Risk Management Lessons from the "London Whale"
Understanding Relative Size of Trading Positions*

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August 8, 2014

Abstract

On May 10, 2012 JPMorgan Chase & Co. started to report losses on its London based credit derivative portfolio. By now, these losses have accumulated to roughly 6.2 bln USD. Starting from a lessons learnt perspective, this paper focuses on implications for risk management, especially the understanding of large trading positions and their specific risks, that might not be covered by classical risk measures. We begin by consolidating publicly available information to provide a detailed view on the strategy, trading and risk management of the underlying portfolio. We show that risk measures, which incorporate market liquidity and concentration, help to explain the risks associated with JPMorgan’s portfolio more accurately than the classical measures. The tractable methods, that are presented in this paper, are likewise applicable to other portfolios of noticeable size.

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*This work is funded, in part, by the Global Association of Risk Professionals (GARP), with one of their 2013 research fellowships. The author thanks Natalie Packham for invaluable support and Thomas Heidorn as well as Martin Helimich for very helpful comments and suggestions. Additional thanks go to the Centre of Practical Quantitative Finance, at Frankfurt School of Finance & Management, for their hospitality and support at the time this research was undertaken.

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1 Introduction

On May 10, 2012 JPMorgan Chase & Co. reported a loss of two billion USD on its credit derivative portfolio that had accumulated on the books of the relatively small Chief Investment Office in London. CEO James Dimon publicly stated that the company could face additional losses due to market volatility. These additional losses, by now, have accumulated to a total loss of about six billion USD, not including subsequent settlement and litigation payments. This case, often subsumed under the name ”London Whale”, is particularly interesting, as it is based on an authorized trading position by one of the world’s largest investment banks that was known for its outstanding risk management, not least as being innovator of the widely recognized RiskMetrics and CreditMetrics frameworks (Gupton et al., 1997). The case of the London Whale raises questions on whether the involved risk management procedures appropriately captured all risks involved in the credit index derivatives position, which was later commented by Mr. Dimon as being ”flawed, complex, poorly reviewed, poorly executed, and poorly monitored” (JPMorgan, 2013).

The ”London Whale” case provides a good opportunity to lift the veil on risk management at one of the world’s largest banks. The discussion of JPMorgan’s portfolio is of particular importance because it provides insights, not least on incentivisation problems, that reach beyond this single case. We show that the classical risk measures are not capable of portraying the special properties and risks of large trading positions. Namely, the market impact that can make up a large portion of profit-and-loss (PnL) as well as the size effect on diversification within the portfolio. Market impact is caused by the trade-off between selling a position in a short period and thus minimizing the uncertainty about future prices versus the supply that is forced on the market, where a lack of demand could yield a price decrease. The latter effect can be as extreme as a 1,000 points drop in the Dow Jones, as was evidenced by the so called ”Flash Crash” in 2010 (CFTC, 2010).

By understanding the trading and choices during the life time of the portfolio, we are able to draw conclusions on the problems that finally led to the loss. We explain that position size was an essential factor to determine the strategy and PnL from inception until the portfolio was liquidated in 2012. In particular, we introduce market impact that arises from the liquidation of a given position and is an important factor for the risk management of such positions. Additionally, we analyse the impact of size on the portfolio itself, hence analysing diversification, correlation and risk concentration effects within a portfolio.

This paper is structured as follows. In Section 2 we provide a short primer on the market that is relevant to understand the SCP as well as its unique risks. Section 3 presents the events that where governing the 6.2 bln USD loss, by consolidating relevant and publicly available information on the case. Section 4 provides a view on the risk management that was insufficient to prevent JPMorgan from this loss. In Section 5 we introduce models that help to describe the problems that we explained in the previous sections. Section 6 combines insights from the relevant sections in lieu of the market environment of the time where the portfolio was actively managed. Finally, the last section provides some concluding remarks.
2 A Primer on Credit Indices and Tranches

JPMorgan’s portfolio that generated the 6.2 bln USD loss was purely based on credit derivatives. In particular, derivatives on credit indices and tranches. Hence, we provide a short primer on this markets and their unique properties before discussing the actual ”Whale Case”. For the quantitative applications of this paper we use a tractable credit valuation model in continuous time. This model is discussed and derived in Appendix A.1. The basics on credit index tranche modelling follow in Appendix A.2.

Soon after credit derivatives, in particular credit default swaps\(^1\) (CDS), turned into a quite developed market, participants initiated various credit indices which nowadays build the foundation of a liquid credit index derivatives market. Here, we focus on the two major credit index families, namely CDX for North America and Emerging Markets, as well as iTraxx for Europe and Asia. The indices are available in CDS format (unfunded) and Credit Linked Note format (funded). Both index families are enriched by standardized tranches. As we describe in Section 3.1, JPMorgan’s credit derivatives portfolio comprised more than 120 different index and tranche positions, all from these two index families. Hence, in the following we introduce these indices in more detail, as well as explain the mechanics of their respective tranches.

Both CDX and iTraxx provide different sub–indices with equally weighted constituents. For CDX, this includes the 125 name Investment Grade (IG) and 100 name High Yield (HY) index. The most important iTraxx is the 125 name Europe (EU) index.\(^2\) The IG and EU series comprise the top single name CDS contracts by market volume, where all names have to meet certain credit quality standards and ratings. Credit indices roll every six month, where a new series is created with updated constituents, thus, all index names are reviewed where entities which do no longer qualify are excluded due to corporate actions, rating changes, lack of liquidity or dealer poll results. Inclusion is enforced to keep the predefined number of constituents. The decision is made upon a liquidity poll for iTraxx and a dealer poll for CDX (Markit, 2008).

Knowledge about the composition of CDS indices is important to understand the risks involved when rolling into another series. When CDS indices are utilized as a credit hedging tool, the index constituents play an important role. The hedger can not necessarily expect to create identical default insurance just by rolling over to a new series of the same index, because the underlying names may have changed. The most recent issue of an index is also called the on–the–run index and usually provides the highest liquidity. Henceforward, the hedger might unwillingly be forced to roll over due to liquidity or simply the maturity of his series. This also influenced the JPMorgan loss and will be revisited in Section 3.2.

Credit Indices are quoted either on spread or price basis. This reflects the convention of the underlying cash instrument, where, for example, the main indices of iTraxx and CDX quote on spread but CDX.HY on price. These are exclusively over–the–counter (OTC) products, which can be traded with licensed dealers providing liquidity. Most indices trade

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\(^1\)A credit default swap (CDS) is a bilateral agreement to exchange a premium against protection on a reference entity. In a simplistic case, the reference entity, e.g. a bond, defaults and the insurance seller pays out the loss on the bond (cash settlement) or buys the bond from the insurance buyer for par (physical settlement). The premium is paid until the insurance is triggered or matures.

\(^2\)Further details on this and other credit indices are provided in Appendix A.3.
in maturities of 3, 5, 7 and 10 years, where the 5 and 10 year maturities are usually the most liquid (O’Kane, 2008). Buying the index means being exposed to defaults in the underlying CDS portfolio and is similar to providing protection on a portfolio of bonds. By selling the index, e.g. buying protection, the exposure is passed to the counterparty, where a coupon has to be paid to the protection seller in return for the risk transfer. For clarification, buying the index means selling protection and, therefore, being long credit risk and vice versa.

The coupon that is paid to the protection seller is standardized, e.g. 100 bps for most investment grade and 500 bps for most high yield products (Markit, 2009a). This is analogue to the plain vanilla CDS trading conventions that were introduced in 2009, after the so-called “Credit Big Bang”. Hence, the contracts are not set-up in a way that the two legs net by a contractual spread, but by an upfront payment instead. In case of a credit event the protection buyer receives a payment from the protection seller, which is analogous to the payment on a single name CDS where the notional is scaled down to reflect the index weight. After the credit event, a new version of the affected series is issued with the defaulted entity removed and the premium relevant notional reduced by one over the number of entities in the index times its notional.

The trading of credit index tranches is in principle similar to its underlying index. The major difference is that payments are only triggered when the attachment point of the corresponding tranche is reached, e.g. there is no more subordination that protects the tranche. In this sense, a CDS index tranche is a collateralised debt obligation (CDO) where the underlying portfolio is defined by the respective index (O’Kane, 2008). Naturally, the lowest (equity) tranche bears the highest risk of default and is, therefore, compensated with the highest spread. For CDX.IG and iTraxx.EU, the corresponding equity tranche attaches at 0% and detaches at 3%, the highest (senior) tranche in contrast attaches at 35% and detaches at 100%. The value of CDS portfolio products is sensitive to the default correlation of its underlying assets. Complexity is increased for tranches, as a change in correlation affects them differently. In short, we can expect the spread of the senior tranche to widen with increased correlation whereas the equity tranche’s spread is expected to tighten. For the middle (mezzanine) tranches, the picture is not that obvious. Clearly this adds additional complexity to a trading book, where correlation effects need to be monitored carefully.

For a thorough discussion of CDS, credit indices and tranche products also see Blum et al. (2003), Duffie and Singleton (2003), Lando (2004) as well as Saunders and Allen (2002). The models that we use to evaluate credit indices and tranches are derived in Appendix A.1 and A.2.

The credit event is determined by one of five Determination Committees of the International Swaps and Derivatives Association (ISDA). Credit events can include bankruptcy, failure to pay, restructuring, obligation default, obligation acceleration and repudiation. It is important to note that the indices differ in the definition of credit events that trigger a payout; the relevant credit events are published by the index provider, i.e. in Markit (2008).
3 How JPMorgan Lost 6.2 Billion USD

In this section we analyse the 6.2 bln USD loss that occurred on the books of JPMorgan during the first half of 2012. The actual loss took place within the Chief Investment Office (CIO) of JPMorgan. We therefore outline the CIO’s role within the corporation together with the loss generating Synthetic Credit Portfolio (SCP). Concluding remarks on the factors that lead to the losses are outlined in 3.2. Information are drawn together from different entities involved in investigating the case, including: news agencies, JPMorgan’s internal task force (JPMorgan, 2013) and the United States Senate – Sub Committee of Investigations (United-States-Senate, 2013b). These sources provide several internal documents including email, messenger or telephone communications between JPMorgan traders and management personnel and hence a deep look into the internal affairs that were governing the loss.

3.1 The Synthetic Credit Portfolio

JPMorgan’s major businesses include financial services for consumers and small businesses, commercial banking, financial transaction processing, investment banking and asset management. Since the total amount of deposits taken in outsizes the amount of loans, the firm is endowed with excess cash that must provide reasonable returns while also ensuring future liquidity requirements. The primary role of the Chief Investment Office (CIO), as a spin–out of the treasury function, is to manage these excess deposits. From 2005 until May 2012, Ina Drew headed the CIO, with its 140 traders and 288 middle– and back–office employees (JPMorgan, 2013).

