \quad (1)$$

where  $R(A)$  is the total risk of company A,  $R_M(A)$ ,  $R_C(A)$  and  $R_{OR}(A)$  are the market, credit and operational risk, respectively, of company A. The credit risk is defined as the risk of the company defaulting on any payments it is obliged to fulfil [43], the market risk is the risk associated with market movements affecting the market valuation of the company [44].

If we apply the Eq. (1) model to a PT and we assume we are long in stock A and short in another stock B, then the overall PT position has risk:

$$R(A) - R(B) = R_{OR}(A) - R_{OR}(B). \quad (2)$$

Thus the net return in a PT occur due to the differences in OR between the stocks in the PT. Hence PT profits are directly impacted by the relative operational performance between firms. We obtain Eq. (2) because the market and credit risks will be similar in a PT, as similar stocks are chosen (i.e. same sector, market etc.). This means that we cancel out credit and market risks. Market risk cancellation is supported by financial models (for instance similar stocks in the CAPM model [45] would cancel each other’s market risk), and has also been well documented in a number of PT studies; see for instance [26, 46, 47] to name a few. The credit risks are also cancelled out because credit risk is typically determined by fundamentals of a company [48], and since similar stocks have similar fundamentals the credit risk would also be cancelled out in the PT.

The result of Eq. (2) or PT returns depending on OR is not an unexpected outcome. This is because it is already well known that operational factors lead to key strategic advantages (and so relative firm value growth) over competitors [12]. For example, [13] claims that OR is directly related to Porter’s five forces of competitive advantage (see [49, 50] for more detail). Additionally [13] directly relates the risk in business operations to a company’s competitiveness.

To the best of our knowledge there is no literature on financial technology, OR and PT (or equivalently relative firm value growth). Although, there is a vast amount of research on OR and operations technology (for instance see [50–55]), the research typically focusses on a single aspect (see for instance [22, 23, 56–58] rather than a wide range of factors, for example in [59] only two operational factors are analysed. Moreover, the majority of research focuses on individual firm value, independent of its competitors, rather than the firm value added relative to its competitors.

Given that firms make substantial investments (multi-million dollar) in operational technology (see for instance [60, 61]), it is surprising that there is little literature on

the relation between this, OR and PT (or relative firm value). Furthermore, there are substantial incentives to understand such relationships, such as improved OR management and better expenditure. With the rise of FPAS, it is important for financial firms to understand what factors maximise firm value and minimise OR.

A possible cause for the little research upon financial technology, OR and PT (or relative firm value) is that firstly financial technology has only recently been gaining importance. Previously, operational technology and FPAS were not perceived as major components to competitive advantage in firms. Similarly, it has not been understood until recently that financial technology can directly impact profitability; nowadays the impact is more noticeable, for example [59] estimated the median loss from operations in US financial institutions to be \$11.8 million.

The literature that is closest to our research is [24], which investigates the relation between firm value (share price) and the introduction of operational technology. However, the relative firm value gains are not investigated, rather the firm value gains independent of its competitors are quantified. This means that such firm value gains may not provide any gains relative to its peers, and so may not provide any competitive advantage. Additionally, [24] do not consider a wide range of factors but a small number of generic factors (e.g. industry sector and firm size).

The lack of literature on financial technology, OR and PT (or equivalently relative firm value growth) implies it is not well understood. In particular, one may wish to understand how key operational aspects such as business lines and operational event types impact performance? Is there any impact on firm risk as a result of increasing financial technology and to what extent? This therefore leads us to address the following research questions:

- To analyse the impact of operational events upon firm performance, in terms of relative firm value.
- To analyse the impact of operational events upon firm performance, in terms of OR.
- To analyse the impact of the type of operational event on firm performance, in terms of the operational activity and business line.

### 3 Methodology and data

In this section we explain our methodology, the experiments executed and the data sample used in our study.

#### 3.1 Pairs trade methodology

In PT we setup a pairs trade by taking a long position in one firm's shares and a short position in a similar firm's shares simultaneously; at the point we wish to exit the pairs trade we simultaneously exit both positions, that is we sell the long position stock and exit the short position.

The PT return  $r_{PT}$  is calculated using Eq. (3):

$$r_{PT} = \left( \frac{S_L(t) - S_L(0)}{S_L(0)} - \frac{S_S(t) - S_S(0)}{S_S(0)} \right) * 100 \quad (3)$$

where  $S_L(t)$ ,  $S_L(0)$  are the long position stock prices at time  $t$  and  $0$ , respectively;  $S_S(t)$ ,  $S_S(0)$  are the short position stock prices at time  $t$  and  $0$ , respectively.

