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BANK OF ENGLAND

Working Paper No. 451

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Evangelos Benos, Rodney Garratt and Peter Zimmerman

June 2012

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Working Paper No. 451

Bank behaviour and risks in CHAPS following the collapse of Lehman Brothers

Evangelos Benos,⁽¹⁾ Rodney Garratt⁽²⁾ and Peter Zimmerman⁽³⁾

Abstract

We use payments data for the period 2006–09 to study the impact of the global financial crisis on payment patterns in CHAPS, the United Kingdom's large-value wholesale payments system. CHAPS functioned smoothly throughout the crisis and all CHAPS settlement banks continued to meet their payment obligations. However, the data show that in the two months following the Lehman Brothers failure, banks did, on average, make payments at a slower pace than before the failure. Our analysis suggests this was partly explained by concerns about counterparty default risk as well as system-wide risk. The ratio of payments made to liquidity used was 30% lower in the period from 15 September 2008 to 30 September 2009 than in the period preceding the default of Lehman Brothers. This was due initially to payment delay, but later was due to banks making more payments with their own liquidity, probably because quantitative easing increased the amount of reserves in the system. To assess the economic significance of the observed delays in the value of payments settled, we develop risk indicators, based on Markov models, to quantify the theoretical liquidity impact of delays during an operational outage. We find that payment delays in the months following the failure of Lehman Brothers led to a statistically significant but economically modest increase in these risk measures.

Key words: Payments, intraday liquidity, credit default swap, operational outage, insurance.

JEL classification: E42.

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Summary

During the period of financial stress, in the wake of the Lehman Brothers default, infrastructures used by banks to make payments to one another held up well. The Bank of England's *Payment Systems Oversight Report 2008* explains that although the crisis placed unprecedented demands on payment and settlement systems, these continued to provide a robust service. We examine how this stress affected payment patterns in CHAPS, the United Kingdom's large-value wholesale payment system. This is important to the Bank in its role as the overseer of recognised interbank payment systems, including CHAPS, and as host of the infrastructure that supports the operations of CHAPS.

CHAPS payments data show that, in the two months following the failure of Lehman Brothers, banks on average made payments at a slower pace than prior to the failure. This delay was partly explained by concerns about bank-specific and system-wide risks. 'Turnover', which is defined as the average number of times each unit of liquidity employed by banks to make payments is used during the day, was 30% lower in the period from 15 September 2008 to 30 September 2009 than in the period preceding the Lehman default. In the immediate aftermath of Lehman this was due to payment delay, but later may have been related to increased reserves balances associated with quantitative easing. This may have led to banks being more willing to make payments with their own liquidity rather than relying on liquidity from payments received from others.

We also find that the payment delays observed in the months following the failure of Lehman Brothers modestly increased the liquidity risks associated with operational outages. An operational outage is an event during which a single settlement bank (ie a bank which is a member of CHAPS and is able to submit payments directly into the system) may be unable to send payments. Since such a settlement bank is unable to provide liquidity to the payment system, the impact of an operational outage depends on the liquidity that the affected bank would have provided to the system during the outage.

We compute two estimates of the impact of operational outages. One measure considers the impact of a single outage that occurs at the worst possible time on a given business day, while the other measure computes the expected impact of a single outage occurring at a random point in



time during the day. Both measures of risk show a statistically significant increase in the period following the collapse of Lehman Brothers. Thus, our results show that, although operational risks did not crystallise, the potential for disruption in CHAPS did increase during the period of financial stress in the wake of the collapse of Lehman Brothers.

To provide some indication of the economic cost of these risks, we calculate how much additional money banks would on average have had to pay to insure themselves against the loss of liquidity due to an operational outage. Although the amount of liquidity loss to be insured against increased in the wake of the Lehman Brothers collapse, a mitigating factor to this increase was a sharp decline in the cost of obtaining liquidity during the same period. The combined effect was an increase in the hypothetical premium until mid-October 2008, followed by a fall to levels lower than those seen in Summer 2008, on account of lower borrowing rates. Despite the temporary increase, the daily hypothetical premium was about £6,700 per bank during the month after the Lehman Brothers collapse. While the economic cost was low, in absolute terms, an interesting question is whether the cost — and the underlying risk exposure — would have increased to a greater extent in the absence of CHAPS throughput requirements, which oblige settlement banks to settle minimum proportions of their payments by specific times of the day.



1 Introduction

In this paper we study the impact of the global financial crisis on CHAPS (Clearing House Automated Payment System), the United Kingdom's system for large value unsecured payments. Our analysis covers the period from 2006 Q1 to 2009 Q3. However, we focus primarily on the period immediately following the collapse of Lehman Brothers, on 15 September 2008. While signs of the crisis appeared well before this event (many point to the announcement of fund redemption restrictions by Bear Stearns and BNP Paribas in the summer of 2007), this date is commonly taken as heralding a period of intense financial stress.

Payment activity in CHAPS increased in September and October 2008, following the collapse of Lehman Brothers. This has been attributed to increased trading.¹ In addition, it is likely that the compression of term funding (ie a preference to roll overnight loans rather than maintain long-term exposure to other banks)² and increased liquidity provision by the Bank of England³ were contributing factors. However, the levels of payment activity reached during this period were not extraordinary compared with patterns over the previous few years.

In CHAPS, banks access liquidity to make payments by using their reserves balances and by borrowing funds from the Bank of England at zero marginal cost, secured by posting Bank of England-eligible collateral to their central bank account.⁴ Liquidity is also recycled throughout the day as banks use incoming payments to fund outgoing ones. Nevertheless, the ability of banks to make payments is, at least in aggregate, related to the amount of reserves and collateral posted.

Liquidity available to banks to make payments fluctuated significantly in the first few months following the collapse of Lehman Brothers, but stocks stayed well above the amounts actually used to make payments. While banks, in aggregate, had sufficient liquidity to make payments during this period, we find evidence of increased delay in payment processing.⁵ We compute a

¹See Bank of England (2009a). Trading may increase in volatile markets because investors have more opportunities, or they may wish to exit from positions with which they are no longer comfortable.

²Bank of England (2008), Chart 2.

³Bank of England (2008), Chart 32.

⁴The list of eligible assets is restricted to highly liquid and safe securities, such as high-quality sovereign debt. See Bank of England (2010).

⁵We assume banks do not have a choice whether or not to make a payment on a given day. However, in many cases they have some discretion as to precisely when, during the day, to make a payment. Exceptions include time-critical payments such as CLS payments or those that need to be made before certain markets close.



measure of delay based on the deviation, from the pre-collapse average, of observed aggregate throughput — the rate at which payments are made during the day — following the collapse of Lehman Brothers. A reduction in throughput is evident in the two months immediately following the collapse, but there is an improvement in throughput thereafter.

We conjecture that the motives for delay observed in the two months following the collapse of Lehman Brothers relate to increased perceptions of counterparty risk. This was evident in almost all financial markets during this period. If a bank thinks that the receiver of a payment is at risk of defaulting during the day it may not want to send payments to that counterparty in advance of payments that it expects to receive. In the event of a counterparty failure, a bank will likely prefer, where possible, to net its obligations so as to minimise any amount to be recovered through bankruptcy proceedings.⁶ In addition, many of the direct participants in CHAPS (these are called settlement banks) process payments on behalf of client banks which are not CHAPS members themselves.⁷ If a settlement bank thinks that one of its clients might default during the day, then it may delay making that client's payments for the same reasons, ie it does not want to pay money out in advance of incoming funds which may be withheld if the client defaults. Furthermore, it may reduce the client's overdraft limit, meaning it will be more likely to wait for incoming payments to the client before sending.

We conduct empirical tests to determine whether a heightened perception of the risk of counterparty default led to increased payment delay. We attempt to capture default risk using either a bank's credit default swap (CDS) price or the spread between the rate at which the bank expects to be able to borrow in the overnight market and the Bank of England policy rate.⁸ Controlling for overall market conditions, available liquidity and the value of payments sent, we find evidence that concerns over counterparty risk explain some of the variation in delay: an increase in the CDS price by one standard deviation (roughly 0.6%) has the statistically significant effect of causing the delay measure to increase by about 0.52%. The effect of the Libor-policy rate spread, our measure of overall market conditions, is also statistically significant, suggesting that concerns about system-wide risk also had an effect. Finally, some of the delay seems to be driven by the availability of liquidity, despite the fact that aggregate

⁶See Manning, Nier and Schanz (2009).

⁷Bank of England (2009a), Section 3.1.