The majority of the CIO’s investments go into high credit quality, fixed income securities, which reflects the intended long term nature of the CIO function within JPMorgan. In the beginning of 2007, the CIO launched its synthetic credit portfolio (SCP) as a tail risk hedge to protect the firm against adverse credit scenarios (JPMorgan, 2013). Owing to the nature of its business JPMorgan, along with other lenders, is naturally exposed to (long) credit risk. Thus, the firm would suffer under a credit downturn and gain under improving credit markets. The hedge strategy proved to be effective during the 2008–2009 credit crisis, where the CIO’s traders managed to cash in 1 bln USD in 2009, the year when General Motors filed for bankruptcy. Overall, the SCP generated revenues for the bank of roughly 1.8 bln USD from 2008 to 2011 (United-States-Senate, 2013a, Exhibit 1i). In 2010, after the credit environment recovered, the bank decided to shrink the portfolio as stated by Bruno Iksil, the trader in charge of the SCP, in JPMorgan (2013).

From mid 2011, the CIO traders began to re–evaluate their strategy for the SCP. This was most likely due to the deteriorating credit environment in Europe. The proposed strategy was a ”Smart Short” (United-States-Senate, 2013b, p. 51), which translates into a long–short strategy where credit protection on mainly CDX.HY indices is financed by selling protection on the more senior name credit indices. Hence, the upfront and cash flow payments can be netted while the resulting portfolio is sensitive to changes in the spread between the two position sides. Obviously, this type of strategy requires a bigger portfolio size as both sides contribute notional. The balancing of this portfolio will be discussed
later. Within six months, the SCP’s factored net notional\textsuperscript{4} increased by more than 200% to a value of 44 bln USD as per September 2011 (United-States-Senate, 2013a, Exhibit 6).

By the end of 2011, JPMorgan’s senior management and the CIO’s personnel determined that the global credit environment was improving again, thus requiring less default protection and hence, the decision was made to reduce the SCP’s risk weighted assets (RWA). In reaction, the traders in charge estimated that a direct reduction of RWA, by liquidation of their positions, would cost about 590 mln USD, as evidenced by internal meeting documents in United-States-Senate (2013a, Exhibit 8). Faced by this number, the CIO management decided against a direct reduction and in favour of managing profit and losses (PnL) while gradually reducing RWA over time (JPMorgan, 2013, pp. 29 ff.). The implemented strategy aimed at reducing RWA by balancing the portfolio, e.g. increasing positions with opposite market sensitivity, as the traders strategized that long credit risk positions would offset the SCP’s shorts. Javier Martin–Artajo, Head of Europe Credit & Equity, ordered to implement this strategy by forward spread trades, in order to comply with stress limits, as he stated later during an interview with JPMorgan’s internal task force (United-States-Senate, 2013b, p. 52). In context of the SCP, forward spread trades meant buying protection on short maturity indices, while selling protection on longer maturities. This would hedge in the near term but generate credit exposure on the long term. Clearly, this strategy would add a curve trade to the SCP.

When American Airlines bankrupted on November 29, 2011 the SCP generated a payout of 400 mln USD to the CIO. This was mostly due to large positions in CDX.HY that were funded by positions in CDX.IG and iTraxx.EU (United-States-Senate, 2013a, Exhibits 41, 84a). During strategy reviews in the following weeks, also in light of the above mentioned RWA reduction, Ms. Drew instructed her traders to recreate this kind of situation “because those were the kinds of trades they wanted at the CIO”, as stated in United-States-Senate (2013b, p. 63). This sheds light onto the conflicting guidance that was provided by the involved management personnel. On one hand, the exposure in terms of RWA was ordered to be reduced, while at the same time, the portfolio was supposed to provide default protection, which was to be financed as cheaply as possible by selling protection, i.e. creating default exposure.

In contrast to the American Airlines event, the SCP suffered a loss of 50 mln USD when Eastman Kodak filed for bankruptcy on January 19, 2012. This rooted back to December 2011, where in preparation for a large expiry in CDX.HY, the exposure was rolled to a newer series. However, owing to the RWA reduction efforts, not all of the expiring protection was rolled. By the time Kodak defaulted, the SCP’s long positions had Kodak exposure whereas the protection had already been reduced during the roll. This was the reason for another increase of position size on both ends, i.e. buying protection to prevent another ”Kodak Moment”, while incorporating a positive economic view on credit markets by going long credit risk. General market movement, however, went against the SCP. By the end of January, Mr. Iksil reported losses on the SCP while clarifying that ”... the loss in HY is higher than expected because of equity tranche moves (linked to Kodak default). The gain

\textsuperscript{4}Factored notional reflects the settlement procedure of credit indices in case of a default event. Each name in the index has its contribution factor which can be determined by one over the number of names in the index (equal weighting). In case of a credit event the calculation base for the index payments is reduced by this contribution factor, thus, creating factored notional.
in IG is lower than expected due to the lag in series forward spreads...” (United-States-Senate, 2013a, Exhibit 14). At that time, the total losses on the SCP had accumulated to about 100mm USD as depicted in Figure 1.

By the end of January 2012, the traders were faced with three main objectives that reflected the preceding events as well as guidance by the management. In particular, the more senior CIO management decided against the advice of Mr. Iksil to ”take the pain fast” (United-States-Senate, 2013a, Exhibit 53) and in favour of reshaping the portfolio in a way that would put a stop to the losses and reduce the RWA gradually over time (United-States-Senate, 2013b, pp. 66 ff.). The three objectives are:

- Stem year–to–date (YTD) losses of the SCP,
- Reduce risk weighted assets (RWA),
- Maintain/increase default protection to prevent Kodak moments

They could theoretically be addressed simultaneously by adding more positions to the portfolio, namely, long risk positions to participate in the upward moving market, while generating carry to fund the YTD losses and short risk positions. Additionally, protection was bought to create positive PnL from American Airline type events, i.e. providing default protection. Therefore, the traders increased the size of their long and short positions.

From February 2012, the traders would also experience liquidity problems, in particular for CDX.IG Series 9. Despite efforts to trade more liquid on–the–run indices, the CIO traders accumulated a Series 9 position that would double that market’s net notional within the first three month of 2012 as depicted in Figure 2. During this time, the traders believed the market prices to be wrong and started to defend their positions (United-States-Senate, 2013b, pp. 81 ff.). This meant influencing the market price by taking large positions in the desired direction and increasing the book even further. The book was increased until March 2012, when Mr. Iksil proposed a last attempt to put the book into a net long position, which would capture the general market direction as well as providing revenues to fund the YTD losses. This triggered a series of trades so large that they would later be referred to as ”doubling down” in United-States-Senate (2013a, Exhibit 78).

Additionally, on March 19, Mr. Iksil warned his supervisor via email that ”the market is very small now and we are too visible with likely some of our trades creating a concern among dealers...” (United-States-Senate, 2013a, Exhibit 38). This situation was likely to influence the MTM value as well as the bid–ask spread that the traders had to pay on their positions. In the same email Mr. Iksil described a situation where the traders could be trapped in their positions by other market participants. This meant that if they wanted to continue defending their positions, the JPMorgan traders would have to further increase their portfolio. By the end of March 2012 this increase led to a net notional of about 157 bln USD (United-States-Senate, 2013a, Exhibit 1a) which is 260% up from the September 2011

5In fact, on February 2, 2012 during the Harbor Investment Conference, Boaz Weinstein, founder of Saba Capital a 5.5 bln USD hedge fund, had already advised buying protection on CDX.IG.9, the very same index that the CIO sold protection on (La Roche, 2012). Other market participants including Blue Mountain Capital, Blue Crest Capital and Credit Suisse would follow Weinstein and help to increase pressure on the JPMorgan trades (Celarier, 2012).
Figure 1: Cumulative PnL of the SCP in USD (2012). On January 19, 2012 the SCP suffered a single day loss of 50mln USD due to the default of Kodak. When trading was halted by senior management on March 23, 2012 the portfolio collapsed. Source: JPMorgan (2013)

Figure 2: CDX.IG.9 Untranched Total Net Notional in USD (2011 – 2014). On March 30, 2012, after senior management seized trading, the largest single position on the SCP was a 73bln USD position in CDX.IG series 9. That was 50% of the entire worldwide net notional. Source: DTCC (2014)
value and slightly more than Vietnam’s 2012 GDP. At peak, the SCP held about 10% of all outstanding net notional in the global credit index market (DTCC, 2014).

On March 23, 2012 Ms. Drew ordered the CIO traders to “put the phones down”, meaning to halt any further trading (United-States-Senate, 2013a, Exhibit 1i). This, of course, meant that the positions could no longer be defended, hence, the losses in Figure 1 skyrocketed. On March 30, 2012 Achilles Macris, the direct report to Ms. Drew, contacted John Hogan, the firm’s Chief Risk Officer, stating that he had ”lost confidence” in his team and requested help with the SCP (United-States-Senate, 2013a, Exhibit 23). In the following month, the SCP continued to generate losses until many of the index positions were transferred to the Investment Bank on July 2, 2012 (United-States-Senate, 2013b, pp. 87 ff.). By that time, the YTD losses had reached about 4 bln USD. As of now, the final number associated with the SCP and reported by JPMorgan (2012) accumulates to a market loss of 6.2 bln USD.

3.2 Why the SCP went sour

From late 2011, the SCP became an increasingly complex portfolio, comprising more than 120 CDS index and tranche positions, with its factored net notional being increased to a peek value of 157 bln USD. While several operative trading objectives increased the complexity of the book, the overall strategy, that was implemented from early 2012, can be condensed as follows: With the ordered RWA reduction being estimated costly, CIOs management decided to balance the book and reduce RWA gradually over time. When the SCP, which was initially intended as a default protection book, lost money during the default of Kodak, the strategy was further adjusted to provide higher default protection. Additionally, the traders tried to balance the book in a way that would incorporate the general market direction at that time, which was a strengthening of the global credit environment. This resulted in buying protection on mostly CDX.HY, to generate default protection, while financing the positions as well as the YTD losses by selling protection on CDX.IG and iTraxx. At that time, the SCP comprised several different indices, index series, tranches, as well as maturities.

Owing to unexpected market movements but mostly unanticipated behaviour of the SCP, the CIO started to lose significant amounts of money from mid January (Figure 1). A major reason for this unanticipated behaviour was the high complexity of the SCP, and the reliance on measures of linear dependence to balance the book (United-States-Senate, 2013a, Exhibit 55), whereas the sub–position price movements did not correlate as expected. One of this measures is Credit Spread Widening of 10% (CSW10), which is the change in MTM value of a credit derivative for a 10% upward shift in its credit spread.  