To analyse PT in more detail we model PT returns similar to stock returns. According to MacKinlay [62] the stock returns consist of two components:

$$r_{se} = r_e + r_n, \quad (4)$$

where  $r_e$  (also known as the abnormal returns) is the stock return component due to the event itself (if an event occurs), and  $r_{se}$  is the total stock return. The  $r_n$  is defined as the normal or the expected stock return when no event occurs. For PT we now have:

$$r_{ALL} = r_E + r_{NPT} \quad (5)$$

where  $r_{ALL}$  is the overall PT return,  $r_{NPT}$  is the PT return when there is no operational event and  $r_E$  is the PT return due to the operational event itself only (if an event occurs). For convenience we define

$$r_{ALL} = r_{PTE}, \text{ if an event occurs} \quad (6)$$

and  $r_{PTE} = r_E + r_{NPT}$  when an event occurs. Therefore PT returns during an operational event ( $r_{PTE}$ ) do not equal the PT returns due to the operational event itself ( $r_E$ ). To obtain the operational event (hereon OE) returns relating to the OE itself we require  $r_E$  returns, which requires  $r_{PTE}$  and  $r_{NPT}$  as well. The  $r_{NPT}$  can be calculated from empirical results by using the PT returns when there are no events.

As  $r_{NPT}$  is defined as returns outside an OE,  $r_{NPT}$  therefore includes two types of possible returns: (i) mismatching error based returns (ii) OR related returns that occur outside OE. In both cases, although their returns maybe non-zero we would still consider them to be negligible in expectation. In relation to (i): theoretically two stocks in a PT should eliminate common risks (and their associated returns), however stocks are not able to completely eliminate common risks as stocks are difficult to perfectly match with common risk factors. Consequently we expect this mismatching in common risk factors to lead to a small but insignificant return. Note that we do not expect the mismatching to give significant returns, otherwise it would not be usable as an industry

method to make consistent profits. The insignificant returns are also supported by our practical results discussed in preceding sections.

In relation to (ii), not all returns related to OR should be expected to occur during an OE; some of the OR related return will occur outside an OE, although this would be negligible compared to  $r_E$ . A similar process occurs in other risk factor returns, for example in credit risk not all credit risk related returns occur during a credit risk event (such as default), there will be returns outside the events (see [56, 63], for examples). Hence corporate bonds must provide higher returns to investors, to provide a return that is consistent with returns related to credit risk (regardless of credit events occurring).

The PT are traded for time intervals of 1 week; a period of 1 week was chosen to so that all operational information is completely reflected by the share prices (a shorter time interval would not allow this). The efficient market hypothesis [64] implies that a firm's stock price fully reflects all the available information of the firm. This means that the stock price will change to fully reflect all the available information on its performance and its impact upon firm value [65]. In a highly traded and well informed stock market, such as the US stock market, the incorporation of information within stock prices is not a stringent assumption and has been used in Ref. [66].

### 3.2 Operational risk measurement

We require an OR measure to conduct our experiments. In Ref. [67] a downside risk measure is used but this is a generic risk measure rather than an OR specific risk measure, in Ref. [68] a real options risk measure is applied but this is suitable for evaluating a single project, rather than hundreds or thousands of events. There already exist generic OR measures (such as the Basic Indicator Approach and Standardised Approach [34] which have a wide range of applicability due to their minimal data requirements. However both measures are unsuitable for our study for a number of reasons; firstly, they do not measure risk with respect to particular events, rather they are quite broad measures. Consequently, we would not be able to analyse the risk related to particular OE or PT, which is the main focus of our study. Secondly, both OR measures are measuring risk on low frequency periods (e.g. risk over annual or quarterly periods; given that our PT are conducted on a weekly basis and we would likely to examine a number of OE through a year, such measures are not suitable for our study. The OR measure is not sensitive to frequency of data, rather the occurrence of events.

Using risk measurement theory [69] we can measure the risk related to a given risk factor, by applying a risk measure to the return distribution related to the risk factor

(e.g. quantiles or value at risk, and standard deviation [70]). Therefore to measure OR we require the return distribution related to OR returns. In formal terms, OR risk  $\lambda$  is given by applying some statistical measure (e.g. quantile), denoted by  $f(\cdot)$ , upon the return distribution  $\kappa$  associated with OR returns:

$$\lambda = f(\kappa). \quad (7)$$

To obtain the return distribution  $\kappa$  (from which one can obtain a measure of OR), we need to obtain returns due to OR only. Using Eq. (2) we see that PT returns are due to OR only, hence to measure OR we require the distribution of PT returns. We can measure the OR during an OE using the return distribution for  $r_{PTE}$  or we can measure the OR during no OE using the return distribution for  $r_{NPT}$ .

Unlike other risk measures, Eq. (7) enables us to measure OR on weekly time scales, its data requirements are not highly demanding (only requires stock price data) and can be easily implemented. Such properties are not available with other OR measures, for example the Basic Indicator Approach and the Standardised Approach risk measures use gross income data [34], which is typically published on an annual basis and harder to obtain than stock price data.