⁸We discuss the relative merits of each approach in Section 4.2.

available liquidity was always much greater than the amount of liquidity actually used. There is also, however, substantial variation in payment delay that our variables do not explain.

In pre-crisis times, CHAPS settlement banks were able to settle an aggregate daily value of payments that was approximately fifteen times the amount of liquidity used. However, almost immediately following the collapse of Lehman Brothers this ratio, which we label ‘turnover’, fell to an average of around eleven and had not recovered by 30 September 2009, the end date of our sample time span. This seemed puzzling at first, because our prior was that the reduction in turnover was caused by timing mismatches associated with *decreased* throughput. However, timing mismatches associated instead with *increased* throughput could — and it appears actually did — have a similar effect.

We observe that, after November 2008, the aggregate value of payments in CHAPS fell substantially while liquidity usage barely changed. This may be due to the way banks used their internal schedulers, which allow them to set net sender limits against other banks. It is possible that, by not adjusting internal schedulers in line with falling payment values, banks used more liquidity per unit of payment sent. There is also a possibility that banks intentionally maintained or even increased internal limits due to an abundance of available liquidity. Either way, the reduction in turnover could be caused by banks making a larger portion of payments with their own reserves rather than waiting for incoming funds. This explanation seems consistent with the various data series, but we do not observe internal schedulers and so cannot confirm this hypothesis.

The processing delay that was observed in the first two months following the collapse of Lehman Brothers made the system more vulnerable to disruption caused by operational outages. Operational outages are incidents where a settlement bank is unable to send payments due to a system failure.⁹ While short duration outages are in practice more common than longer ones, outages that last until the end of the day are particularly disruptive because banks that were expecting to receive payments from the disrupted bank must use liquidity from other sources to meet their payment obligations. Therefore, as increased counterparty credit risk concerns leads to payments being made later in the day, not only does the proportion of total payments that is

⁹Here, and throughout the paper, we refer only to operational outages at the settlement bank level. The RTGS service itself had close to 100% availability throughout the time period we analyse — see Chart 2 of Bank of England (2009a).

vulnerable to disruption at a particular point in time increase, but the expected liquidity impact of an operational outage increases as well.

We produce two measures of liquidity risk, each of which is based on the value of unprocessed payments during an operational outage, and assumes that outages arise according to a Markov process. The first measure assumes the worst-case scenario and calculates the expected amount of liquidity that would be withheld from the system due to an operational outage which occurs at the worst possible time for any bank. We find that the average value of this measure rose by roughly £257 million over the three months following the collapse of Lehman Brothers, compared with the three previous months. This increase is statistically significant and represents about 1.3% of the £20 billion system-wide liquidity usage. The second measure captures the expected amount of trapped liquidity from a random operational outage at any single bank. This amount rose by around £7 million after the failure of Lehman Brothers, which equates to approximately 0.5% of the average liquidity used by individual banks. However, we do not measure the extent to which other banks were dependent on this liquidity to make their own payments in a timely fashion.

A mitigating factor to the greater liquidity impact of operational outages was a sharp decline in the cost of obtaining liquidity over the period after the Lehman Brothers collapse. To demonstrate the combined effects, we compute the implied cost of insuring against the liquidity impact of operational outages over a pre and post-Lehman Brothers default horizon.¹⁰ This premium increased in the wake of the Lehman Brothers collapse until mid-October 2008. At this point, a fall in borrowing rates led to a fall in the value of the premium, which by November 2008 declined to levels below those of Summer 2008. Nevertheless, despite the temporary increase, the daily premium always remained at low absolute levels of about £6,700 per bank during the month after the Lehman collapse.

2 Data

We use data on payments, collateral posted and settlement account balances for all CHAPS settlement banks from 1 January 2006 to 30 September 2009. The CHAPS settlement banks during this period were ABN Amro, Bank of England, Bank of Scotland, Barclays, Citibank,

¹⁰We propose this as a hypothetical exercise. At present there is no third-party insurance of payment system liquidity.



Clydesdale, Co-operative Bank, CLS Bank, Danske Bank, Deutsche Bank, Lloyds, HSBC, NatWest, RBS, Santander/Abbey, Standard Chartered and UBS. Membership is not constant throughout this period: UBS joined on 8 October 2007, ABN Amro left on 19 September 2008 and Danske Bank joined on 20 April 2009. The payments, collateral and account data are obtained from the payments database maintained by the Bank of England in its role as operator of the RTGS system. We aggregate any figures that are reported separately for NatWest and RBS, since these banks belong to the same group.

We also use daily CDS prices and interbank borrowing rates for several CHAPS settlement banks. The CDS data are obtained from Markit and overnight borrowing rates are from the British Bankers' Association via Bloomberg.¹¹

3 CHAPS activity during the crisis

Payment values and volumes followed an upward trend from the start of our sample period in January 2006 until mid-2007 (Chart 1).¹² From this date, values continued to rise while volumes levelled off. Both values and volumes fell from the start of 2008 until mid-September 2008. Values rose after this, but maximum levels reached during October and November 2008 were below levels reached on several occasions in the build-up to the Lehman Brothers default (Chart 2). From December 2008 until September 2009, payment values and volumes declined steadily.

The amount of liquidity banks had available to make payments, measured as the sum of reserves plus the value of intraday repos with the Bank of England, also increased fairly consistently from January 2006 until the failure of Lehman Brothers. Meanwhile, the amount of liquidity actually drawn from central bank accounts remained well below the amount available (Chart 3).

Following Lehman's failure, there was increased volatility in aggregate liquidity available in the payment system, and the gap between availability and usage temporarily narrowed. From 2008

¹¹We use average CDS prices for senior debt with maturity of five years. This is the most traded term and therefore should have a price which most accurately reflects the market's view of default risk. CDS are traded for each of the CHAPS settlement banks relevant to our analysis, with the exception of the Co-operative Bank. There are no credit default swaps which reference CLS Bank or Bank of England, but these are in any case not relevant to our analysis in Section 4.2. CDS is not traded in Clydesdale's name, so we use that of its parent National Australia Bank. As usual, we treat RBS and NatWest as a single settlement bank: CDS is not traded in NatWest's name.

¹²In all charts in this paper, the date of the Lehman Brothers default is marked by a red vertical line.



Chart 1: Monthly averages of daily aggregate values (£ billions, left axis) and volumes (000s, right axis) for all CHAPS settlement banks, 1 January 2006 – 30 September 2009.

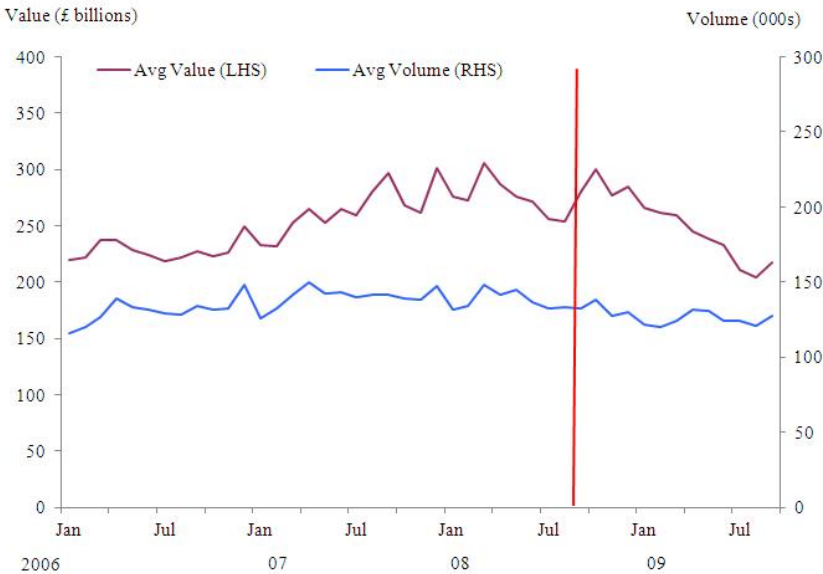


Chart 2: Maximum, over each month, of daily aggregate value (£ billions, left axis) and volume (000s, right axis) for all CHAPS settlement banks, 1 January 2006 – 30 September 2009.