In reaction, the traders tried to defend their strategy and increased notional to its peak value, until they were ordered to stop trading by the end of March 2012. At that time JPMorgans CIO held about 10% of all net notional outstanding in the global credit index market. Taking a more granular look on the positions in Table 1, we find market shares

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6 When balancing a portfolio of credit derivatives by this measure one has to make the implicit assumption that the positions are moving linear, at the same time and amplitude and thus are highly correlated.

7 In this case market share refers to the percentage share of a position in comparison to data from the DTCC (2014) – Trade Information Warehouse. This publicly available data may not contain all live positions.
of up to 117.01%. The size of the trades alone led to changes in the market price, this was partially desired by the traders to defend their position. However, the size also trapped the traders in their strategy, as they were no longer able to opt out or take alternative action, in particular, when other market participants, such as Boaz Weinstein, gained awareness and started trading against JPMorgan.

From March 2012, through unwinding the book in the following six months, JPMorgan lost a total amount of 6.2 bln USD. The biggest intra-day losses occurred after March 30, 2012 (Figure 1), indicating that when the traders were no longer able to defend their position, the SCP simply collapsed. This figure incorporates only the market loss, further legal and litigation payments would increase the final losses even further. These additional costs are outlined in Section 4.3, as part of the regulatory perspective. One of the biggest problems was the high complexity of the SCP, which was balanced by relying heavily on the CSW10 measure. When the sub-positions’ price movements were not correlating as expected, the book started to generate losses. Miscommunication between senior management and traders as well as ambiguous guidance together with insufficient risk management can be captured as the drivers of the CIO loss. Overall, the strategy was "flawed, complex, poorly reviewed, poorly executed and poorly monitored" as would later be stated by JPMorgan’s CEO James Dimon (JPMorgan, 2013).

### 4 Risk Management and Regulation

Clearly, a trading position that generates 6.2 bln USD losses, while being monitored from a risk management perspective raises questions on the effectiveness of the monitoring function. In case of JPMorgan, the innovators of RiskMetrics, it is even more surprising how the

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**Table 1: Top 10 Positions of the SCP as per March 30, 2012**

<table>
<thead>
<tr>
<th>Name</th>
<th>Series</th>
<th>Tenor</th>
<th>Tranche (%)</th>
<th>Direction</th>
<th>Net Notional ($)</th>
<th>Share (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CDX.IG</td>
<td>9</td>
<td>10yr</td>
<td>Untranched</td>
<td>Long</td>
<td>72,772,508,000</td>
<td>50.19</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>7yr</td>
<td>Untranched</td>
<td>Long</td>
<td>32,783,985,000</td>
<td>22.61</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>5yr</td>
<td>Untranched</td>
<td>Short</td>
<td>31,675,380,000</td>
<td>21.85</td>
</tr>
<tr>
<td>iTraxx.EU</td>
<td>9</td>
<td>5yr</td>
<td>Untranched</td>
<td>Long</td>
<td>23,944,939,583</td>
<td>37.01</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>10yr</td>
<td>22 – 100</td>
<td>Long</td>
<td>21,083,785,713</td>
<td>22.04</td>
</tr>
<tr>
<td></td>
<td>16</td>
<td>5yr</td>
<td>Untranched</td>
<td>Long</td>
<td>19,220,289,557</td>
<td>64.18</td>
</tr>
<tr>
<td>CDX.IG</td>
<td>16</td>
<td>5yr</td>
<td>Untranched</td>
<td>Short</td>
<td>18,478,750,000</td>
<td>78.92</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>10yr</td>
<td>30 – 100</td>
<td>Long</td>
<td>18,132,248,430</td>
<td>50.35</td>
</tr>
<tr>
<td></td>
<td>15</td>
<td>5yr</td>
<td>Untranched</td>
<td>Short</td>
<td>17,520,500,000</td>
<td>117.01</td>
</tr>
<tr>
<td>iTraxx.EU</td>
<td>9</td>
<td>10yr</td>
<td>Untranched</td>
<td>Long</td>
<td>17,254,807,398</td>
<td>26.67</td>
</tr>
<tr>
<td>Net Total</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>137,517,933,681</td>
<td></td>
</tr>
</tbody>
</table>

Source: United-States-Senate (2013a, Exhibit 36) and DTCC (2014).
portfolio described in Section 3 and its associated risks could slip through nearly any kind of risk management and risk limit. This section analyses JPMorgan’s risk function, in particular, the one applied within the CIO, as well as providing a technical view on involved risk measures and finally the regulatory perspective on the case.

4.1 The Failure of JPMorgan’s Risk Management

As described in Section 3.1, the core function of JPMorgan’s CIO was to manage excess deposits as well as to provide tail risk hedging, whereas proprietary trading activities were organized through the Investment Banking (IB) division. This led to a difference in risk management standards and limits for the SCP compared to IB portfolios. The risk metrics and limits in place were dependent on models, in particular VaR and other models described in Section 4.2, that were subject to change whereas the corresponding risk limits remained constant. Also, the risk function and risk personnel within the CIO was not sufficient to prevent the loss generating SCP trading strategy. Finally, the risk measures in place that picked up problems on the SCP did not cause remedial action, even when reported to JPMorgan’s most senior management.

As reported by the internal task force (JPMorgan, 2013), the risk limits for the CIO were fixed only on a global basis, meaning there were no risk limits in place which were tailored to the type of trading that evolved around the SCP, but only for the CIO as a whole. In contrast, according to the same report, risk limits for JPMorgan’s designated proprietary trading divisions are tailored to the type of business. In case of a trading book similar to the SCP, this would translate into limits concerning in particular market liquidity, concentration, counterparty risk and notional size. None of these granular limits had been in place for the CIO and its SCP.

The five key risk metrics for the CIO at the time of the losses were value at risk (VaR), credit spread widening of one basis point (CSW01), credit spread widening of 10% (CSW10), stop loss advisories and stress loss limits. A technical view on these metrics is given in Section 4.2. Between January 1 and April 30, 2012 the CIO recorded more than 300 breaches of limits and advisories, all primarily caused by the SCP. Some of these exceedances were in the scale of 100% to 1000% of the initial limit. One of the more significant exceedances at an early stage of the process occurred on January 30, 2012 where the “CSW01–MTM limit”, a level 2 limit for the CIO, was violated in excess of 200% (United-States-Senate, 2013a, Exhibit 39). According to JPMorgan (2013) on February 13, 2012 Ms. Drew was informed that the CSW01 limit had been in breach for most of the year. She responded by stating that she had no memory of this particular limit and that it needed to be “recast with other limits” for being ”old and outdated”.

From January 2012, the CIO also started to breach the 10–Q credit VaR limit, which is a level 2 limit based on the VaR, as it would be reported in JPMorgan’s quarterly reports. In reaction to the breach, the CIO’s personnel requested a temporary limit increase. The justification of the increase was the ongoing process of reducing VaR and that a more
accurate VaR model would be introduced soon (JPMorgan, 2013, pp. 124 ff.). This model was implemented in January 2012 and subsequently reduced the VaR figure of the CIO by about 50%. Thus, the CIO did no longer exceed its VaR limits and the temporary limit increase could be removed; the original limit itself, however, was not adjusted when the new model took effect (United-States-Senate, 2013a, Exhibit 1e). JPMorgan employs a business support unit with the purpose of verifying new models by understanding its calculations and applying back–testing procedures to verify accuracy. This so called Model Review Group (MRG) was also in charge of approving the new VaR model that the CIO had developed. As described in JPMorgan (2013), the model was authorized by the MRG on January 30, 2012, where a fast decision was likely to be influenced by senior CIO personnel. According to the same source, the review process could not be conducted as thoroughly as usual, because of missing observations for back–testing and time constraints. Additionally, the MRG issued an action plan with the purpose of removing apparent problems in the operation of the model – this action plan was never completed.

In May 2012, after the series of losses that is depicted in Figure 1, the MRG was ordered to review the methodology again. The action plan from initial approval already pointed at problems in the operation, namely, that entries for the model had to be made manually, via copy and paste, and that there was no clear methodology on the treatment of illiquid index tranches, such as a mapping to more liquid tranches. After the second review, the analysts of the MRG also found calculation errors in the model itself and problems with 3rd party analytical software that was utilized. In particular, they found a spreadsheet error that was likely to introduce a downward bias of the VaR.\(^9\) After this review, as part of JPMorgan’s remedial measures in the wake of the SCP losses, the decision was made to abolish and no longer rely on the new VaR model.

This demonstrates that JPMorgan’s and, in particular, the CIO’s risk management was not sufficient in managing the risks that accumulated on the books of their business unit. The reports of JPMorgan and the United States Senate focus mainly on operational problems within the risk function. These are in particular the enforcement of risk limits, including the missing granularity to tailor the limits to the associated portfolio and subsequently its risk; the rush into new models that are not thoroughly reviewed and back–tested; as well as insufficient resources and independence for the risk function that was employed within the CIO. The conclusions of both reports are similar in that if the limits had been applied appropriately, if the risk function independent and sufficiently endowed with resources and if open communication with the regulator had been in place, the incident might had been prevented.

4.2 Risk Measures

This section provides a technical view on the risk measures that are applicable or applied for the risk management of the SCP. From publicly available reports, which we already

\(^9\)This error occurred in the calculation of relative hazard rate changes, where the spreadsheet divided by their sum, instead of the average, as would have been intended by the modeller (JPMorgan, 2013). Hazard rates are explained in Appendix A.1 as a vital parameter of modelling the probability of default in the valuation of credit derivatives. As the dividing factor was larger as intended, the resulting hazard rate changes must have been lower. This is likely to bias the resulting VaR outcome and thus could at least partially explain the significant VaR reduction that came with the new model.
used to outline the events that where governing the SCP loss, we can also draw information on the measures and figures that the CIO risk personnel was using in assessing the SCP’s risk. Hence, we are able to provide a view on the risk measures that the CIO risk unit was looking at, before and after the SCP started to lose money.