### 3.3 Experiments and data

In this study we examine over 11,000 pairs trade data; the PT positions are arranged so that we short the firm that incurs the operational event (and we are long the other stock in the pair). Therefore, PT have net positive returns if an operational event occurs, as such an event should reduce the firm value of the shorted firm (leading to a positive return) while the other stock is unaffected. We identify PT during and excluding OE by using the specific dates of OE provided by the Fitch database on OE. We note that within each PT we are long one stock only and short one stock only; given that we include eight different banks in our sample therefore we have 28 different types of pairs in total in our study.

Using Eq. (3) we calculate the PT returns for each PT, so that we can produce a distribution of PT returns. Once we have a distribution of returns we can measure the OR (see OR measurement section for more information). The return in Eq. (3) is calculated using the closing prices for each stock and  $t$  is set to 1 week for all trades. The trades in the same pair of stocks are executed in non-overlapping time intervals, so that an identical pair is never in trade more than once at any point in time.

The stocks for the PT were all taken from the US banking sector, namely eight different banks and gives 28 different pairs in total; we note in passing that the same number of banks were used in Ref. [66] to study OR. The stocks were chosen on specific criteria: firstly, we required large

market capitalisation because such stocks tend to be efficiently priced and so their stock prices would fully reflect OE information. Secondly, we eliminated stocks with gaps in their stock price data during our sample of study, as gaps can distort results. Finally, we chose stocks with sufficient OE in our period of study, to enable adequate analysis of their results.

The sample period for study was chosen to be 2000–2007; a 7 years sample period would provide a sufficiently representative distribution of results for our analysis, which would also provide reliable OR measurements (see OR measurement section for more information). Moreover, a longer sample period of study removes biases in the economic cycle affecting PT results. No data was used prior to the Global Financial Crisis (2007) as many financial stocks were affected by non-rational pricing after the start of the Global Financial Crisis. Such irrational pricing would be contrary to the efficient market hypothesis and therefore our methodology would no longer be valid; this is because our methodology relies on rational pricing in the market in order to have PT to give correct returns.

The year 2000 was chosen as the start period of our data as this coincides with the beginning of the FinTech era. Although the beginning of the FinTech era has no widely accepted start date (e.g. some researchers claim it is from the introduction of ATMs, others with more sophisticated technologies such as sophisticated predictive analytics), we consider a viable starting point to be the time the majority of banks began offering internet banking facilities to the public (approximately the year 2000). This is because this marked a pronounced change in the financial services offered by banks, along with a pronounced change in financial technology used by banks (the extensive usage of the internet).

The PT returns during OE were investigated in terms of their operational origin, specifically the OE's originating business line and the type of OE. These two factors were chosen because they are deemed to have the most significant impact on FPAS; FPAS are being offered across all different financial business lines (from business analytics to retail banking transactions) therefore it is important to see the impact of business lines upon OE. Additionally FPAS include a wide range of products and services (from bitcoins to crowdfunding) hence it is important to understand how a wide range of OE types impact the firm.

The operational database provided us with details on OE themselves, in terms of their business line and event type origins. Hence in our PT analysis we were able to classify returns by both factors. The business line categories followed the Basel banking regulator categories (see [71]), and reflect the generic business lines that would exist in banks. Similarly, the OE categories chosen followed the international banking regulators Basel's categories and were as follows:

- Internal and external fraud: for example unauthorised or unreported activities such as impersonation, manipulation of IT systems and theft of information. The World Bank claims financial technology has a major role in preventing fraud.
- Workplace practices and business practices: examples of errors in workplace practices would be usage of unauthorised systems and lack of security e.g. Ebay reported cyber attacks on their IT systems due to a lack of workplace security practices. Workplace practices have been cited as sources of firms failing to realise the IT system's full potential [72]. Examples of errors in business practices would be disclosure of sensitive information to third parties (see for an example [49, 50]), market manipulation using IT systems and exceeding client exposure limits. For example, the LIBOR scandal led to market manipulation of interest rates and Barclays Bank being fined multimillion dollar amounts.
- Physical assets damage: for example physical damage (accidental or deliberate) to IT systems such as data centres or networks.
- Process management: for example data entry errors, other incorrect recording and outsourcing issues (see [70–75] for examples).

## 4 Results and analysis

In this section we present our results and analyse them.

### 4.1 Results

See Tables 1, 2, 3, 4, 5, 6, 7, 8, 9, 10 and 11.