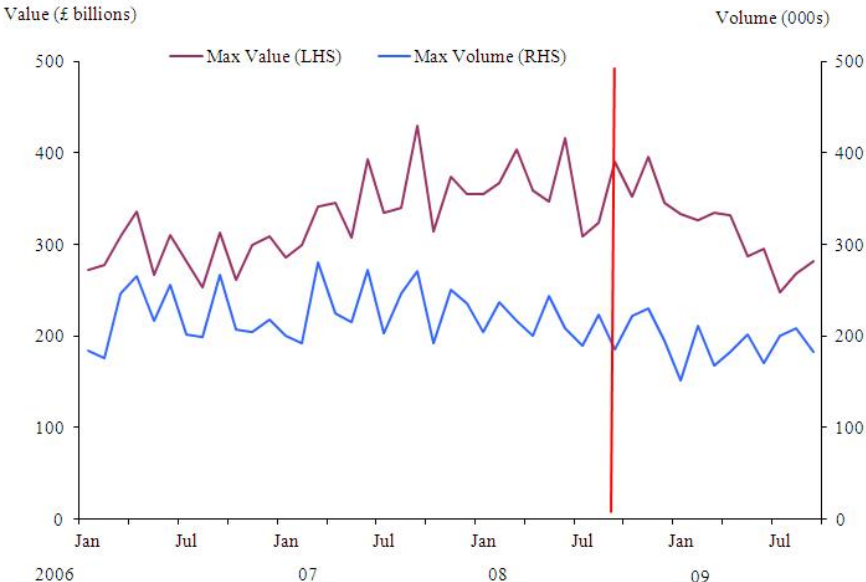
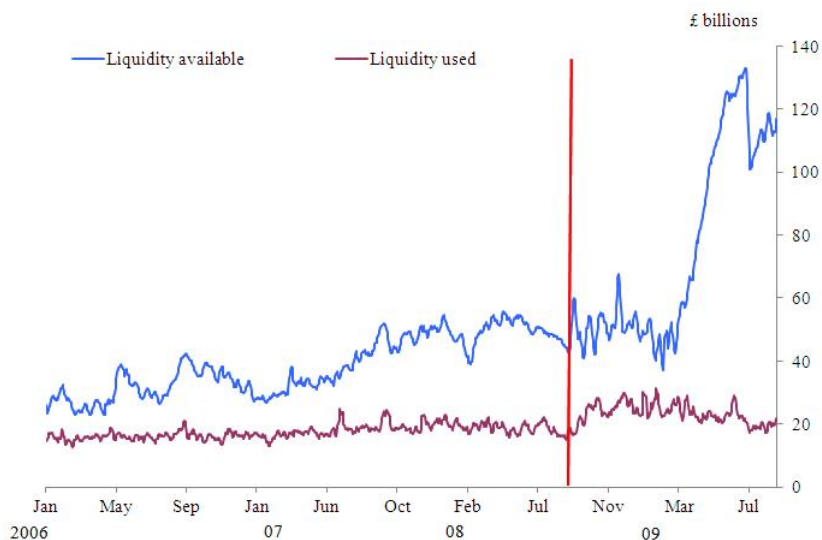


Chart 3: Liquidity available and liquidity used (£ billions), 1 January 2006 – 30 September 2009, plotted daily. Liquidity used is the sum of the daily minimum cumulative net positions of CHAPS settlement banks, where negative.



Q4 to 2009 Q2, aggregate liquidity available increased threefold, while liquidity usage declined. The increase in liquidity available can be attributed to the Bank of England’s quantitative easing policy from March 2009 which increased the amount of reserves in the system. To accommodate this, the Bank of England suspended the reserves targeting regime, allowing banks to increase their reserves holdings without incurring charges (Bank of England (2009b)). The decline in usage also corresponded to an overall decline in payment activity in part because banks did not need to enter the money markets to manage their reserves to the target; see Chart 1.

4 Change in bank behaviour following the collapse of Lehman Brothers

4.1 Measuring delay

CHAPS settlement banks face throughput guidelines during the day. This means that they are expected to settle a certain proportion of their daily payment values by certain times — 50% by noon and 75% by 2.30pm. Compliance with these throughput targets may not, however, be an appropriate measure for delay. First, the guidelines apply only on average over the course of the

month. Second, the guidelines only relate to two points in time each day. Therefore, to capture delay more accurately, we construct a more ‘continuous’ measure that adds up the deviations in throughput, relative to a pre-crisis benchmark average, at many points during the day. We do this by dividing the day into 62 ten-minute time slots, from 6.00am to 4.20pm.¹³

Let $P_{s,\tau}^{OUT}$ denote the total payment value settled in CHAPS on day s during time slot τ . Then throughput by the end of time slot t on day s is defined as:

$$x_t^s = \frac{\sum_{\tau=1}^t P_{s,\tau}^{OUT}}{\sum_{\tau=1}^{62} P_{s,\tau}^{OUT}} \quad (1)$$

The benchmark period consists of the 680 business days between 1 January 2006 and 14 September 2008 inclusive. This includes all of our data prior to the Lehman default. The benchmark throughput at time slot t is then computed as:

$$\beta_t = \frac{1}{680} \sum_{s=1}^{680} x_t^s \quad (2)$$

which is the average daily throughput at time t over the benchmark period. The deviation score for day s in the period after the Lehman default is thus:

$$d^s = \frac{1}{62} \sum_{t=1}^{62} (\beta_t - x_t^s) \quad (3)$$

Positive values in this deviation score signify delay in payments relative to the benchmark period, whereas negative values mean that payment throughput has increased relative to the benchmark period. Chart 4 shows the deviation measured in equation (3) aggregated across all banks over the period from 1 January 2006 to 30 September 2009. Deviations for the benchmark period are shown in blue and deviations for the post-Lehman default period are shown in red.

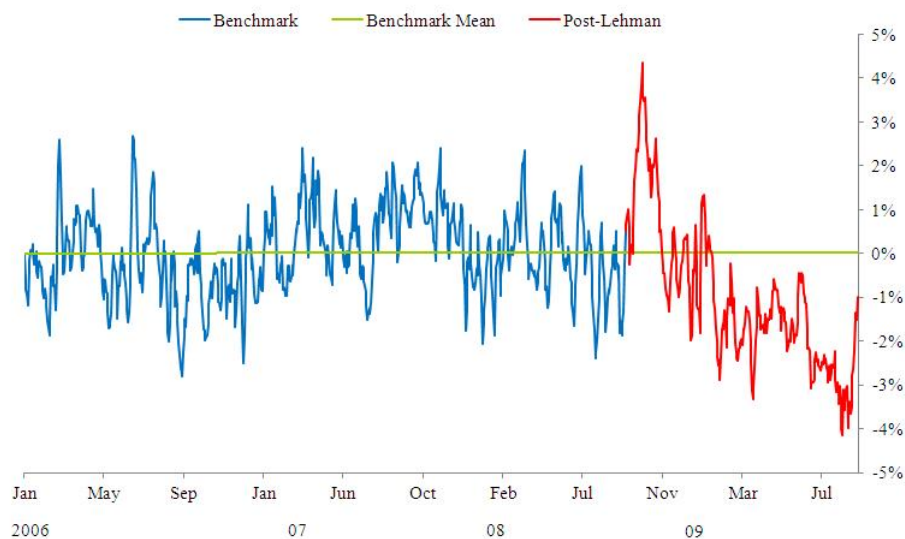
According to this measure, aggregate delay is highest in the two months following the failure of Lehman Brothers (eight of the ten worst days fall between the Lehman Brothers default and the end of October 2008); from February 2009 payments tend to be completed earlier than during the

¹³CHAPS usually closes at 4.20pm but settlement banks can request an extension which may last up to 7.00pm. This allows them time to deal with operational problems. If an extension was called on a particular day, we cut off at 4.20pm and look at throughput relative to the total amount paid by 4.20pm.

benchmark period.

To give a sense of the magnitude of the delay measure, remember that an increase in delay of 1 percentage point is equivalent to the payment schedule being 1% behind the benchmark at all points during the day. For example, suppose that in the benchmark schedule the bank makes 50% of its payments by noon and 75% by 2.30pm. Then, an increase in delay of 1 percentage point means that throughput at those times falls to 49% and 74% respectively, and similarly at all other times of the day. To put it another way, if payments are made at a constant rate throughout the day, then 1 percentage point of delay is equivalent to every payment being made 6.2 minutes later. This implies that at the peak of the delay measure in September and October 2008, payments were on average being made about 25 minutes later than in the benchmark period.

Chart 4: Delay in aggregate CHAPS payments, 1 January 2006 – 30 September 2009. The delay measure is defined in equation (3). The plot shows a five-day moving average.