One of the most popular and widely used risk measures is Value at Risk (VaR). This is also a central risk measure that was utilized in assessing the SCP from a risk management perspective. Jorion (2009) defines VaR as the maximum loss \((-\Delta V)\) over a target horizon that will not be exceeded with some probability \((1 - \alpha)\). For \(\alpha = 0.05\) we would, therefore, expect a loss worse than VaR to occur 5 times out of 100, thus VaR is nothing else than the \(\alpha\) quantile of the loss distribution. Formally, we can write

\[
VaR_{\alpha, \Delta t}(-\Delta V) = \inf \{ I \in \mathbb{R} : P(-\Delta V) \leq 1 - \alpha \} = Q_\alpha(-\Delta V) \tag{1}
\]

VaR can be defined in absolute terms where the figure is in scale of the initial portfolio size or in relative terms, which would essentially be the worst return under the definition above. In practice, there are different approaches for calculating VaR. One common method is Historical Simulation\(^{10}\), where the scenarios are taken from (joint) historical factor changes. Here, the dependencies are aromatically taken into account and no assumption on the distribution of the factor changes is required. This, however, implicitly assumes that the historical distribution of factor changes is also representative for the future, where the choice of the retrospection period could include too few (or too many) extreme factor changes and, therefore, underestimate the measure. This is the methodology underlying JPMorgan’s daily 10–Q\(^{11}\) VaR, which is provided with the quarterly reports as well as basis for internal risk limits. Since 2008, this VaR is calculated using a 95% confidence level.

In JPMorgan’s quarterly report for the period ending on March 30, 2012 the average daily VaR for the entire CIO was reported with 129 mln USD, i.e. approximately 591 mln USD monthly \((129 \times \sqrt{21})\). VaR does not tell anything about the size of losses, but clearly there is a mismatch when comparing the 591 mln USD to losses of 2,976 mln USD in the following 30 trading days. Even more questionable is the VaR that was applied by the CIO’s risk function by that time. As depicted in Figure 3 this was approximately half the usual 10–Q VaR. Meaning, that the CIO’s VaR model was exceeded 13 times in the following 30 trading days. This is quite far away from 5 out of 100 trading days.

Another risk measure that was used in conjunction with the SCP is the so called Credit Spread Basis Point Value (CSBPV)\(^{12}\). This is a measure of the mark to market value change caused by a credit spread shift of 1 bp. To determine behaviour under stress scenarios, JPMorgan also estimated the impact of a 10% increase of credit spreads on the portfolio. This measure is called Credit Spread Widening of 10% (CSW10) and was utilized not only as a risk measure for stress scenarios but also to balance the book, as we described in Section 3.2. This are linear sensitivity measures. Utilizing such measures for portfolio

\(^{10}\)Other methodologies are Monte Carlo Simulation, which is also a non-parametric method such as Historical Simulation, and the Delta–Normal approach, which requires an explicit distribution assumption.

\(^{11}\)10–Q refers to the quarterly report mandate by the SEC. Therefore, we refer to the VaR measure as it would be filed by JPMorgan.

\(^{12}\)This similar to the Risky Present Value of One Basispoint (RPV01) that is automatically derived together with the mark-to-market model in Appendix A.1.
balancing implies the assumption that the positions are also moving linear, at the same time and amplitude, thus are highly correlated. We will point at this correlation problem again when analysing the market environment of the SCP in Section 6.

Further risk management tools that are used within JPMorgan are Stop–Loss advisories and Stop–Loss limits. These are no risk measures in the classical sense but important tools for loss prevention. Many brokers around the world implement the Stop–Loss as an order that is automatically triggered to close a position when the loss falls below a certain threshold. This threshold could be defined for cumulative or instantaneous losses, on portfolio or single position level. Usually not being implemented in an automated way, the Stop–Loss for a large (proprietary) trading desk serves the same purpose. The term advisory suggest a lower priority level, that if breached should possibly trigger a review of the position. The Stop–Loss limit suggests to be the trigger of some remedial action on the loosing position or portfolio. For the SCP there is evidence in United-States-Senate (2013a, Exhibit 39) that Stop–Loss advisories as wells as Maximum–Stress–Loss limits, which we interpret as a form of Stop–Loss limit, had been breached. We did however not find evidence of any direct remedial actions that would follow the usual definition of a Stop–Loss, i.e. closing of the loosing positions.

Apart from the obvious issues with the CIO’s VaR model implementation, there is no research on the risk measures and models themselves, in particular not on the question if they would have been sufficient to detect the risk, even if they had been applied properly. When comparing the two VaR models until trading was seized for the SCP, the highest values for the old and new VaR model where around 140 mln USD and 60 mln USD, respectively (United-States-Senate, 2013a, Exhibit 1e). Applying a simple Delta–Normal VaR with 95% confidence and the more conservative 140 mln USD daily VaR (or 641 mln USD monthly VaR), when compared to the losses of 3,5 bln USD in the following month, lets conclude that JPMorgan experienced a nine sigma event, which should – in a statistical sense – occur once every 2.78e+16 years. This, compared to the age of the universe of about 1.38e+10, is quite a long time or low probability, respectively. Of course, this is a
heavy simplification and JPMorgan did not use a plain vanilla Delta–Normal VaR. On the other hand, the models in place did also not provide a reliable representation of the risk associated with the SCP. A lack of market liquidity and the enormous size of the SCP could be an explanation for the poor performance of VaR and the other measures. Therefore, we shall extend the measure by incorporating market liquidity risk in Section 5.1.

4.3 Regulatory Perspective

On top of the 6.2 billion USD market loss, JPMorgan agreed on settlements with various regulatory institutions, that is, JPMorgan agreed to pay a total of 920 million USD to regulators in the US and UK, which ranks 3rd in the list of top 10 bank fines (The Telegraph, 2013). More precisely, this includes 200 mln USD to the Federal Reserve (FED, 2013), 300 mln USD to the Office of the Comptroller of the Currency (OCC, 2013), 200 mln to the Securities and Exchange Comission (SEC, 2013a) and about 220 mln USD to the United Kingdom’s Financial Conduct Authority (FCA, 2013). As losses are not per se illegal or punishable, this section provides a detailed view on the different reasons for the regulatory involvement.

On September 18, 2013 the FCA issued a notice to JPMorgan, imposing a financial penalty of 220 mln USD (138 mln GBP). This includes a 30% discount as JPMorgan agreed to settle at an early stage of the authority’s investigation. The document describes the alleged failings of JPMorgan that led to the fine. According to the FCA, JPMorgan failed to conduct its business with due skill, care and diligence, because of the failure to appropriately manage the SCP’s trading strategy, inadequate response to indications of increased risk, mispricing of certain sub positions and unreliable valuation for the SCP, where relevant control functions had not been in place for the CIO. In addition, its stated that JPMorgan failed to organise and implement adequate risk management systems. This is, that the firm did not provide relevant training and guidance on how it expected its traders to mark their positions, relied on manual processes and failed to utilize relevant capabilities from other business areas that had more experience in the management of complex derivative portfolios. The defensive trades that were described in Section 3.1 are referenced to for not showing proper standards of market conduct. Lastly, the FCA found that JPMorgan did not cooperate with its regulators in an open and cooperative way. This is, in particular, the failure to inform the regulator about problems with the SCP and later deliberately misleading the authorities about the SCP’s situation.

One day later on September 19, 2013, the SEC issued a letter to JPMorgan, accepting the 200 mln USD offer of settlement that the bank had issued prior. As stated in SEC (2013a), the commission found that: ”Public companies are responsible for devising and maintaining a system of internal accounting controls sufficient to, among other things, provide reasonable assurances that transactions are recorded as necessary to permit preparation of reliable financial statements.” This refers to JPMorgan’s restatement of its first quarterly report in 2012, due to losses on the SCP. According to this document, the full extent of the losses was not reported due to ineffective internal control functions within the CIO. The Valuation Control Group (VCG), a CIO support function in place to avoid miss marking of trading positions, is explicitly mentioned as understaffed, insufficiently supervised and without adequate documentation of its actual price testing policies. Furthermore, the price
testing process is stated to be influenced by the traders themselves where a lack of escalation to top management created a situation where the traders could manage the SCP as described in Section 3.1. In addition, insufficient communication with its Audit Committee made JPMorgan file an amended form 10–Q (quarterly report) with the SEC on August 9, 2012.

This was followed by an OCC consent order for a civil money penalty, accepting settlement with JPMorgan over 300 mln USD, the highest single fine. As per the consent order, the OCC engaged in targeted examinations of JPMorgan and the CIO, where they established that the bank had "...deficiencies in its internal controls and engaged in unsafe or unsound banking practices ...". The OCC clarifies that JPMorgan’s oversight and governance of the SCP were insufficient to protect the bank from this material loss; the risk management function could not provide the foundation to identify, understand, measure and control the involved risks; the bank’s valuation control process could not provide effective assessment of the CIO’s valuation; the internal audit process was not effective; and the bank’s model risk management did not provide sufficient control of certain risk measurement and pricing models. Additionally, it is stated that JPMorgan failed to provide significant information on the SCP in a timely and appropriate manner to the OCC.

The remaining 200 mln USD go to the FED as part of another civil money penalty order. Similar to the OCC’s report, the FED states that JPMorgan conducted unsafe or unsound business practises. Explicitly mentioned is the inadequate oversight of the CIO, including the failure to implement sufficient controls that would have ensured the timely disclosure of relevant information to senior management. Furthermore, it stated that JPMorgan allegedly failed to provide the significant information on the SCP that would have been vital for the FED examiners to adequately assess the risks associated with the SCP.

In addition to the regulatory engagement, two CIO employees face personal charges by US prosecutors. Javier Martin–Artajo and Julien Grout were charged by the US – Department of Justice (2013a) and (2013b) as well as the SEC (2013b), this charges include four counts of falsification of books, wire fraud and making false statements to regulatory agencies. This is in line with the reports above, in particular, the alleged miscommunication and accusation of providing false reports to the regulator. One related piece of evidence, that already showed up in the regulators investigations, is the so called “Grout Spreadsheet” which is partially reproduced in Table 2. The Table shows the PnL that was reported by the CIO versus the PnL that would have resulted from marking the position to Mid–Prices. It is not clear if the traders violated firm policy with their position marks, if not, they, however, tried to mark their PnL in the most favourable way. The Grout Spreadsheet was initially used only internally by the traders to keep track of the divergence.