### 4.2 Analysis

In Tables 1, 2, 3, 4, 5, 6, 7, 8 and 9 we present the results for all our PT in our study; Tables 10 and 11 detail our OE types and business lines used in our study. In Table 1 the

**Table 1** Returns for all pairs trades ( $r_{ALL}$ ), pairs trades during an operational event ( $r_{PTE}$ ), and pairs trade event returns ( $r_E$ )

Return (%)	Pairs trade		Event ( $r_E$ )
	All ( $r_{ALL}$ )	PTE <sup>a</sup> ( $r_{PTE}$ )	
Expected return	0.04	0.12	0.17
Annualised expected return	2.28	6.19	8.79
Annualised median return	5.14	13.52	16.12
Annualised return interquartile range	184.42	160.98	160.98

<sup>a</sup>PTE denotes PT during an operational event, and SD denote standard deviation, for all tables

**Table 2** All pairs trades ( $r_{ALL}$ ) distribution measures, risk measures and test statistics

Measure	Value (%)	Test statistic
SD <sup>a</sup>	3.65	Kolmogorov–Smirnov test <sup>b</sup> :
Third moment	-0.20	$D_{crit}=0.07$
Fourth moment	4.25	$D_{5\%}=0.013$
VaR 99%	-10.22	$D_{10\%}=0.011$
VaR 98%	-8.14	
VaR 95%	-5.84	
VaR 90%	-3.99	

<sup>a</sup>PTE denotes PT during an operational event, and SD denote standard deviation, for all tables

<sup>b</sup>Test for  $r_{ALL}$  distribution against Normal distribution  $N(0,3.65)$

**Table 3** Change in values and test statistics: pairs trades during an operational event  $r_{PTE}$  compared to all trades ( $r_{ALL}$ )

Measure	Change in value (%)	Test statistic
Expected return	0.08	Sampling confidence levels $\pm 0.066\%$ (95%) $\pm 0.056\%$ (90%)
SD	-0.37	F test <sup>a</sup> :
Third moment	0.35	$F_{crit}=1.24$
Fourth moment	-2.44	$F_{5\%}=1.15$ $F_{10\%}=1.12$

<sup>a</sup>Two sample F test for test of equal variance

**Table 4** Change in value at risk and test statistics: pairs trades during an operational event  $r_{PTE}$  compared to all trades ( $r_{ALL}$ )

VaR risk	Change in VaR (%)	Test statistic
VaR 99%	1.70	Kolmogorov–Smirnov test <sup>a</sup> :
VaR 98%	0.49	$D_{crit}=0.08$
VaR 95%	0.78	$D_{5\%}=0.08$
VaR 90%	0.14	$D_{10\%}=0.07$

<sup>a</sup>Test for  $r_{PTE}$  distribution against Normal distribution  $N(0, 3.27)$

‘All’ results denote the results relating to all 11,648 PT, including all PT during and outside any OE; the ‘PTE’ results denote PT returns during OE only, and ‘Event’ results denote  $r_E$  returns (that is PT return due to the event itself). The figures in all the tables refer to values over the 1 week duration for the PT; however the annualised values are the weekly values converted to their annual equivalent e.g. weekly expected returns are converted to their annual equivalent.

**Table 5** Change in values, risk measures and test statistics: pairs trade event returns  $r_E$  compared to all trades ( $r_{ALL}$ )

Measure	Change in value (%)	Test statistic
Expected return	0.13	Kolmogorov–Smirnov test <sup>a</sup> :
SD	-0.37	$D_{crit}=0.08$
Third moment	0.35	$D_{5\%}=0.08$
Fourth moment	-2.44	$D_{10\%}=0.07$
VaR 99%	1.76	
VaR 98%	0.54	
VaR 95%	0.83	
VaR 90%	0.19	

<sup>a</sup>Test for  $r_E$  distribution against Normal distribution  $N(0, 3.27)$

We note in passing that in order to calculate  $r_E$  requires  $r_{ALL}$  (given in tables) and  $r_{NPT}$ ; mean  $r_{NPT}$  was calculated to be -0.05% per trade. On an annualised basis this is approximately equivalent to a magnitude of 2.6%, which is also approximately equal to the risk free rate during the period of study (the US interest rates fluctuated between 1 and 6%, with an approximate average of 3%). Hence the  $r_{NPT}$  return is negligible and not economically significant. We also note that we would not expect  $r_{NPT}$  to be economically significant because  $r_{NPT}$  is defined as the return during no event, and as discussed previously such returns would be expected to be negligible.

The OR was calculated using risk measures: VaR (value at risk) at different quantiles, SD (standard deviation), the third and fourth moments (skewness and kurtosis, respectively). The OR associated with the results in Table 1 are presented in Tables 2, 3, 4 and 5; Table 2 provides the risk measures under  $r_{ALL}$  results, in Tables 3, 4 and 5 we present the change in the risk measure’s value under the  $r_{PTE}$  and  $r_E$  when compared  $r_{ALL}$  risk measure results.

To test the empirical distributions for following a Normal distribution but with the same SD, we conducted Kolmogorov–Smirnov tests. The Normal distribution test was conducted to determine the empirical distribution’s likelihood of outliers in its distribution (compared to a Normal distribution) but also a non-Normal distribution typically increases the likelihood of incorrectly modelling and estimating risk. In Table 2 a Kolmogorov–Smirnov test is executed, to test  $r_{ALL}$  distribution against a Normal distribution with 0 mean but with same SD (3.65); we denote the Normal distribution by  $N(0, 3.65)$ . Similarly, in Table 4 a Kolmogorov–Smirnov test is executed to test  $r_{PTE}$  distribution against  $N(0, 3.27)$ , a Normal distribution with 0 mean but with same SD as  $r_{PTE}$  distribution (3.27).