4.2 Understanding the reasons for delay

We attempt to understand why delay increased following the failure of Lehman Brothers. As liquidity was plentiful, there did not appear to be an increased need to economise. An alternative explanation is that banks delayed payments to their counterparties to limit their exposure to counterparty default risk. The idea is that a bank might delay a payment to a counterparty if it

thinks there is a material chance that the counterparty will default during the day. Even though the bank may be obliged to settle payments by the end of the day, it may prefer, in the event of the counterparty defaulting, to net its obligations against incoming payment obligations from the counterparty, rather than attempt to recover the money via bankruptcy proceedings.

This implies that delay in the recovery of money may take a settlement bank below its reserves target, forcing it to borrow overnight on the standing facilities (from the Bank of England) or the interbank market at a higher rate. Furthermore, during the crisis, use of standing facilities became stigmatised, meaning that the true cost of using them may have been more than just the interest rate paid to the Bank of England (see Wetherilt, Zimmerman and Soramäki (2010)).

Empirical specification

To assess whether and to what extent concerns about counterparty default risk or other factors can explain payment delay, we estimate the following dynamic panel model:

$$\begin{aligned}
 Delay_{i,s} = & \sum_{j=1}^4 b_j Delay_{i,s-j} + c_1 DRisk_{i,s-1} + c_2 LibSpr_{s-1} + c_3 Liq_{-i,s} + c_4 Pmt_{-i,s} \\
 & + \sum_{k=1}^N d_k I_{[k=i]} + \sum_{l=1}^4 e_l I_{[l=\text{weekday of } s]} + u_{i,s}
 \end{aligned} \tag{4}$$

where i denotes banks, s denotes days in the post-Lehman default period and $u_{i,s} \sim IID$. The dependent variable is the delay (in %) in incoming payments to bank i on day s . That is, for each bank we calculate a daily value of delay in incoming payments from the rest of the system, using a variation of equation (3): let $x_{i,t}^s$ denote the fraction of all incoming payments to bank i that are completed on day s by time t and let β_t be the aggregate benchmark throughput defined in (2). We then measure the delay in incoming payments to bank i on day s by:

$$Delay_{i,s} = \frac{1}{62} \sum_{t=1}^{62} (\beta_t - x_{i,t}^s) \tag{5}$$

As with the aggregate delay measure, positive values of $Delay_{i,s}$ mean that bank i receives payments from the rest of the system with a delay relative to the benchmark period, whereas negative values mean that it receives payments faster.



$DRisk_{i,s-1}$ is the one-day lagged value of a measure of the individual bank's perceived default risk. To measure individual bank default risk, we consider two alternative variables:

- the one-day lagged value (in %) of the spread between the announced individual bank overnight sterling borrowing rates (we term this 'Ibobr'¹⁴) and the Bank of England policy rate; and
- the one-day lagged value (in %) of the bank's five-year CDS price.¹⁵

We use one-day lagged values for both variables, on the assumption that banks are likely to condition their payment behaviour on their perception of a counterparty's condition as of the previous day because yesterday's information has already been disseminated and absorbed by the market. In particular, the recorded individual bank borrowing rates do not become public information during the day. Moreover, we only have data on end-of-trading day CDS prices. Thus, the previous day's values are the most convenient measure of counterparties' views of creditworthiness prior to payment timing decisions being made.

We use the two alternative variables to capture individual institution risk because each has different merits. The spread between the Ibobr and the Bank of England policy rate is by definition highly correlated with the Libor spread and thus, by including both Libor and Ibobr, it may be difficult to establish significance for either one. Furthermore, if today's announced borrowing rate by a bank depends to some extent on whether the bank received payments with delay the previous day, then there is potential for endogeneity. Additionally, Ibobr rates do not necessarily correspond to the rates at which banks actually borrowed in the overnight market. Indeed, there is some evidence that banks deliberately understated their borrowing costs (see Mollenkamp and Whitehouse (2008)). Finally, the sterling Libor panel is comprised of 16 banks, only eight of which were CHAPS settlement banks over this period, and hence several CHAPS settlement banks must be excluded when using the Ibobr variable. This is a subset of the banks for which we have CDS price data.

¹⁴Ibobr values are as reported to the British Bankers' Association each morning. Ibobr values may of course differ from the actual borrowing rates but the latter are not observable. Algorithms have been developed to identify overnight loans from payments data — see, for example, Wetherilt, Zimmerman and Soramäki (2010) — but these cannot distinguish between loans made to or from a settlement bank and those made to or from its customers for the time period that our data spans. Therefore, in a highly tiered system such as CHAPS, the implied interest rate derived from the algorithm would be a weighted average of the rate paid by the settlement bank and that paid by its customers.

¹⁵Individual bank default risk, as captured by the CDS prices and/or Ibobr, also reflects a bank's difficulty in obtaining funding. CDS prices are strongly correlated with corporate bond spreads (since bonds are the underlying securities of CDS contracts) and bond spreads reflect a bank's cost of raising public debt. Libor spreads are more informative about the difficulty of borrowing in the interbank market but this measure is strongly related to the ability of a bank to borrow from investors, since both types of debt are unsecured.

The daily CDS prices do not suffer from these problems, but as they are based on five-year contracts they reflect market expectations about the probability of default over a five-year horizon.¹⁶ This is, in principle, problematic because daily payment behaviour will most likely be influenced by concerns of immediate credit risk. On the other hand, the period over which we do our estimation was marked by elevated concerns over credit risk and thus one could argue that changes in the five-year prices largely reflect default probabilities in the short term.

$LibSpr_{s-1}$ is the previous day's spread between the overnight Libor and the Bank of England policy rate, which captures changes in the perceived level of overall riskiness in the entire banking system.

Other independent variables are $Liq_{-i,s}$, the total amount of liquidity available¹⁷ to banks sending payments to bank i , and $Pmt_{-i,s}$, the total value of all day s payments sent to bank i , both measured in £ billions. The latter aims to capture potential effects arising due to internal bilateral limits or compliance with throughput requirements. If bilateral limits exist and are binding, then a larger daily amount of outgoing payments could mean that some of the payment orders will be executed later in the day. Alternatively, if banks are concerned about leaving large payment values to the end of the day, they may try to process a larger proportion of payments early. In addition, if larger payments tend to be more time-sensitive, then a large value of payouts will be associated with less delay.¹⁸ Finally, we include bank and day-of-the-week dummies to control for unobservable individual bank effects and payment patterns over the course of a week. Table A shows the summary statistics of the variables used in the empirical specification.

Estimation and results

We include four lags of the dependent variable in our specification in order to capture autoregressive time-varying effects on delay that we fail to include in the model.¹⁹ This also corrects the potential endogeneity bias that may arise when the Ibobr-BoE rate spread is included

¹⁶We use five-year CDS prices because these are the most liquid term and therefore should have a price which most accurately reflects the market view of default risk; see Mengle (2007), page 7.

¹⁷ie the sum of reserves and the amount of collateral posted with the Bank of England.

¹⁸For example, Armantier *et al* (2008) find that Fedwire payments tend to settle earlier on days when customer payments are larger.

¹⁹Four is the minimum number of lags required to eliminate the serial correlation in the error terms.

Table A: Summary statistics of the variables used in the empirical specification (4). The time horizon is 15 September 2008 to 12 February 2009. ‘Delay’ (measured in %) is the delay in incoming payments to each bank and is defined in equation (5). ‘Ibobr’ is the individual bank overnight borrowing rate (in %) as reported to the British Bankers’ Association each morning. ‘Libor’ is the average individual bank overnight borrowing rate (in %). ‘BoE’ is the Bank of England overnight policy rate (in %). ‘Liquidity (Liq)’ is the liquidity available (in £ billions) of the banks making payments to bank i . ‘Payments (Pmt)’ is the total amount (in £ billions) paid by all banks sending payments to bank i . All variables are observed on a daily basis.

	<i>Delay</i> (%)	<i>CDS price</i> (%)	<i>Ibobr-BoE spread</i> (%)	<i>Libor-BoE spread</i> (%)	<i>Liquidity</i> (£bn)	<i>Payments</i> (£bn)
Obs.	1,178	1,178	857	107	1,178	1,178
Mean	1.67	1.48	0.15	0.16	46.00	248.58
StDev	7.23	0.61	0.37	0.37	7.24	44.22
Min	-21.83	0.57	-0.75	-0.50	25.30	99.75
Max	30.38	4.86	2.00	1.79	71.48	378.66

as a regressor.²⁰ The inclusion of lags of the dependent variable in a fixed-effects panel regression also gives rise to a dynamic bias.²¹ However, our panel is characterised by a ‘small’ cross-sectional dimension and a ‘large’ time-series one²² which means that the dynamic bias should be minimal; we therefore report standard fixed effects estimates.²³

The results of the estimation are shown in the two panels of Table B. The first panel shows the results that are obtained when using the Ibobr-BoE rate spread as a proxy for default risk and the second panel shows the results that are obtained using the banks’ CDS prices. Since the Ibobr-BoE rate spread variable is not available for all CHAPS banks, the empirical analysis is done using the smaller number of CHAPS banks for which this variable is available. However, we run both regressions over the same time horizon (15 September 2008 to 12 February 2009²⁴)

²⁰This is because if causality also runs in the opposite direction, ie lagged delay influences borrowing spreads, it effectively gives rise to an autoregressive model for delay.