In essence, the available reports show that JPMorgan had obvious problems in maintaining a conduct of risk awareness and escalation that is vital to the operation of banks and, in particular, proprietary trading activities. The shadow PnL that was maintained by the traders points at an incentivisation problem that is not limited to this single case. Even though a highly qualified trader is aware of the extent of his activities, there is no noticeable incentive to provide this information for the purpose of managing risk. Iksil’s

13The buy (Ask) price of a financial asset at a given point in time is higher than the sell (Bid) price. The difference is called Bid–Ask–Spread and the average is called Mid–Price. The MTM value of a position is obviously sensitive to the type of price it is calculated on, thus it is important to adopt clear standards on the prices within the Bid–Ask range that are used to mark a position.
**Table 2: Distance to Mid-Price Marking**

<table>
<thead>
<tr>
<th>Date</th>
<th>Reported</th>
<th>Distance</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>12-Mar-12</td>
<td>152,763,837</td>
<td>202,543,647</td>
<td>355,307,484</td>
</tr>
<tr>
<td>13-Mar-12</td>
<td>152,819,162</td>
<td>206,639,426</td>
<td>359,458,588</td>
</tr>
<tr>
<td>14-Mar-12</td>
<td>156,474,000</td>
<td>268,984,074</td>
<td>425,458,074</td>
</tr>
<tr>
<td>15-Mar-12</td>
<td>157,202,181</td>
<td>292,470,549</td>
<td>449,672,730</td>
</tr>
<tr>
<td>16-Mar-12</td>
<td>161,168,940</td>
<td>432,348,435</td>
<td>593,517,375</td>
</tr>
</tbody>
</table>

Source: United-States-Senate (2013a, Exhibits 1g and 28)

idea, from early 2012, to "take the pain fast", as in United-States-Senate (2013a, Exhibit 53), meaning to close the positions with a loss, was not realized, because it would have possibly resulted in the same consequences as after the 6.2 bln USD loss, however, without the chance to turn the position. Chat transcripts in United-States-Senate (2013a, Exhibits 32b) from the time the traders had to reveal the losses, demonstrate the anxiety towards reporting losses to senior management, one trader finally commented the PnL figure that had to be reported with: "this is the end". The described doubling down risk is a form of operational risk that is not exclusive to this case. Another famous example is Baring’s Leeson. Even more concerning might be the unobservable number of cases where this sort of strategy worked out and the risk taking that was necessary for it.

Before we continue with our analysis of the risk impact that is induced by position size, we provide a primer on the underlying instruments and their valuation.

## 5 Risk Impact of Position Size

The objective of this section is to study models that incorporate size effects and thus allow for comparing market risk under different trading scenarios, such as increasing or decreasing a position. This can increase the adequacy of operative trading decisions, in particular, on portfolios in scale of the SCP. In the first part of this section, we introduce market impact as a driving factor for the risk of large trading positions. In other words we derive a measure that models the impact of a position change on an existing risk measure. For the second part, we take a portfolio view, hence incorporate correlation, and analyse the impact of a position change to a portfolio under diversification effects. In short, we analyse the problem of diminishing diversification and concentration risk on portfolio level.

### 5.1 Market Liquidity Risk

Liquidity, in our sense, is the readiness of a market instrument to be monetized. The size of a market is directly related to liquidity and often used synonymously. With prices being a result of supply and demand it is clear that even without any fundamental reason, the market price can be influenced just by the trading itself, where the size of the trade, in respect to its market, is a driving factor. Even worse, when closing a position the self-inflicted market price change is always in an adverse direction. For our risk management application and
to analyse the market impact caused by liquidation of a given trading position, we borrow insights from research fields that are nowadays applied in algorithmic and high frequency trading, where participants try to find means on minimizing the impact on market prices when closing their positions. Pioneering work on this topic was published by Almgren and Chriss (1997), Lawrence and Robinson (1995), Subramanian and Jarrow (2001), Bertsimas and Lo (1998) and Jarrow and Subramanian (1997) in pursuit of finding strategies for optimal liquidation where also risk management applications had been considered.

Faced with the problem of trading large quantities that could influence the market in an undesired direction, Almgren and Chriss (1997) consider methods with the aim of minimizing volatility risk and transaction costs, that arise from temporary and permanent market impacts. Their considered problem is two-sided with:

- **Market impact**, where trading itself moves the market in an undesired direction because it is executed rapidly and with high volume.

- **Volatility risk**, where the market impact is reduced by trading less frequently in smaller quantities but in return increasing the holding period of the asset and therefore the uncertainty/risk associated with adverse market movements.

With standard risk models (e.g. VaR) focusing on volatility risk, we want to add the impact side to the problem and find a measure that might prove to be more accurate in explaining the risks of the SCP and also applicable for other portfolios of significant size.

In liquidating a security or portfolio over a fixed period, Almgren and Chriss (1999) identify two important occurrences. First, for a choice of trading trajectory there is an impact to the market price at each trade along the path. The sum of these market impacts is the total cost arising from the trading activity. Second, at each step the remaining portion of the portfolio is exposed to changes in market prices and therefore risky. Thus, the chosen liquidation trajectory directly determines its uncertainty/risk and market impact. We start our analysis from the view of a trading entity that is closing a position by selling (buying back for short positions) a block of shares $X$. Almgren and Chriss (1999) present a method to optimize market impact versus volatility for a given period $T$, until the entire position is closed. As in Hisata and Yamai (2000) we continue on this idea but use an approach that turns the sales period $T$ into an endogenous variable, e.g. optimizing $T$ while assuming sales at a constant rate.

To model the market prices, Almgren and Chriss (1999) propose to use an arithmetic Brownian motion that is sensitive to the executed trades. As in with Holthausen et al. (1990) they differentiate between temporary and permanent effects on the market. Both occur simultaneously, where the permanent effect changes the long-term equilibrium price and is, therefore, relevant to all subsequent trades. The temporary effect also pushes the price the moment a trade is executed, however, the effect will not last until the next trade is triggered. Following this definition the temporary effect diminishes directly after the trade and is, therefore, dependent on the recovery speed of the individual market. We

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14In many finance applications the geometric Brownian motion is proffered over the arithmetic. Not least for avoiding prices that fall below zero. For the relatively short liquidation period this problem is however neglectable.
follow the approach of Hisata and Yamai (2000) in continuous time that allows for closed-form solutions and compares in notation to the MTM valuation model from Section A.1. Including both the permanent and temporary effect, this yields the price process

\[ S_t = S_0 + \mu t + \sigma W_t - \epsilon - \eta v_t - \gamma \int_0^t v_s ds \]  

(2)

with \( \mu \) the stock price drift, \( \sigma \) the stock price volatility, \( W_t \) a standard Brownian motion, \( \epsilon \in \mathbb{R} \) the bid ask spread, \( \eta \) the temporary market impact coefficient, \( v_t \) the portion of position size \( X \) that is sold in \( t \) and \( \gamma \) the permanent market impact coefficient. The transaction costs \( C \) for closing the position at a constant rate \( v \) can be written as the difference between the initial value of the position and the sales value, \( S_0X - \bar{S}X \). As \( X = \int_0^T vdt \), we write

\[ C = S_0 \int_0^T vdt - v \int_0^T S_t dt \]

\[ = S_0 \int_0^T vdt - v \int_0^T \left\{ S_0 + \mu t + \sigma W_t - \epsilon - \eta v_t - \gamma \int_0^t v_s ds \right\} dt \]

\[ = vS_0T - vS_0 - \frac{1}{2} \mu vT^2 - v \sigma \int_0^T W_t dt + \epsilon vT + \eta v^2 T + \frac{1}{2} \gamma v^2 T^2 \]

(3)

with expected value

\[ \mathbb{E}[C] = -\frac{1}{2} \mu XT^2 + \epsilon vT + \eta v^2 T + \frac{1}{2} \gamma v^2 T^2 \]

\[ = -\frac{1}{2} \mu XT + \epsilon X + \frac{\eta X^2}{T} + \frac{1}{2} \gamma X^2 \]  

(4a)

and variance

\[ \mathbb{V}[C] = v^2 \sigma^2 \mathbb{V} \left[ \int_0^T W_t dt \right] \]

\[ = \frac{1}{3} v^2 \sigma^2 T^3 = \frac{1}{3} T \sigma^2 X^2 \]

(4b)

Following Hisata and Yamai (2000), we assume that the investor is selling his position at a constant speed, hence, the liquidation period is optimized while also assuming that the investor is not changing his strategy once it is triggered. This is in contrast to the Almgren and Chriss (1997) methodology that is optimizing the trading trajectory with a given liquidation period. Time optimization is possible because the two considered factors, namely, market impact and volatility risk, are oppositely affected by time. In general, a short liquidation period requires more rapid trades and thus a higher market impact whereas the volatility risk is reduced and vice versa. The personal risk tolerance of the investor is modelled by the level of confidence \( 1 - \alpha \) which assigns a weight to volatility risk.\(^{15}\) Therefore, the objective function to determine the optimal liquidation period is

\(^{15}\)We can compare this to modern portfolio theory where the efficient frontier is found by minimizing \( W^\top \Sigma W - qR^\top W \), with \( W \) being a vector of portfolio weights, \( \Sigma \) the covariance matrix, \( q \in [0, \infty) \) the risk tolerance factor and \( R \) the return matrix of the portfolio assets. When scaling the portfolio variance with \( q^{-1} \) we see that the weight is increasing in \( q \) which is similar for our weight \( N_{1-\alpha} \) that is strictly increasing in \( 1 - \alpha \) (for \( \alpha > 0.5 \)), the level of confidence.
formulated as
\[
L = E[C] + N_{1-\alpha} \sqrt{\text{Var}[C]}
\]
\[
= -\frac{1}{2} \mu X T + \epsilon X + \frac{\eta X^2}{T} + \frac{1}{2} \gamma X^2 + N_{1-\alpha} \sqrt{\frac{1}{3} T \sigma X}
\]
\[(5)\]

where \(N_{1-\alpha}\) the \(1 - \alpha\) quantile of the normal distribution. The first term of Equation (5) is the expected value of transaction costs and therefore comprising the permanent and temporary market impact. The second term uses the standard deviation of liquidation costs, that is the risk incurred from holding the position for a given confidence level. Multiplying with \(N_{\alpha}\) is simply a VaR measure for holding the position during the sales period, thus we are optimizing the risk trade–off that arises from liquidation.