In Table 3 we conduct a two sample equal variance F test, to test the similarity in variance between the  $r_{PTE}$  and  $r_{ALL}$  distributions; this was to determine the similarity in

**Table 6** Pairs trade return during an operational event ( $r_{PTE}$ ) by operational event type

Return (%)	Event type <sup>a</sup>						
	OPR	FIN	FEX	PME	WPS	PDA	BP
Expected return	4.35	-0.82	0.43	0.49	-2.76	0.69	-0.69
Annualised expected return	226.20	-42.64	22.36	25.48	-143.52	35.88	-35.88
Annualised median return	208.90	-17.31	14.81	4.75	-37.45	48.00	-43.55
Annualised Return Interquartile range	210.67	240.53	181.93	104.20	333.08	274.76	133.52

<sup>a</sup>See Table 10 for abbreviations of event type categories**Table 7** Change in pairs trades during an operational event ( $r_{PTE}$ ) compared to all pairs trades ( $r_{ALL}$ ) values: by operational event type

Measure	Event type						
	OPR	FIN	FEX	PME	WPS	PDA	BP
SD (%)	-0.87	0.08	0.03	-2.12	0.83	-0.36	-1.08
VaR 99% (%)	10.07	-1.26	0.80	8.82	0.04	4.05	3.63
VaR 98% (%)	8.14	-1.51	-0.25	6.74	-1.90	2.58	2.87
VaR 95% (%)	6.27	-0.04	0.43	4.45	-3.79	2.12	1.60
VaR 90% (%)	4.86	-1.15	1.21	3.14	-4.96	1.25	0.56
Third moment (%)	0.43	-0.69	-0.16	1.30	-0.64	-0.36	0.61
Fourth moment (%)	-4.97	-2.67	-2.51	-3.66	-5.23	-4.54	-1.83

**Table 8** Pairs trade returns during an operational event ( $r_{PTE}$ ): by business line

Return (%)	Business line <sup>a</sup>							
	EXT	DCM	CSD	CRT	CRF	CMB	AMA	ABL
Expected return (%)	-1.36	-0.59	2.48	0.85	0.97	-0.97	1.80	-0.70
Annualised expected return (%)	-70.72	-30.68	128.96	44.20	50.44	-50.44	93.60	-36.40
Annualised median return (%)	-73.35	-34.67	166.68	40.34	46.43	-33.93	84.10	-3.17
Annualised return interquartile range (%)	64.42	74.42	392.54	54.66	112.86	214.89	149.63	108.64

<sup>a</sup>See Table 11 for abbreviations of business line categories**Table 9** Change in pairs trade returns during an operational event ( $r_{PTE}$ ) compared to all pairs trades ( $r_{ALL}$ ): by business line

Measure	Business line							
	EXT	DCM	CSD	CRT	CRF	CMB	AMA	ABL
SD (%)	-2.30	-1.95	1.37	-2.55	-1.66	-0.63	-1.11	-1.09
VaR 99% (%)	6.44	7.05	6.27	9.07	6.86	1.89	6.30	4.17
VaR 98% (%)	4.49	4.99	4.27	7.08	5.07	0.75	6.45	3.10
VaR 95% (%)	2.57	2.77	2.11	5.03	3.64	0.47	4.15	0.80
VaR 90% (%)	1.24	1.06	0.50	3.62	2.95	-0.76	4.17	-0.25
Third moment (%)	0.42	0.70	0.23	0.27	-0.11	-0.03	-0.77	-0.81
Fourth moment (%)	-3.27	-3.56	-5.50	-3.73	-3.88	-3.72	-1.76	-4.12

risk between  $r_{PTE}$  and  $r_{ALL}$  on a SD risk measurement basis. In Table 3 we also provide the  $r_{ALL}$  expected return sampling confidence intervals, so that the range of potential  $r_{ALL}$  expected return values (for the given sample size) are known (at the given confidence intervals). This would enable us to determine if the expected return for  $r_{PTE}$  is statistically different to  $r_{ALL}$ , or if  $r_{PTE}$  is different.

In Table 5 we provide the change in values for risk measures and other measures in comparing  $r_{ALL}$  against  $r_E$  results. We also conduct a Kolmogorov–Smirnov test for the  $r_E$  distribution against  $N(0, 3.27)$ , a Normal distribution with 0 mean but with same SD as  $r_E$ . The PTE results of Table 1 (or Tables 3, 4) are analysed further by OE type and business line in Tables 6 and 8, respectively; the PTE results of



**Table 10** Categories for operational event types and abbreviations

Abbreviation	Event type
BP	Business practices
PDA	Physical asset damage
PME	Process management and execution
FEX	Fraud (external)
WPS	Workplace practices
FIN	Fraud (internal)
OPR	Other operational events

**Table 11** Categories for business lines and abbreviations

Abbreviation	Business line
ABL	All other business lines
AMA	Asset management business line
CSD	Custody business line
CMB	Commercial banking business line
CRF	Corporate finance business line
CRT	Corporate trust business line
DCM	Discretionary fund management business line
EXT	External clients business line

Table 2 are also analysed further by OE type and business line in Tables 7 and 9, respectively.