²¹See Nickell (1981).

²²The cross-sectional dimension N is 8 for the model using the Ibobr variable and 11 for the one using the CDS prices. The time-series dimension S is 107.

²³The dynamic bias tends to zero as $S \rightarrow \infty$. Accordingly, the Arellano-Bond consistent estimator is almost exactly the same in our case as the simple fixed effects estimator and is therefore omitted.

²⁴15 September 2008 is the day of the Lehman default. We chose to end at 12 February 2009 due to data limitations and in order to focus on the disruption after the Lehman failure. The Bank of England suspended reserves targeting in March 2009, so we might expect behaviour to change under that regime.

to make the results comparable.

Table B: Delay in incoming payments, fixed effects estimation. We estimate model (4) over the period of 15 September 2008 to 12 February 2009. The dependent variable is ‘*Delay*’ (measured in %) and is the delay in incoming payments to each bank as defined in equation (5). ‘*Ibobr*’ is the individual bank overnight borrowing rate (in %) as reported to the British Bankers’ Association each morning. ‘*Libor*’ is the average individual bank overnight borrowing rate (in %). ‘*BoE*’ is the Bank of England overnight policy rate (in %). ‘*Liquidity (Liq)*’ is the liquidity available (in £ billions) of the banks making payments to bank *i*. ‘*Payments (Pmt)*’ is the total amount (in £ billions) paid by all banks sending payments to bank *i* on day *s*. p-values are in parentheses.

Ibobr-BoE policy rate spread	Libor-BoE spread (LibSpr)	Liquidity (Liq)	Payments (Pmt)	Lag Delay F-test	Bank dummy F-test	R^2_{adj}	Obs.
1.868 (0.13)	-0.304 (0.81)	– –	– –	(0.00)	(0.00)	47.5%	824
– –	– –	-0.057 (0.01)	-0.009 (0.08)	(0.00)	(0.00)	47.3%	824
1.600 (0.19)	0.159 (0.90)	-0.061 (0.01)	-0.011 (0.04)	(0.00)	(0.00)	48.2%	824
CDS price	Libor-BoE spread (LibSpr)	Liquidity (Liq)	Payments (Pmt)	Lag Delay F-test	Bank dummy F-test	R^2_{adj}	Obs.
0.924 (0.01)	1.513 (0.00)	– –	– –	(0.00)	(0.00)	57.6%	1133
– –	– –	-0.053 (0.02)	-0.002 (0.74)	(0.00)	(0.00)	57.3%	1133
0.849 (0.02)	1.618 (0.00)	-0.048 (0.04)	-0.005 (0.32)	(0.00)	(0.00)	57.7%	1133

In the basic models (first row of each panel) we attempt to explain delay using the individual institution default risk measure as well as the Libor-BoE policy rate spread. For comparison, we also explain delay using only the liquidity (Liq) and payment (Pmt) variables in the second row of each panel. In the augmented models (third row of each panel) we use all the independent variables. In all cases we keep the day-of-the-week and individual-bank dummies.

Concern over specific counterparty default risk does seem to be a determinant of delay; the



coefficient on the individual bank CDS price is statistically significant with a one standard deviation increase in the CDS price (about 0.6 percentage points) causing an increase in delay by roughly 0.52 percentage points. The coefficient on the Ibobr-BoE policy rate spread is statistically insignificant; this may be because of collinearity with the Libor-BoE policy rate spread.

Given that a 1% increase in delay corresponds to a 6.2 minute clock-time delay, an increase in delay by 0.52% caused by a one standard deviation increase in the CDS price is equivalent to every payment being made on average roughly three minutes later.²⁵

The overnight Libor-policy rate spread is statistically significant only when we regress it with the individual bank CDS prices in the second model.²⁶ In this case, a one standard deviation increase in the Libor-BoE policy rate spread (about 0.4%), causes the delay measure to increase by 0.6% which corresponds to an average delay of around four minutes.

Available liquidity is also statistically significant: a one standard deviation increase in liquidity (£7.3 billion) leads to a decrease in delay by between 0.34 and 0.44 percentage points, depending on the model specification. Finally, the coefficient on total payments is statistically insignificant in both models.

Overall, it seems that concerns about counterparty risk, concerns about system-wide risk and also available liquidity are all factors that contribute to delay. Nevertheless, the estimated coefficients of the autoregressive terms and of the individual dummies in the empirical model also turn out to be significant, suggesting that a good part of the variation in delay is left unexplained.

5 Turnover

The amount of liquidity needed to make payments in a real-time gross settlement system such as CHAPS can be reduced by recycling incoming payments from others. This requires that some banks make the first payments. Not every bank can wait for incoming payments or the system would fall into gridlock. A measure of how successful settlement banks are at recycling liquidity

²⁵In Section 6, we calculate the monetary cost associated with the risks arising from payment delays to gauge the economic significance of this delay.

²⁶Presumably because of collinearity with the Ibobr-BoE policy rate spread.

is ‘turnover’: the average number of times each pound of liquidity provided by a bank to make payments is used during the day. Turnover is calculated as the ratio of the total value of payments made to the sum of the maximum net debit positions of all banks (the total amount of liquidity employed). Thus, if $P_{i,s,t}^{OUT}$, $P_{i,s,t}^{IN}$ are the payments that bank i makes and receives respectively on day s and during time slot t , then the aggregate turnover on day s is given by:

$$TURNOVER_s = \frac{\sum_{i=1}^N \sum_{t=1}^{62} P_{i,s,t}^{OUT}}{\sum_{i=1}^N \max\{\max_T [\sum_{t=1}^T (P_{i,s,t}^{OUT} - P_{i,s,t}^{IN})], 0\}} \quad (6)$$

The five-day moving average of this series is shown in Chart 5.

Before the collapse of Lehman Brothers, CHAPS settlement banks were able to complete an aggregate daily value of payments that was on average fifteen times as large as the amount of liquidity employed. After the default of Lehman Brothers, the same ratio fell to an average value of eleven. This was a significant change empirically (p-value=0.00) and economically; it represents a drop of almost 30%.

Chart 5: Aggregate turnover, 1 January 2006 – 30 September 2009, five-day moving average. Turnover for a given day is the ratio of total outgoing payments among CHAPS settlement banks on that day, over total liquidity used for the same day.

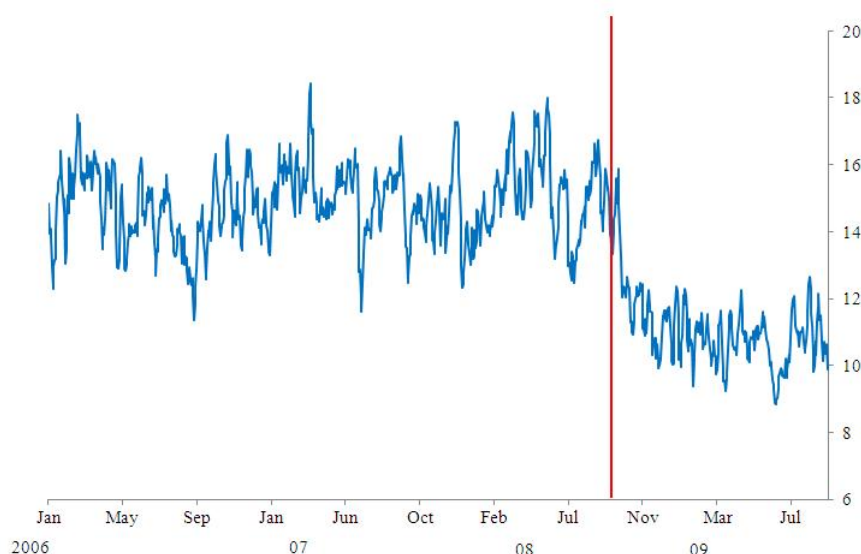
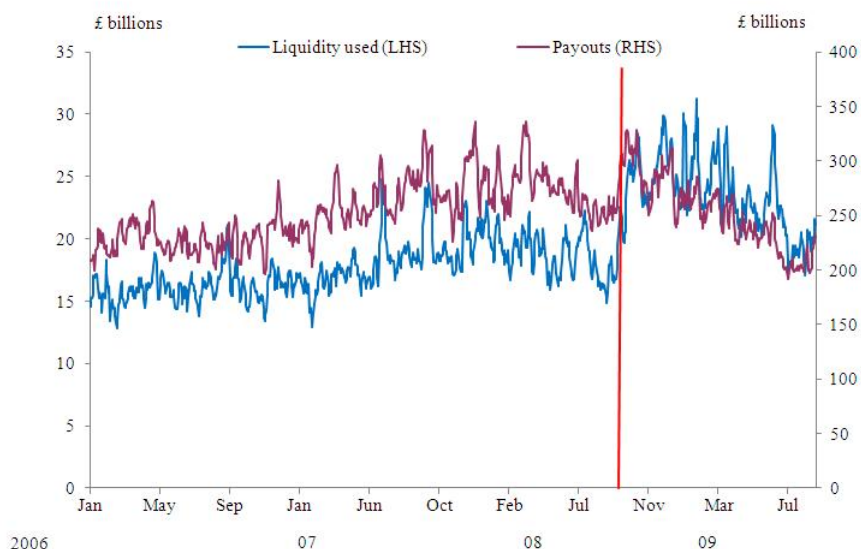