To minimize the liquidity cost function, we can now simply set the first partial derivative, with respect to time \(T\), equal to zero
\[
\frac{\partial L}{\partial T} = -\frac{1}{2} \mu X - \frac{\eta X^2}{T^2} + \frac{N_{1-\alpha}}{2} \sqrt{\frac{3}{T} \sigma X} = 0
\]
\[(6)\]

Ignoring \(\mu\) which we assume to be zero for the relatively short time period \(T\), the optimal liquidation period can be calculated as
\[
T = \left(\frac{2 \sqrt{3} \eta X}{N_{1-\alpha} \sigma}\right)^{\frac{2}{3}}
\]
\[(7)\]

To derive the VaR measure of the position including market impact, let us consider the Delta–Normal approach with confidence level \(1 - \alpha\) where we assume normal distributed value changes, i.e. \(\Delta V \sim N(\mu_{\Delta V}, \sigma_{\Delta V}^2)\). Hence, we can write
\[
1 - \alpha = P\left(\frac{\Delta V - \mu_{\Delta V}}{\sigma_{\Delta V}} \leq \frac{-\text{VaR}_{\alpha, \Delta t} - \mu_{\Delta V}}{\sigma_{\Delta V}}\right)
\]
\[
= N\left(\frac{-\text{VaR}_{\alpha, \Delta t} - \mu_{\Delta V}}{\sigma_{\Delta V}}\right)
\]
\[(8a)\]

as before we ignore \(\mu_{\Delta V}\) and rewrite this as
\[
\text{VaR}_{\alpha, \Delta t}(\Delta V) = -N_{1-\alpha} \sigma_{\Delta V}
\]
\[(8b)\]

Substituting the optimal liquidation period from Equation (7) into Equation (4b) yields the variance for the optimal liquidation period \(\bar{V}[C]\). When substituting this into Equation (8b) we arrive at the liquidity component VaR. With the standard deviation of the position \(\sigma_{\Delta V} = \sigma X\) and the repeated use of Equation (8b), we write our Liquidity Adjusted Value at Risk (LaVaR) as
\[
La\text{VaR}_{\alpha, \Delta t}(\Delta V) = -N_{1-\alpha} \sigma_{\Delta V} - N_{1-\alpha} \sqrt{\bar{V}[C]}
\]
\[
= -N_{1-\alpha} \sigma_{\Delta V} - \left(\frac{2 \sigma^2 N_{1-\alpha} X^4}{3}\right)^{\frac{1}{3}}
\]
\[(9)\]
The first term in Equation (9) is a standard VaR measure, the second term comprises the additional risk that we expect to incur through a liquidation of the entire position. Together with the Delta–Normal VaR, comes the assumption of normally distributed risk factor returns, this is the biggest problem of the simple measure as it is easily shown that many market returns are simply not normally distributed, we will revisit the empirical properties of our specific risk factor returns in the next section.

As depicted in Figure 4, LaVaR is a convex function of the position size $X$, in contrast to the vanilla approach that is linear in $X$. This demonstrates that, under the given model, the marginal increase in risk of the position increases with its size. This is explained naturally by liquidation factors that become more (or only) relevant for large positions. In case of the SCP, this was prominently the ”Weinstein problem”, i.e. the exposure to other market participants that gained awareness of the position. But, also at an earlier stage, during the build up period, there is evidence (see Section 3) that liquidity effects made it increasingly difficult to manage the SCP.

One concern about this risk measure is the estimation of the market impact coefficient $\eta$. Hisata and Yamai (2000) follow an approach that is based on stock exchange tick data and essentially an application of the classical paper of Kyle (1985) on market micro–structure theory. From publicly available information, this approach is hardly applicable to the SCP and its credit derivatives. This is because the underlying market is OTC, where deals must not necessarily be reported or made public in a timely manner. The DTCC (2014) provides market volume (notional) data for credit indices, which is published on a weekly basis and partially condensed to only reflect the most relevant indices. Therefore the market volume data that is available, is not sufficiently granular to apply market micro–structure theory on the level that would be required to infer an accurate $\eta$ coefficient. Within a bank like JPMorgan the available data for risk management should be much better. In particular, the MTM efforts of trading desks and the Bid–Ask spreads that are observed through active trading, should provide valuable insights on the relative position size and resulting market impact. The percentage change in LaVaR as a function of $\eta$ is depicted in Figure 5. We observe that the estimation is relatively robust to smaller estimation errors. For example, an upward misspecification by a factor of two would result in LaVaR change of less than 30%, on the lower side the change would be about -20% if we half the value for $\eta$.

Another possible error source is our assumption that the trading strategy must be fully executed once it is triggered and can not be adjusted during the liquidation period. The possible error is also related to $\eta$, because a misspecification could result in an over– or underestimation of the impact. Once the liquidation is executed, there is a gain in information, particularly on the impact, that would possibly influence the trading behaviour. A recent development in this field is to capture the operative adjustment of trading behaviour by dynamic programming. Current research on this topic can be found, for example, in Guéant et al. (2012). For our purposes the model which is tractable and intuitively describing the risk situation of the SCP is sufficient. Additionally, the dynamic programming efforts are only able to account for dynamics in strategy, the estimation problem of $\eta$, or similar variables that describe the market impact, remains.

Apart from the estimation of $\eta$, LaVaR is straight–forward to use, closed form solution to incorporate market risk when the position in question cannot be assumed to be liquidated, without causing an impact on the corresponding market price. Through this measure,
Figure 4: LaVaR as a function of a relative change in position size $X$. In contrast to the classical Delta–Normal VaR, the liquidity adjusted VaR measure is a convex function of position size. This reflects the non linear increase in risk that also the CIO experienced with its SCP.

Figure 5: LaVaR as a function of a relative change in market impact coefficient $\eta$. LaVaR is a concave function of $\eta$ and, therefore, more sensitive to an underestimation of $\eta$. This reflects the lower natural bound of 0, the effect of a possibly infinite overestimation of $\eta$ is marginally decreasing.
we derive the natural result that the risk function is convex in terms of position size. This describes a major factor that was governing the SCP loss. Additionally, we exhibit that LaVaR as a function of market impact coefficient $\eta$ is relatively robust to estimation errors, the concave shape of the function decreases the misspecification error and, therefore, provides an additional buffer, or, in other words, provides a more conservative measure. In the following, we take a portfolio view and explain the size impact on diversification and thus incorporate a correlation view on position size.

5.2 Marginal Risk Contribution

In this section, we take a portfolio view and analyse the risk contribution change that is caused by adding positions. This means that we incorporate asset correlation and thus analyse the diversification effect behaviour under changing position size. From a risk management perspective, this is particularly relevant to foster awareness on risk concentrations as well as positions that must be monitored with particular care. In a highly complex book like the SCP, it might, therefore, be beneficial to identify the main risk driver to either manage concentration risk in terms of adjusting the position, or at least review the specific risks of these positions. In the following, we derive general results on the behaviour of risk concentration. This results are well known to practitioners but not thoroughly covered by academic literature.

For our discussion, we use the standard deviation $\sigma_P$ as risk measure of a portfolio $P$ with $M$ assets that we index by $m = 1, ..., M$. Let us write the portfolio return $\mu_P$ and variance $\sigma^2_P$ as

\begin{align}
\mu_P &= \sum_{m=1}^{M} w_m r_m \\
\sigma^2_P &= \text{Var} \left( \sum_{m=1}^{M} w_m r_m \right)
\end{align}

(11a) (11b)

From here, we can analyse the derivatives of our risk measure $\sigma_P = (\sigma^2_P)^{1/2}$ with respect to the relative position size, i.e. the weight $w_m$. With

\begin{align}
\frac{\partial \sigma^2_P}{\partial w_m} &= 2\sigma_P \frac{\partial \sigma_P}{\partial w_m}
\end{align}

(12)

and hence the derivative

\begin{align}
\frac{\partial \sigma_P}{\partial w_m} &= \frac{\partial \sigma^2_P}{\partial w_m \cdot 2\sigma_P} \\
&= \frac{\partial \left( w_m^2 \sigma^2_m + \sum_{m=1}^{M} \sum_{k \neq m}^{M} w_m w_k \rho_{m,k} \sigma_m \sigma_k \right)}{\partial w_m \cdot 2\sigma_P} \\
&= \frac{2w_m \sigma^2_m}{2\sigma_P} + \frac{\sum_{k \neq m}^{M} w_k \rho_{m,k} \sigma_m \sigma_k}{2\sigma_P}
\end{align}

(13)
For a homogeneous portfolio with \( w_m = \frac{1}{M}, \sigma_m = \sigma_k = \sigma \) and \( \rho_{m,k} = \rho \) and variance

\[
\sigma_P^2 = \text{Var} \left( \frac{1}{M} \sum_{m=1}^{M} r_m \right) = \frac{1}{M^2} \left[ M\sigma^2 + M(M - 1)\rho \sigma^2 \right]
\]  

(14)

the partial derivative is simply

\[
\frac{\partial \sigma_P}{\partial w_m} = \frac{1}{M} \sigma^2 \sigma_P + \frac{M - 1}{M} \rho \sigma^2 \sigma_P = \sigma_P
\]  

(15)

Trivially, adding positions to a portfolio has a risk impact, which can be measured by the first partial derivative above. This relationship might not be linear and thus requires understanding of the risk contribution change, that is driven by position size. This non-linearity effect is related to correlation because it describes a reduced diversification effect, i.e. losing the opportunity to diversify by concentrating the portfolio on one or a few assets. Thus, the interesting part is the second partial derivative, which can be used to describe the concentration impact of a position change. The second partial derivative of \( \sigma_P \) with respect to \( w_m \) is

\[
\frac{\partial^2 \sigma_P}{\partial w_m^2} = \frac{\partial}{\partial w_m} \left( \frac{w_m \sigma_m^2}{\sigma_P} \right) + \sum_{k \neq m}^{M} w_m \rho_{m,k} \sigma_m \sigma_k \frac{\partial^2 \sigma_P^{-1}}{\partial \sigma_P \partial w_m}
\]  

\[
= \frac{\partial \sigma_m^2}{\partial \sigma_P} + w_m \sigma_m^2 \frac{\partial}{\partial w_m} \sigma_P^{-1} + \sum_{k \neq m}^{M} \rho_{m,k} \sigma_m \sigma_k \frac{\partial \sigma_P^{-1}}{\partial \sigma_P} \frac{\partial}{\partial \sigma_P}
\]  

\[
= \frac{\sigma_m^2}{\sigma_P} - \left( \frac{w_m \sigma_m^2}{\sigma_P^2} + \sum_{k \neq m}^{M} w_k \rho_{m,k} \sigma_m \sigma_k \right) \sigma_P^{-2} \frac{\partial}{\partial \sigma_P} \sigma_P^{-1}
\]  

\[
= \frac{\sigma_m^2}{\sigma_P} - \left( \frac{w_m \sigma_m^2}{\sigma_P} + \sum_{k \neq m}^{M} \rho_{m,k} \sigma_m \sigma_k \frac{\partial}{\partial \sigma_P} \right)
\]  

(16)

for the homogenous portfolio this simplifies to

\[
= \frac{\sigma_m^2}{\sigma_P} \left( 1 - \frac{1}{M} - \frac{M - 1}{M} \rho \right)
\]  

\[
= \frac{\sigma_m^2}{\sigma_P} \left( 1 - \frac{1}{M} \right) (1 - \rho)
\]  

(17)

This result shows that the concentration impact is increasing with decreasing correlation \( \rho \). This effect has the boundaries that are introduced with correlation. For \( \rho = 0 \) the concentration impact is at its maximum. In the extreme of \( \rho = 1 \) there is no concentration impact because everything is already concentrated. In this sense concentration impact describes a loss of diversification benefits.