In Table 1, we observe there is significant variation in expected PT returns by categories; expected PT returns are 2.28%/year for All trades (PT for  $r_{ALL}$ ), 6.19%/year for PTE trades (PT trades for  $r_{PTE}$ ) and 8.79%/year for event trades ( $r_E$ ). The difference in average returns in  $r_{ALL}$ ,  $r_{PTE}$  and  $r_E$  is also supported by the annualised median returns in Table 1, which is considered a more robust indicator of average values than the mean. The interquartile range for annualised returns for  $r_{ALL}$  is approximately 15% more than the range for  $r_{PTE}$  or  $r_E$ . As the interquartile range is a standard measure of variability or dispersion, therefore the probability distribution for  $r_{ALL}$  is more dispersed than for  $r_{PTE}$  or  $r_E$ . Also, recall that  $r_E$  represents the PT return due to the OE itself, hence the OE itself leads to a PT return that is almost four times the  $r_{ALL}$  returns.

Table 1 results show that PT returns increase by more than double during an OE compared to no OE occurring during the PT, that is  $r_{PTE}$  is more than double  $r_{ALL}$ . For statistical robustness, we calculated  $r_{ALL}$  expected return's sampling confidence intervals, at the 95% and 90% quantile values, and the values are given in Table 3. Therefore the 0.08% increase in expected return from  $r_{ALL}$  to  $r_{PTE}$  is outside the range of any sampling error, hence it is a statistically significant increase in expected returns.

Table 1 results clearly demonstrate that OE significantly impact relative firm value. In fact the  $r_E$  annualised expected

returns are almost equivalent to the average annual returns on the stockmarket (approximately 10%/year). The impact of OE upon firm value, and more importantly relative firm value, implies that financial technology has an important role in competitive advantage and therefore strategy. For example financial technology could provide insight into competitive advantage and relative firm value being lost from poor process management and execution, or poor workplace practises (e.g. unnecessary losses due to overriding trading limits). The results also suggest that any operational gains through FPAS could lead to significant increases in relative firm value.

The contribution of financial technology to relative firm value also occurs through them having a key role in enabling any strategic goal. For example, firms frequently focus on good customer service to gain strategic advantages over competitors [76]. The financial technology would enable strong customer service by ensuring there is low external fraud, internal fraud and strong business practices. In an industry sector such as banking, the operational advantage of a competitor can be a significant and unique selling point.

In Table 2 we conduct the Kolmogorov–Smirnov test to assess the similarity of the  $r_{ALL}$  distribution to  $N(0, 3.65)$ . As can be seen in Table 2 the test statistic is  $D_{crit} = 0.07$  and does not exceed the critical values at the 5% and 10% significance levels (0.013 and 0.011, respectively). Consequently, we cannot reject the hypothesis that the  $r_{ALL}$  distribution is different to a Normal distribution [ $N(0, 3.65)$ ]. This implies that the  $r_{ALL}$  distribution is not an unusually shaped distribution, that is neither heavily bias towards positive or negative values (as might be the case with other distributions), hence easier to model and risk manage.

Table 2 provides some useful results. Firstly, OR measured on the basis of VaR is not negligible; at the VaR 99% level we have  $-10.22\%$  and  $-3.99\%$  at the 90% level, both relating to a 1 week time interval. As the approximate annual return on the stock market is 10%/year, the VaR results at the 99% level imply that an average share price growth can be erased in a period of 1 week. Although the 99% level is a highly unlikely event, the results imply that OR can cause significant losses to relative firm value. Hence it is important for operational systems not to be complacent about a lack of significant losses to relative firm value, for when they occur they can be large in magnitude.

In Table 3 we conducted a two sample equal variance F test upon  $r_{PTE}$  and  $r_{ALL}$  distributions' variances, to determine if both distributions have the same risk, statistically, on a SD risk measurement basis. The test statistic is  $F_{crit} = 1.24$  and this exceeds the significance values at the 5% and 10% significance levels (1.15 and 1.12, respectively). Therefore we can reject the hypothesis that the  $r_{PTE}$  and  $r_{ALL}$  distributions have equal variance. Hence the OR and relative firm value changes during OE will be different to those during

All trades, implying that financial technology impact the OR and relative firm value in companies.