Chart 6: Liquidity used (in £ billions, left axis) and outgoing payments (in £ billions, right axis) for all CHAPS settlement banks, 1 January 2006 – 30 September 2009.



The reduction in turnover was driven by a large increase in liquidity usage in the two months immediately following the collapse of Lehman Brothers. After this period, usage fell in step with the reduction in payment values, as shown in Chart 6. The initial drop in turnover is associated with decreased throughput, but the lower level persists in an era of increased throughput (Chart 4). The explanation seems to lie in the fact that both reduced and increased throughput can lead to timing mismatches that reduce turnover. With reduced throughput, banks make payments using their own reserves because incoming funds are delayed. Increased throughput may, however, reflect a greater willingness to make payments more quickly because banks do not feel the need to wait for incoming funds. Either explanation is difficult to confirm from the data because we do not observe when payment requests arrive. Moreover, while banks make use of internal processors to manage outgoing payment flows, we do not know whether banks adjusted the parameters or the use of these processors during the crisis.

6 Payment delay, operational outages and liquidity risk

Although the CHAPS payment system functioned smoothly throughout the crisis, payment delays meant that potential operational outages, had they occurred, would have had a greater liquidity impact than the pre-crisis benchmark period. In this section, we develop a Markov

model which allows the computation of the expected amount of liquidity that would have been withheld from the system, had these operational outages occurred. We show that the expected amounts of withheld liquidity increased in the wake of the collapse of Lehman Brothers.

6.1 Measuring liquidity risk

We define a measure, at the settlement bank level, of liquidity risk induced by operational outages and demonstrate how the reduction in throughput observed in the two months following the collapse of Lehman Brothers led to a rise in this measure. An operational outage is an event during which a single settlement bank is unable to send payments (eg as a result of a system technical problem). Such outages can be short (eg they may last a few seconds) or significantly longer (eg several hours). During the period of the outage, the bank is effectively isolated from the system and the other banks are unable to benefit from any liquidity it may otherwise have sent. In modelling an outage, we assume that the stricken bank does not receive liquidity from other banks — this may be because it is unable to, or because the other banks do not send to this bank while the outage lasts as this would contribute to any ‘liquidity sink’. We further assume that outages only have an impact if they last until the end of the day. Should the affected bank recover before this time, we assume that it is able to send all of its delayed payments instantaneously, and that there is no lasting impact. In other words, it is as if the outage had never occurred. This makes the process path-independent.²⁷ Therefore, the impact of an operational outage depends on the net liquidity that the affected bank *would have* provided to the system.

To formalise this idea, let $\eta_{i\tau}^s$ be the net sender position of bank i at time τ on day s . This is the total amount sent by bank i minus the amount received up to time τ . Then, the maximum amount of liquidity that bank i provides to the system from time t until the end of day s (which we normalise to time $\tau = 1$),²⁸ is given by:

$$V_{it}^s = \max_{\tau \in [t, 1]} \eta_{i\tau}^s - \eta_{it}^s \quad (7)$$

If bank i were to suffer an operational outage during this period, then the other settlement banks

²⁷Merrouche and Schanz (2009) find both theoretically and empirically that banks may continue to make payments to a bank suffering an outage. This is not a concern for this paper since we do not assume any intraday welfare loss from a bank which recovers from an outage before the end of the day. If banks do make payments during outages, this may make the risk of a ‘liquidity sink’ worse. But we would only expect banks to do this when they do not expect to be reliant on incoming liquidity to make further payments.

²⁸The discrete-time nature of our data means that we check for peaks every ten minutes, instead of over continuous time. It is possible therefore that we miss peaks in between, meaning that this measure may understate the risk.

must supply V_{it}^s of liquidity to the system to compensate.²⁹ If the settlement banks do supply this amount of liquidity, then there will be sufficient liquidity in the system to settle all other payments until the end of the day even if i does not recover, since the system will never need more than $\max_{\tau \in [t,1]} \eta_{i\tau}^s$. Note that although V_{it}^s could be zero (for example, if $t = \arg \max_{\tau \in [t,1]} \eta_{i\tau}^s$), meaning that the other banks suffer no liquidity reduction from i 's absence, it cannot be less than zero.

We assume that operational outages are exogenous events and occur with the same probability for every bank i and for every time t and day s . Also, the probability of an outage and the probability of recovery are constant over time and so will give rise to exponential distributions.

We explicitly assume that for small h , the probability of having an operational problem in the next time interval h is $ph + o(h)$, where the notation $o(h)$ refers to some function of h such that $\lim_{h \rightarrow 0} \frac{o(h)}{h} = 0$. Similarly, the probability of recovering from an operational problem is $qh + o(h)$. Let X_{it}^s be a random variable equal to 1 if bank i is operating at time t on day s and 2 if there is an operational problem. Then each X_{it}^s is a continuous-time Markov process with respect to t and has transition rate matrix $\begin{pmatrix} -p & p \\ q & -q \end{pmatrix}$.

6.2 The expected liquidity loss of a worst-case outage

We next construct a measure to quantify the impact of a single outage at the worst possible time: conditional on an outage occurring, how bad could the impact be? The worst possible time for an outage is the point in the day when the expected value of a stricken bank's future net sender position is maximised. Let $f(t)$ denote the probability that, given there is an outage at time t , it lasts until time 1 (that is, the end of the day). The value r_{it}^s , defined below, represents the expected impact of bank i having an outage at time t on day s :

$$r_{it}^s = f(t) V_{it}^s \quad (8)$$

Thus, our measure is:

$$R^s = \max_{i,t} \{r_{it}^s\} \quad (9)$$

²⁹This is true only if we assume that the probability of more than one bank being in an outage state at the end of the day is zero. To illustrate this, suppose that bank j has an outage at time t and that bank i is already out. Then the additional liquidity 'lost' to the system from the second outage may be less than V_{jt}^s , because even if j was able to send i would not be able to receive.

and it captures the worst possible impact of a single outage. Algebraically, we can write $f(t) = P(\forall \tau \in [t, 1] : X_\tau = 2 \mid X_t = 2)$.³⁰ This yields an exponential distribution; to see this, begin by conditioning $f(t)$ on the event that there is an outage at time $t+h$:

$$f(t) = P(\forall \tau \in [t+h, 1] : X_\tau = 2 \mid X_{t+h} = 2)P(X_{t+h} = 2 \mid X_t = 2) + o(h)$$

Thus,

$$f(t) = f(t+h)(1 - qh + o(h)) + o(h)$$

and hence, dividing both sides by h and taking the limit as h goes to 0, we get

$$f(t)q = f'(t). \tag{10}$$

With the boundary condition $f(1) = 1$, the solution is

$$f(t) = e^{-q(1-t)} \tag{11}$$

Thus,

$$r_{it}^s = e^{-q(1-t)}V_{it}^s \tag{12}$$

For equal values of V_{it}^s , this measure is increasing in t . The rationale is that large values of V_{it}^s late in the day are particularly risky because if an outage occurs there is less time to recover from it. On the other hand, a large value early in the day carries less systemic risk as there is a good chance that the affected bank will be able to recover and make all of its payments before the end of the day.