Also interesting is the the interference of one with another position and thus the partial derivative in respect to \( w_m \) and \( w_k \). Analogous to the homogeneous portfolio above, this is

\[
\frac{\partial^2 \sigma_P}{\partial w_m \partial w_k} = \frac{\sigma_m^2}{\sigma_P} \left( \frac{1}{M} \right) (\rho - 1)
\]  

(18)
This demonstrates that the correlation driven effect of the prior derivative has the opposite effect on the other assets. Namely, the risk allocation on other assets is reduced.

In this section we had a look at the stories that derivatives of a risk measure can tell. The insights can be applied to the understanding of trading positions and relative size on portfolio level. In the next section we combine this insights with market data from the time of the SCP.

6 Market Environment and Risk

In this section, we analyse the credit market environment at the period in time which is relevant for the SCP. This is merged with the insights from the prior sections, to get a more thorough understanding on the market risk factors that where governing the SCP loss. We continue to exhibit that the impact of position size was an essential factor that was probably not been regarded with the appropriate attention by JPMorgan’s personnel.

6.1 Risk Factor Statistics

The first step is to identify the risk factors of the portfolio. From the prior sections, we know that the SCP was a pure synthetic credit portfolio comprising indices and tranches of CDX and iTraxx. From Section 2, we know the required parameters to evaluate credit index products, this helps to identify the relevant risk factors. In the following, we list relevant risk factors that influence the credit spread and models that are used in the study.

- Recovery Rate ($-\cdot$), the recovery rate is often assumed to be constant. Utilizing the credit triangle from Equation (24) leads to a low sensitivity of the valuation model towards this parameter. On the other hand, we also described that in a high credit spread environment the recovery rate assumption gains significant influence as it defines the payment on default. As this payment is reduced with increasing recovery, the MTM value of a protection buyer is decreasing with an increasing recovery rate.

- Probability of Default ($+\cdot$), this was introduced in Section 2 and treated as a Poisson variable where we used the credit triangle relationship to model the default intensity $\lambda$. Obviously, an increased likelihood of experiencing a default increases the premium (spread) that has to be paid for protection.

- Interest Rate ($+\cdot$), the interest rate defines the discounting on both sides, contingent and coupon leg. In its sensitivity, it is comparable to other fixed income products and elaborately described in the according literature.

- Default Correlation ($\pm\cdot$), every multi asset product is exposed to correlation. This is true for the index but of particular importance for tranche products. The spread of high subordination tranches increases with correlation as the increasing risk of joint defaults also increases the chance that the senior tranche is affected by a default. For equity tranches, we find the opposite effect. The picture is not that clear for mezzanine tranches.
The listed risk factors are either unobservable or stochastic. The observable figure that combines this information is the traded credit index spread. For single entity CDS, those parameters are modelled explicitly. For CDS portfolios, it can be useful to model the combined (index) spread directly as a stochastic variable with a model that captures its unique statistical properties.

Research on the statistics of credit markets by Cont and Kan (2011) suggests that credit spread returns appear to be stationary with positive autocorrelation, conditional heteroskedasticity, leptokurtosis, mean-reversion, and large co-movements (jumps) that are not necessarily linked to defaults. For the modelling of credit index spreads, Cont and Kan (2011) suggest a discrete–time $AR(1) – GARCH$ model. This line of research is continued in O’donoghue et al. (2014) where the mean reversion component is incorporated by utilizing a hybrid of the Black and Karasinski (1991) and the Ornstein and Uhlenbeck (1930) model. In recent literature on credit modelling, it is standard to explicitly model the jump property. Recent work on this field is published by Packham et al. (2013) and Hellmich et al. (2013).

Figure 6 depicts the credit spread for CDXNAIG.9.10Y as well as iTraxxEur.9.5Y. These are two of the 120+ SCP credit indices with the highest weight (see Table 1), that also represent the major markets the CIO was trading in, namely the US and Europe. We see the increase in credit spread from July 2011 that was caused by the worsening perception of Europe’s credit environment and root for increased trading activity on the SCP. From Section 3.1 we know that the portfolio was initially intended as a hedge portfolio and, therefore, short credit risk. Short credit risk means being the protection buyer and thus loosing MTM value on decreasing spreads. For both indices, we see a decrease in spread for the first quarter of 2012 and thus a general market direction which would have gone against a short position. In their efforts to trade against their losses, we also know that the book’s direction was reversed to a net long position by the end of the first quarter in 2012. Ironically, this is about the time where we see that the spread is increasing and thus going against the SCP again. From the information we have on the SCP trading and the credit spread information from Figure 6 it seems that the SCP was constantly positioned in the opposite market direction. Market direction alone does however not explain the 6.2 bln USD loss.

The SCP that also incorporated curve as well as Long–Short trades, was highly dependent on correlation. In Section 5.2, we explain how position size impact is influenced by correlation. Referring to Figure 7 we see that, together with the credit spreads, the average correlation between the SCP assets decreased significantly. From the decreasing correlation follows an increasing concentration impact. This, however, did not prevent the CIO traders to increase the size of their positions and, in particular, the ones mentioned above to enormous levels. A risk management with diminishing diversification at heart would possibly have prevented this trading to some degree.

### 6.2 VaR and LaVaR

To comprehend the VaR figures of the SCP, we reassemble the portfolio as of March 30, 2012. For this date, we have precise information on the composition of the portfolio, including net notional. This provides 107 indices and tranches for our analysis, where we have market
Figure 6: Index spread levels, returns and normal QQ–Plots (2011/12). The two time series are in place of the major credit index markets that the CIO was trading in. Additionally, they rank among the SCP assets with the highest weight (see Table 1). Data–Source: Markit

Figure 7: Rolling (30d) average correlation of the SCP assets (2011/12). In early 2012 the average correlation of the assets within the SCP decreased significantly. Data–Source: Markit
data as well as net notionals to compute portfolio weights and returns. The credit index data is in spread format, which we convert to upfront payments, by the use of Equation 23a. For the conversion, we use the corresponding recovery, interest rate and maturity of each index. The tranche data is already in upfront format and thus not converted. To compute the relevant risk factor returns, we utilize the relationship of upfront to the clean price. For credit indices, this price is the percentage of notional adjusted for the upfront payment without including accrued interest and hence $1 - \text{Upfront}$ (Markit, 2009b). To maintain portfolio additivity, we compute discrete returns on these prices.

Now that we arrived at risk factor returns, it is simple to compute the common VaR measures, including Historical Simulation and Delta Normal. Computing the LaVaR measure is not that straightforward due to market impact coefficient $\eta$. As mentioned before, there is market microstructure theory that can not be applied to the weekly DTCC position data. Additionally, the internal trade data that could help to determine this coefficient is not publicly available. Hence, we reverse-engineer the coefficient from different VaR measures. This idea has two important assumptions:

- For a historical period, the VaR as computed by Historical Simulation is precise. Because of the long look back period (250 trading days) the measure does not pick up recent developments fast enough and is not sensitive to market liquidity.

- The Delta Normal VaR is usually in understatement of the actual risk. The difference between the two VaR measures is assumed to be the result of market impact.

We fit $\eta$ in a way, such that the two VaR methods equate for a historical period of 250 trading days. With this coefficient we can transit to a VaR model that is able to pick up more recent market information, thus recent volatility. Classical models for this purpose are the class of GARCH models as well as EWMA and EWMA Covariance models (Engle, 2009). This are viable approaches to model volatility in our LaVaR set-up.

In Figure 8, we depict the relative LaVaR with 95% confidence against the returns of our portfolio. For comparison, we also depict a 30 trading days Historical Simulation VaR. LaVaR is the sum of the liquidity risk component and a standard Delta Normal VaR. For this reason, the latter is always below LaVaR and the distance determined by market liquidity. Even for the short period of 30 trading days, we see that LaVaR is much faster in adjusting to volatility changes than Historical Simulation, while at the same time scalable to account for market liquidity. For the entire period, the Historical Simulation VaR was breached\textsuperscript{16} 18 times out of 289 trading days whereas LaVaR was breached 8 times. This means a breach ratio, for the two measures, of 6.23% and 2.77%, respectively. Due to the 95% confidence level, the expected number would be 5% and thus lead to the conclusion that our market impact coefficient is slightly overestimated. In other words, the measure is more on the conservative side.

Our analysis does only reflect the original SCP weights as of March 30, 2012. We know that the portfolio weights were not constant, because the general direction of the portfolio changed from short to long, as described in Section 3. If we compare our VaR calculations to the reported numbers from Figure 3, we find our values to be nearly twice as high. This

\textsuperscript{16}The number of VaR breaches is also the basis for the regulatory (Basel) back-tasting approach (BCBS, 1996). Further methods for the assessment of risk measure goodness in Cremers et al. (2012).
includes LaVaR as well as the 250d Historical Simulation VaR, that was reported to be the basis of JPMorgan’s 10–Q VaR figure (see Section 4.2). The JPMorgan numbers are not exclusive for the SCP, but for the CIO as a whole. Additionally, the underlying calculation methods can not be reassembled entirely and the weights not reproduced for the interim period. This alone does, however, hardly explain the twofold VaR difference.

6.3 Portfolio Balancing under Market Impact

One paradigm of the SCP strategy was to buy protection on high yield that was funded by selling protection on investment grade indices. Because the traders had to balance the book, in order to reduce RWA, they had to do so by focusing on these two index groups. We described in Section 3.2 that this was attempted by the use of linear sensitivity measures, particularly CSW10. In this section we show that market size, i.e. liquidity, had a significant impact on the CSW10 portfolio balancing.

Together with the two indices from Figure 6 we analyse CDXNAHY.9.5Y, the series 9 high yield index that represents the protection side on the book. A simple sensitivity hedge would us a ratio such that the change of two assets is offsetting. For linear measures this ratio can–not be assumed constant. As the ratio is driven by the sensitivity difference between assets, we want to analyse the behaviour of this difference during the lifetime of the SCP. We calculate the CSW10 measure by utilizing Equation (25), while assuming the market standard recovery rate of 40%. Figure 9 shows the CSW10 difference between CDXNAHY.9.5Y and the opposing position, namely CDXNAIG.9.10Y and iTraxxEur.9.5Y, normalized to January 02, 2012. The data shows that this spread increased by about 40% against CDX and more than 200% against iTraxx during the first three month of 2012.