Table 3 results show that the skewness difference between the  $r_{PTE}$  and  $r_{ALL}$  distributions is negligible (close to 0), hence both distributions are fairly symmetric and do not suffer from skewness risk (underestimation of risk). However from Table 3 we observe that there is significant difference in kurtosis between  $r_{PTE}$  and  $r_{ALL}$  distributions ( $-2.44$ ),  $r_{ALL}$  has almost double the kurtosis. A lower kurtosis implies that the  $r_{PTE}$  distribution tends to concentrate around mean more than the  $r_{ALL}$  distribution and so the  $r_{PTE}$  distribution values can be considered more predictable. This is useful for operational analysis because it means losses associated with financial technology would be more predictable, due to the lower kurtosis.

Table 4 results show the difference in VaR between  $r_{ALL}$  and  $r_{PTE}$  and there is a change of 0.14–1.70% in VaR value, which is approximately a 10–20% difference; the change is even greater between  $r_{ALL}$  and  $r_E$ , which is a change of 0.19–1.76% in VaR value. The lower OR in  $r_{PTE}$  and  $r_E$  compared to  $r_{ALL}$  on a VaR risk measure basis is also supported by the SD risk measure. This is an unexpected result, since returns increase during an OE yet risk decreases (typically we expect return to increase with risk under the standard assumption of risk aversion [77]). Therefore not only do operational factors have a contribution to relative firm value, but they also do so at lower risk. Such information is useful for operational products because it suggests that such products can contribute to relative firm value without having to incur substantially more risk.

In Tables 4 and 5, the Kolmogorov–Smirnov tests were undertaken to test  $r_{PTE}$  and  $r_E$  distributions' similarities against a Normal distribution with 0 mean but with the same respective SD. As both distributions have identical SD, both distributions were tested against  $N(0, 3.27)$ . For both tables the test statistic is given as  $D_{crit} = 0.08$  and both distributions reject the hypothesis that either are statistically similar to  $N(0, 3.27)$  at the 10% significance level, as 0.08 exceeds  $D_{10\%} = 0.07$ . However, at the 5% significance level it less certain if both distributions differ from  $N(0, 3.27)$  because  $D_{crit} = D_{5\%} = 0.08$ . Therefore, whereas the  $r_{ALL}$  distribution tends to follow a Normal distribution, the PT distributions during OE can be considered statistically less Normal. This is useful to know because non-Normal shaped distributions tend to be a common cause of mis-estimation of losses, as they are harder to model and risk manage.

Table 5 results relate to the  $r_E$  distribution and we notice they provide similar values for the same measures in Tables 3 and 4. This is partly to be expected because  $r_E$  is related to  $r_{PTE}$  by the equation  $r_{PTE} = r_{NPT} + r_E$ , hence risk and return values will be related. However, the high amount of similarity also implies that the majority of  $r_{PTE}$  values can be attributed to  $r_E$ . This is useful for financial

technology design because it implies relative firm value is driven more by specific OE, hence design should focus around such events rather than generic operational issues.

Tables 6 and 7 decompose the OE returns and risk measurements by OE type, as listed in Table 10. In Table 6 we have the PT returns by OE type and we observe significant variation in returns: OPR has the highest annualised expected return (208.90%), the lowest annualised expected return is WPS ( $-143.52\%$ ) and the average annualised PT return is 6.24%. The annualised median returns also support that OPR has the highest PT return (although at a slightly lower value of 208.90%), however BP has the lowest return at  $-43.55\%$  (instead of WPS). We also notice that there are varying differences between median and expected return values e.g. PME and WPS have substantial differences whereas OPR and BP are similar.

Table 6 provides important insights. Firstly, as mentioned previously, the results support the analysis that relative firm value (or equivalently competitive advantage) is strongly dependent on the type of OE, with wide variation in relative firm values between OE. The wide variation is not just restricted to the expected return but also the interquartile range varies significantly by OE. Secondly, the magnitude of the returns in Table 6 is significant: given that average stock market returns are approximately 10%/year, the OPR return of 226.20% and the WPS return of  $-143.52\%$  the OE represent a high and wide range of returns. Hence financial technology can maximise competitive advantage by strategically reallocating resources to focus on specific OE types, rather than focussing on less critical operations or having a generic operations focus. Moreover the high magnitude supports the point that financial technology have a key role in business strategy.

In Table 7 we provide OR measurement by event type with a range of risk measures, specifically SD, VaR at different quantiles, 3rd and 4th moments. Similar to Table 6, we notice that there is significant dependence and variation in OR by event type, at all different measures of OR. Intuitively, we would expect OR to be considerably dependent on the OE type, as some operations tend to be more risky than others e.g. external fraud (event FEX) is considered more risky than process management errors (event PME).

Table 7 results give important observations into OR. Firstly, the wide variation in OR implies that financial technologies should carefully concentrate on operational areas to minimise risk, rather than having a generic OR management strategy. A strategic reallocation may lead to risk reduction e.g. shifting focus from FEX to FIN (internal fraud). Secondly, given that optimal contributions of relative firm value and OR differ in terms of OE, one needs to examine both aspects to achieve the correct contribution to firms. There is wide variation in magnitude with OE in terms of return

and OR (the change in OR under a VaR 99% risk measure is 0.04% for FEX but 10.07% for OPR).