6.3 The expected liquidity loss of a random outage

Rather than assuming that an outage occurs at the worst time, our next measure endogenises the likelihood that the outage occurs. Thus the process allows outage and recovery — possibly several times — throughout the day. The only important consideration is whether or not a bank is still out at the end of the day.³¹

³⁰We drop the i and s indices since by assumption the probabilities of suffering or recovering from an outage are independent of the bank and day in question.

³¹We take the end of the day as 4.20pm, when CHAPS usually closes. Settlement banks can request an extension which could last up to 7pm — naturally if a bank is out at 4.20pm it will most likely do this. But there is still a cost — all settlement banks have to stay open, staff have to work later, and liquidity managers run the risk of receiving a large payment late in the day which pushes them over their target. Therefore we take 4.20pm as the point at which losses begin to occur.

Let ψ_i^s denote the expected outage liquidity impact for bank i on day s and $g_s(t)$ denote the probability of being operational at time t on day s . We can then measure ψ_i^s as the sum (integral) of a continuum of mutually exclusive events; the bank is operational at time t but then has an outage which lasts until the end of the day. Thus,

$$\psi_i^s = \int_{t=0}^1 g_s(t) p e^{-pt} r_i^s dt \quad (13)$$

We compute $g_s(t)$ by conditioning $g_s(t+h)$ on the state at time t . That is,

$$g_s(t+h) = (1 - ph + o(h)) g_s(t) + (qh + o(h)) (1 - g_s(t))$$

and, dividing both sides by h and taking the limit as h goes to 0, we get

$$g'_s(t) = q - (p+q) g_s(t) \quad (14)$$

To solve this we use $g_s(0) = 1 - \xi$ as a boundary condition, where ξ is the probability that the bank begins the day with an operational outage. In practice, we do observe that banks' systems can fail first thing in the morning — for example as a result of bugs in patches implemented overnight. We therefore assign a positive probability to an outage at time 0. This gives the solution:

$$g_s(t) = \left(\frac{p}{p+q} - \xi \right) e^{-(p+q)t} + \frac{q}{p+q} \quad (15)$$

Note that as $t \rightarrow \infty$, the probability tends to $\frac{q}{p+q}$, the stationary probability of being operational.

This now allows us to compute ψ_i^s for each bank i . Let us assume that no more than one bank can suffer an outage at any point in time.³² Then our empirical measure for system risk will be the average of the ψ_i^s values, which we denote by Ψ^s :

$$\Psi^s = \frac{1}{N} \sum_{i=1}^N \psi_i^s. \quad (16)$$

³²This can be justified by a linearisation argument, since the probabilities involved are small.

6.4 Empirical estimation

Values for p , q and ξ can be estimated from empirical observations. The Bank of England maintains a data set of operational outages among CHAPS settlement banks, and we use the period from 3 December 2007 to 27 October 2009, which covers 65 outages.³³ The data set is summarised in Table C. Recall that a CHAPS day (620 minutes) is defined as a time period of length 1.

These data do have limitations. System rules require settlement banks to report operational outages within fifteen minutes of them occurring (Merrouche and Schanz (2009), page 8), so there may be some minor outages that the data fail to capture. Conversely, there are several occasions when a bank reports recovery from an outage only to have another a short time later. We view these cases as a single continuous outage since the two events are probably not independent.

Table C: Summary statistics of outages among CHAPS settlement banks, 3 December 2007 – 27 October 2009. A unit of time corresponds to a CHAPS day: 6.00am to 4.20pm (10 hours and 20 minutes).

No. of outages	65	Avg. length of intraday outage (days)	0.11
No. of start-of-day outages	5	Avg. time between intraday outages (days)	7.91
Daily avg. no. of settlement banks	12.69		

Furthermore, outages differ in their severity. The worst incidents result in the affected bank being able to neither send nor receive payments, but some may affect only one of sending or receiving. Others may only affect particular types of payment. For simplicity we ignore these distinctions and assume that an outage means that no payments can be sent or received. An alternative way of justifying this is to assume the following: if a bank is unable to receive, it chooses not to submit any payments in order to conserve its liquidity. And if a bank is unable to send, its counterparties choose not to send to it to prevent it becoming a liquidity sink. This is not an unrealistic assumption, since CHAPS informs its members of any reported outages.³⁴

³³These data were provided by APACS, the UK trade association for payments (it has since been succeeded by UK Payments).

³⁴See Merrouche and Schanz (2009) for further discussion.



As mentioned above, we assume that the probabilities are constant across date, settlement bank and time of day. This is perhaps overly simplistic, but our data set is not large enough to reliably break down the parameters further. For example, we do not observe an outage for every settlement bank, but it would be unrealistic to therefore assume that some banks suffer outages with probability zero.

As one bank withdrew from CHAPS settlement bank status during the period covered by the outage data and another bank joined, we take the daily average number of banks in the system. Since it takes up to fifteen minutes for an outage to be reported, we assume that the five outages reported before 6.15am are start-of-day outages. We therefore estimate $\hat{\xi} = 0.0008$ for each bank. The other 60 incidents are intraday outages.

The Markov process is irreducible and aperiodic. This implies that, in equilibrium, p is equal to the inverse of the expected return time to state 2 (that is, the average time between intraday outages), while q is the inverse of the expected return time to state 1 (the average length of an intraday outage). This gives us $\hat{p} = 0.0100$ and $\hat{q} = 9.2241$, where a CHAPS day is again the unit of time.

We check the assumption of a Markov process by doing chi-squared goodness of fit tests on the lengths of the outages and the interarrival times, to test for fit to an exponential distribution (see Table D). In both cases we cannot reject the null hypothesis: there is no reason to believe that these processes are not Poisson.³⁵

6.5 *Payment delay and liquidity risk*

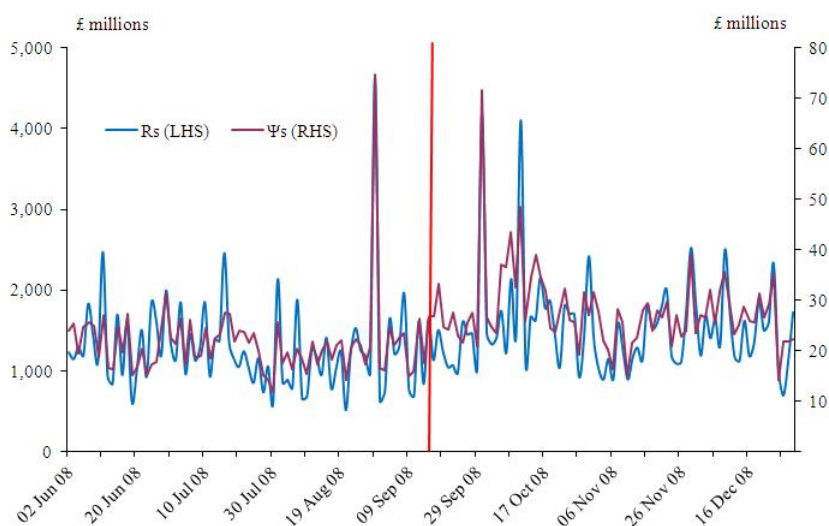
We calculate both risk measures for the period from 1 June to 31 December 2008. Chart 7 shows the worst-case risk measure R^s on the left-hand axis and the expected risk measure Ψ^s on the right-hand axis.

³⁵The length of bins are calculated according to the rule of thumb $(\frac{12}{N})^{\frac{1}{3}} \mu$, where N is the number of observations and μ the observed mean. The final bin is taken as half of the largest observation to avoid having several bins with zero observations.

Table D: Chi-squared goodness of fit testing of the null that outage and inter-arrival times follow a Poisson process.

Outage times				Inter-arrival times					
Observations				60	Observations				59
Mean				0.09	Mean				7.91
Max				0.45	Max				64.38
From	To	Observed	Expected	From	To	Observed	Expected		
0.00	0.05	25	25	0	5	31	28		
0.05	0.10	16	15	5	10	15	15		
0.10	0.15	11	8	10	15	7	8		
0.15	0.20	2	5	15	20	1	4		
0.20	0.25	4	3	20	25	2	2		
0.25	∞	2	4	25	30	0	1		
				30	35	1	1		
				35	∞	2	1		
Chi-squared statistic				3.99	Chi-squared statistic				6.68
p-value				0.55	p-value				0.46

Chart 7: Worst-case (R^s) and expected (Ψ^s) risk measures (in £ millions), 1 June – 31 December 2008.