In Table 7 we notice that there is significant variation in skewness and kurtosis; OPR, PME and BP are more positively skewed (compared to the  $r_{ALL}$  distribution), whereas FIN, FEX, WPS and PDA are more negatively skewed. Hence the positively skewed distributions will lead to more negative returns and similarly the negatively skewed distributions will give more positive returns. In terms of kurtosis, Table 7 implies that the OE tend to have a lower kurtosis compared to the  $r_{ALL}$  distribution, hence the OE distributions tend to be less peaked and so are more spread out. The variation in kurtosis and skewness leads to kurtosis and skewness risk, namely that skewness and kurtosis can lead to over or under estimation of risk. This is important as one may be more exposed to incorrectly estimating risk depending on the type of OE they are engaged in.

In Tables 8 and 9 the PT results during OE ( $r_{PTE}$ ) are categorised by business lines. In Table 8 we notice that the magnitude of the expected PT returns is significant for all business lines. This is also supported by the median returns, which are considered a more robust indicator of average values, in that they are also a similar magnitude to the expected returns. Intuitively, we expect MIS systems to have a significant contribution to relative firm value across all business lines because MIS nowadays play an important function in all aspects of all business lines in banks. Similarly, the results imply that FPAS would be beneficial across all business lines and this may account for the fact that such products being available across a range of banking business lines nowadays.

In Table 8 we notice that the variation in interquartile ranges, medians and expected returns are substantially lower than in Table 6. The interquartile range in Table 8 is an average of 158% whereas in Table 6 it is 211%; the variation in expected returns in Table 8, is approximately half the variation in Table 6. Therefore we can deduce that the variation in relative firm value is more due to the OE type rather than the business line origin. This is an important observation because it implies strategically allocating financial technologies along business lines is not as effective as allocating along particular OE types.

In Table 9 the OR measurement is given in terms of SD and VaR at various quantiles and the OR values are similar in magnitude to the OR values in Table 7. Hence we can infer that OR is not substantially influenced by business line more or less than the OE type in terms of magnitude. However, within the set of different business lines in Table 9 we notice that there is substantial variation in risk; at a VaR 99% level the change in VaR value (compared to the  $r_{ALL}$  distribution) is almost 5 times greater in CRT than in CMB. Therefore in strategically resourcing we cannot purely focus on OE but also must take into account the business line to

optimise contribution to relative firm value and competitive advantage.

In Table 9 the variation in skewness and kurtosis between business lines is higher than the variation in both for OEs in Table 7; in Table 9 the average values for skewness and kurtosis are  $-0.07$  and  $-3.8$  (respectively) whereas in Table 7 they are  $0.01$  and  $-3.4$  (respectively). Therefore in terms of skewness and kurtosis risk, the business lines present a greater challenge in correctly estimating risk compared to OE. This is important as the results imply that firms are more exposed to incorrectly estimating risk depending on the business line, rather than the OE. Hence to minimise risk, firms may wish to change the business line for financial technology to reduce risk.

## 5 Conclusion

In this paper we investigated the relation between financial technology, OR and relative firm value (or equivalently PT returns). We provided a method of measuring relative firm value performance, related to OR, using the PT methodology. Our method is supported by our empirical results which demonstrate PT returns significantly differ during OE compared to general PT returns.

Using over 11,000 PT data and OE data we investigated the impact of financial technology on relative firm value growth and OR. We found that operational factors substantially impact relative firm value growth, implying that financial technology can play a crucial role in the competitive advantage of firms and their strategies. Additionally OR was measured and shown to be of a sufficient magnitude to significantly impact firm value, implying that financial technology has an important role in risk management.

We have found that relative firm value growth and OR is substantially influenced by the origin of the OE in terms of the OE type and the associated business line. Consequently, MIS and FPAS should focus on specific OE and take account of business lines to maximise relative firm value growth, or minimise OR. Additionally, financial technology could play a significant role in new risk management approaches.

In terms of implications for policy and management within the banking sector (especially with respect to IT managers), the firm should take into account the relative value and the risk management contributions that operations potentially provide. In particular, strategically reallocating MIS and FPAS to specific operational areas, rather a generic operational strategy, would be a more effective approach. Operational risk and operational issues should be taken into account varying levels within policy and decision making.

In terms of future research we would like to investigate the impact of FinTech in the area of investment, in particular whether retail and institutional investors are able to

benefit from higher returns in investments without necessarily increasing risk. We would also like to investigate how FinTech is contributing to financial innovation in the market, such as the creation of new financial asset classes and derivatives that are facilitated by technology. Finally, we would like to investigate the impact of FinTech upon future risk management practices, as FinTech may impact how risk is monitored and managed.

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