The two graphs follow a broadly similar pattern. The sharp one-day peaks in late August and September are caused by individual settlement banks having a large net sender position in the afternoon. Ignoring these outliers, there appears to be an increase in the levels of the measures after the Lehman Brothers default on 15 September 2008, which is to be tested. We define 1 June

to 14 September 2008 to be our pre-Lehman default period and 15 September to 31 December 2008 to be our post-Lehman default period. Using a one-tailed Welch's t-test, we reject the null hypothesis that the pre-Lehman default mean is equal to the post-Lehman default mean for either risk measure (Table E). The expected amount of liquidity withheld under a worst-case scenario increases by £257 million, which is about 1.3% of the £20 billion system-wide liquidity usage. The expected amount from a random outage to a single bank rises by an average of £7 million during the two months after the collapse of Lehman Brothers. This is approximately 0.5% of the average usage by each bank.

Table E: Summary statistics of the operational risk measures R^s and Ψ^s over a pre-Lehman default period (1 June – 14 September 2008) and a post-Lehman default period (15 September – 31 December 2008). The risk measures are defined in equations (9) and (16) and are measured in £ millions. The table also shows the results of tests of equality of means for the pre and post-Lehman default periods.

Risk measure	R^s	Ψ^s
Benchmark period mean (£m)	1,276	21
Crisis period mean (£m)	1,533	28
Difference in means (£m)	257	7
Benchmark period stan. dev. (£m)	582	7
Crisis period stan. dev. (£m)	582	8
t-statistic (Diff)	2.71	5.18
p-value (Diff)	0.00	0.00

A similar test for the individual ψ_i^s reveals that this increase in operational risk is not uniform. Of the fourteen banks which were CHAPS members throughout the period, we observe a statistically significant (at a 5% level) increase in operational risk in only eight cases. In fact, in only nine cases is risk higher at *any* level of significance. This indicates that the increase in system-wide operational risk was caused by most, but not all banks. In other words, not all banks attained significantly more risky net sender positions during this period.

6.6 Liquidity insurance

One way to assess the monetary value of the expected withheld liquidity associated with an operational outage is to think in terms of the added cost of insuring against lost liquidity

provision by seeking an alternative provider. Imagine a private insurer who agrees to step in, in the event of an outage, and make and receive all of the payments the stricken bank would have made and received. The expected cost that this insurer faces provides a means of monetising the liquidity risk associated with operational outages in the payment system. The expected amount (in £) the insurer would need in order to replace the lost liquidity of a stricken bank, is Ψ^s .

Assuming the bank would have finished the day with a zero net balance in its settlement account (which is true on average) the insurer will recuperate all of this liquidity by the end of the day. If the stricken bank had a net debit position in its settlement account at the time of the outage, then all of the liquidity will be returned to the insurer in the form of incoming payments by the end of the day. If the bank had a net credit position in its settlement account at the time of the outage, we assume the insurer would have immediate claim to these funds from the Bank of England. Hence the indemnity of the contract does not extend beyond the provision of liquidity on the day of the outage.

For simplicity, we assume the insurer would obtain the funds by borrowing in the overnight market at overnight sterling Libor. The premium of the proposed contract would be equal to the expected value of the indemnity. Hence, the premium it would charge bank i on day s would be given by ψ_i^s times the daily rate of overnight Libor. This varies both with the measure ψ_i^s and changes in the overnight Libor over the crisis period.

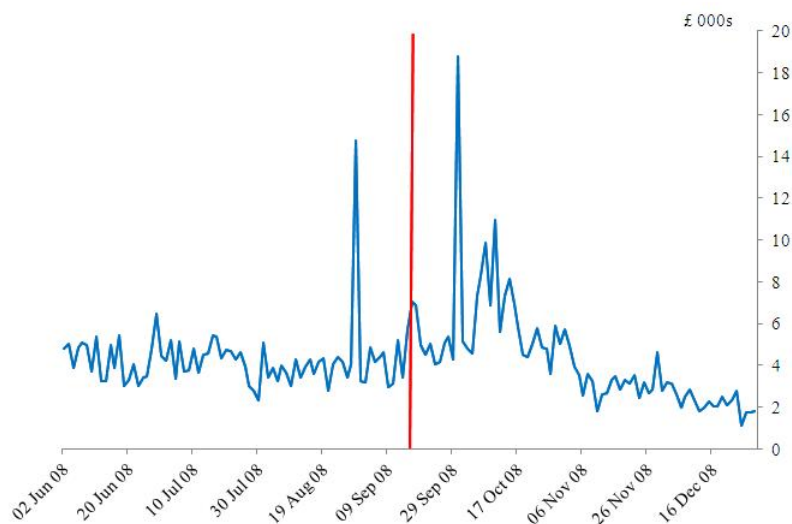
The average of the daily premia for the settlement banks is shown in Chart 8. Although the average daily insurance premium increased in the wake of the Lehman Brothers collapse, it remained, in absolute terms, economically insignificant. In the month following the collapse of Lehman the estimated average premium was around £6,700 per day which corresponds to around £1.67 million per bank, per year. Furthermore, by November it had fallen to levels below these preceding the collapse, driven by a decline in the value of Libor which began in mid-October 2008.

6.7 *Limitations*

We have used the amount of liquidity trapped as a proxy for the impact of an operational outage. We do not consider how beneficial the trapped liquidity would have been to the rest of the system



Chart 8: Average daily premium (in £000s) for insurance against liquidity withheld due to a bank outage. The premium is calculated as the product of the operational risk measure ψ^s with the overnight Libor. The time range is 1 June – 31 December 2008.



— it may be that other banks had plentiful liquidity stocks and were not reliant on recycling the stricken bank’s liquidity. And even if they were reliant, we do not know how important it was that their payments were made that day.

We have assumed that only one incident can occur at a time. This is partly necessary because it is computationally expensive to calculate the impact of several banks being simultaneously non-operational: we would have to take account of flows between them, to avoid double-counting. But since the probabilities discussed are fairly small, a linearisation argument can justify ignoring the probability of such an event.

We assume that payments resume as normal instantaneously upon recovery from an outage. In practice, it may take time to clear the queues, and other settlement banks may treat the affected bank with caution. There may also be some cost to delaying intraday. Furthermore, in reality the process may not be truly path-dependent since empirically we observe that banks are more likely to suffer an operational problem if they have already had one that day (in other words, recovery is not complete). We have also assumed that the probabilities do not vary by time of day. In addition, the probabilities of outage and recovery are assumed to be independent of the date and

settlement bank.

The Markov approach to modelling the impact of operational outages could, in principle, be extended to default events too. Capturing the impact of a default would be similar to modelling an operational outage, except that the probability of recovery would be zero. In other words, default is an absorbing state. However, this may not be a realistic way of modelling a credit event. It is unlikely that a bank would default while it has surplus liquidity – it would pay this out in order to delay the moment of default. Therefore this approach would be more suitable to modelling defaults which are sudden and cannot be foreseen by the bank – for example, a default caused by fraud or physical destruction of capital.

7 Concluding remarks

Our analysis reveals interesting aspects of the CHAPS payment system during the global financial crisis. Most notable are the changes in throughput and the corresponding drop in total value of payments made per unit of liquidity employed (‘turnover’) following the failure of Lehman Brothers on 15 September 2008. The observed reduction in throughput in the two months following the collapse of Lehman Brothers appears to have been, at least partly, driven by a variety of factors including concerns about counterparty risk and system-wide risk.

While turnover continued to fluctuate after the failure of Lehman Brothers, these fluctuations centred around a lower mean than that which existed beforehand. The sustained lower mean in turnover after the failure of Lehman Brothers is interesting given that the reduction in throughput that was observed in the two months following the collapse of Lehman Brothers was reversed by the end of our sample period.

We develop two indicators for measuring liquidity risk due to operational outages, each of which can be examined across the system or at the level of individual settlement banks. We find that both risk measures were higher at the system level after the Lehman Brothers default, suggesting that the impact on the system of an operational outage would have been modestly greater than before the Lehman event on account of payments being delayed. We argue that while the economic cost of insuring against this risk was reduced by the lower cost of obtaining funds (ie the cost of funding liquidity from alternative sources than relying on incoming payments), the



combined effect was that the cost banks would have had to pay to insure against liquidity risk modestly increased in the immediate aftermath of the Lehman Brothers collapse. In other words, it remained low in absolute terms. Furthermore, by November it had already fallen below levels seen in Summer 2008.

An interesting question is whether this cost and the underlying vulnerability to operational outages would have been significantly greater in the absence of CHAPS throughput requirements. Throughput requirements help banks to co-ordinate payments, ensuring that they should not build up very large net sender positions. But they only apply to banks' total daily payments, not those to individual counterparties.



8 References

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