To capture the market impact we compare this findings to gross notional data from the
Figure 9: CSW10 difference between selected high yield and investment grade indices (2011/12). The graph shows the sensitivity difference between high yield and investment grade indices normalized to January 02, 2012. Data–Source: Markit

DTCC (2014) by the use of Ordinary Least Square regression. The gross notional represents the market size and, therefore, liquidity environment. The data range includes the first half of 2012, where the relevant SCP trading took place (2012 sample period) as well as a pre period (2011 sample period). This is, we split the data into a pre period where we would expect no significant impact and the period where the traders defended their positions and thus created artificial market impact.

The results are depicted in Table 3 and show that high yield series 9 gross notional and gross notional, with a lag of one week is statistically significant in explaining the CSW10 difference variation for the 2012 sample period. More specifically, the $R^2$ for this sample period and both spreads range between 16.27% and 37.76% with p–values below 3% without lag and 7% for the lagged variables. We do not find this levels of significance when using gross notional of the investment grade indices. This is not unexpected because the high yield market is smaller than the investment grade market and thus provides less liquidity.

We show that for the period where the relevant SCP trading took place, the market size had a significant impact on the CSW10 difference between this high yield and investment grade indices. This difference was essentially driving the hedge ratio for the SCP. In order to balance the portfolio the traders increased their positions along with the change in CSW10, which in turn had an impact on the market. In this sense, JPMorgan chased its own sensitivity measure. This is again in strong support of risk measures that incorporate market liquidity. From a pure market perspective, the proposed methods for measuring liquidity and concentration could have had an essential impact on the risk management and trading decision making for the SCP.
Table 3: Regression Results for CSW10 Difference

<table>
<thead>
<tr>
<th>Regressand:</th>
<th>HY–iTraxx</th>
<th>HY–CDX</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient</td>
<td>1.9926</td>
<td>0.61087</td>
</tr>
<tr>
<td>P-Value</td>
<td>0.384</td>
<td>0.0275</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.023</td>
<td>0.2204</td>
</tr>
<tr>
<td>DF</td>
<td>33</td>
<td>20</td>
</tr>
</tbody>
</table>

HY–GN = CDXNAHY Series 9 Gross Notional; Data-Source: DTCC (2014)

7 Conclusion and Lessons Learned

"... flawed, complex, poorly reviewed, poorly executed and poorly monitored."

JPMorgan CIO James Dimon (2013)

The story of the trading that evolved around the SCP reads like a drama, where it seems that every single step was in the wrong direction. When the SCP was long, the market was going down. After the traders positioned the portfolio in a net long, the market turned and went up. But, before handing over the gold medal for the most unlucky strategy of 2012, one has to take a closer look. In aviation, a pilot can "fly behind the power curve". For reasons of drag this means flying at a low air–speed with a high amount of thrust required to keep the aircraft flying. This goes well and is the essence of precise landings, as long as the pilot is in full control of both air–speed and power. For the SCP, it seems that the traders were constantly trading behind the power curve at times, where they gradually lost control of their portfolio. In this situation, if the pilot is unable to increase air–speed, i.e. pitch down the aircraft, while at the same time his engine quits, the aircraft will inevitably stall and crash. This is again a perfect analogy of the SCP, at some point, the portfolio had grown so large, that the traders got trapped in their positions and faced only one remaining option – power. This power came from the massive amount of assets that the CIO had at its disposal and helped the traders to defend their positions for some time, until senior management halted trading. At this point, the SCP literally crashed and started to lose the massive amounts of money that are depicted in Figure 1.

The portfolio that was initially intended as a hedge against the natural long credit position of a bank, was managed in a way that seems to neglect any form of risk awareness and management. In contrast to the trading drama, the risk management story reads more like a grotesque. During 2012, the CIO recorded several risk limit violations, some of which were at a stage in the process where the position might have still be closed, with losses far away from 6.2 bln USD. This, however, did not trigger concern on the management or risk side. The latter was possibly busy with developing a new VaR model that would effectively decreased the risk figure by half. One may argue that this was a limited and partially technical problem at JPMorgan, however, the implications from the case range much further. This case, as several others, shed light on a business culture that does not
incentivise risk awareness. Even worse, it seems that the pressure to not lose money is triggering a behaviour that we call doubling down risk. From a trader’s point of view, this is based on the finding, that it seems to be more advisable to take immense amounts of risk, in return for the little chance of making up for losses, than to close down directly on a loss. For the underlying case, this yielded a shadow PnL that might not be that unique, in particular for credit and similar markets with non–trivial mark–to–market valuation methods.

We established that the classical risk measures are not capable of capturing risk as it would be necessary to account for the special properties, that arise from large trading positions. These are, in particular, the market impact that can make up a significant portion of PnL as well as the size effect on diversification within the portfolio. Market impact is caused by the trade–off between selling a position in a short period, and thus minimizing the uncertainty about future prices versus the supply that is forced on the market, where a lag of demand could yield a price impact. This effect can be as extreme as a 1,000–point drop in the Dow Jones, as was evidenced by the so called ”Flash Crash” in 2010. On less liquid markets, e.g. off–the–run credit index tranches, even a smaller position is still likely to cause an impact.

In particular, the liquidity adjusted LaVaR measure yields valuable insights but is problematic to implement for OTC credit derivative markets. The credit spread alone is not sufficient to quantify the market impact. The DTCC data is helpful for describing the relative size of a portfolio, but not granular enough to apply the common market micro structure theories on quantifying market impact. Future research on robust market impact estimation methods would be highly beneficial for the model.
A Appendix

A.1 Credit Index Valuation

As the mark to market (MTM) change of a CDS position is not simply a linear function of the credit spread, it is necessary to find a suitable valuation model before pursuing a risk analysis. Therefore, this section focuses on deriving a simple mark to market formula that is however reasonably close to observations from traded credit instruments. With the credit spreads being observable we can then derive empirical properties of the resulting position changes. This helps to find a suitable set-up for modelling the major risk factors. To derive the valuation formulae we follow O’Kane (2008), while adding the assumption of continuous–time cash flows.

By construction credit indices are traded like a portfolio of equally weighted plain vanilla CDS. We index the constituents by \( m = 1, \ldots, M \) and denote \( T \) as index maturity. The index has two legs, the contingent (protection) leg is only triggered by the default of a reference entity \( m \) and results in a loss of \( (1 - R_m)/M \), where \( R_m \) is the recovery rate of the defaulted entity. For the premium leg on the other side, a default triggers a reduction of the premium basis, this is, that for every default in the index the premium relevant notional is henceforward reduced by \( 1/M \). The cash flow frequency is defined by the index provider. Before moving to a continuous–time model, we assume annual spread payments in \( t = 1, \ldots, T \) that are discounted by a discount factor \( D(t) \).

In portfolio terms this yields the intrinsic expected value of the contingent leg in \( t = 0 \) under the risk–neutral pricing measure as

\[
PV \text{ Contingent Leg} = \mathbb{E}_Q \left[ \frac{1}{M} \sum_{m=1}^{M} (1 - R_m) D(\tau_m) 1_{\{\tau_m \leq T\}} \right]
\]

and for the premium leg with standardized coupon \( C(T) \)

\[
PV \text{ Premium Leg} = C(T) \mathbb{E}_Q \left[ \frac{1}{M} \sum_{m=1}^{M} \sum_{t=1}^{T} D(t) 1_{\{\tau_m > t\}} \right]
\]

The hedge–/ and therefore arbitrage–argument behind the risk–neutral measure \( Q \) is explained in O’Kane (2008). From Equations (19a) and (19b) we see that the valuation problem is subject to the modelling of the recovery rate \( R_m \) of the defaulting entity, the interest rate which we express in terms of risk free discount factors \( D(t) \) and the default \( 1_{\{\tau_m \leq T\}} \) or survival \( 1_{\{\tau_m > t\}} \) until a specific point in time. For the evaluation we assume a constant recovery, where for example 40% is often used as market standard for senior CDS and credit indices. The risk free discount factors could be bootstrapped from interest markets, e.g. from a swap curve. In the following we will further simplify the problem by also assuming a constant interest over the time of the product that is paid continuously, hence \( D(t) = \exp(-rt) \). For the modelling of defaults we consider the associated default times \( \tau_1, \ldots, \tau_n \) defined on the probability space \( (\Omega, \mathcal{F}, P) \). For our credit index valuation we assume a constant hazard rate \( \lambda \), which simplifies the problem of finding the probability of survival to

\[
P(\tau > T) = \mathbb{E}_Q[1_{\{\tau_m > t\}}] = \exp(-\lambda T)
\]
In this case the default time is modelled as the first jump of a Poisson process with jump intensity \( \lambda \), which implies an exponential distribution for the time of default \( \tau \).

Assuming payments in continuous-time we rewrite Equation (19a) to evaluate the credit index analogue to the single CDS, where the default times and respective correlations of the constituents are implicitly modelled by the hazard rate of the index.

\[
PV \text{ Contingent Leg} = (1 - R)\lambda \int_0^T \exp(-(r + \lambda)t)dt
\]

(21a)

and for the coupon leg

\[
PV \text{ Premium Leg} = C(T) \int_0^T \exp(-(r + \lambda)t)dt
\]

(21b)

From Equation (21a) and (21b) we can already see that a fair valuation, i.e. a spread that yields a net present value of zero, is only possible if \( C(T) = (1 - R)\lambda \). This relationship is called credit triangle. We denote the fair spread \( S(T) \) as the coupon that would equate both legs and thus fulfil this relationship. In practise the premium leg payments are determined by a standardized coupon \( C(T) \) we find the resulting present value \( PV_{CDS} \) by subtracting the premium leg from the contingent leg. This value is exchanged between the two counterparties on inception of the deal and called upfront payment:

\[
PV_{CDS} = [(1 - R)\lambda - C(T)] \int_0^T \exp(-(r + \lambda)t)dt
\]

(22a)

As the fair market spread \( S(T) \) can be observed, we rewrite this by utilizing the credit triangle relationship, hence

\[
PV_{CDS} = [S(T) - C(T)] \int_0^T \exp(-(r + \lambda)t)dt
\]

(22b)

Evaluating the integral yields

\[
PV_{CDS} = (S(T) - C(T)) \frac{1 - \exp[-(r + \lambda)T]}{r + \lambda}
\]

(23a)

This can be decomposed into the difference of the fair spread against the standardized coupon which is evaluated by a risky anuity, e.g. by multiplying with the Risky-PV01 (RPV01).

\[
= (S(T) - C(T)) \times RPV01(T)
\]

(23b)

Finally we utilize the credit triangle

\[
\lambda = \frac{S(T)}{1 - R}
\]

(24)
where substituting into Equation (23a) yields

$$PV_{CDS} = (S(T) - C(T)) \frac{1 - \exp[-(r + \frac{S(T)}{1-R})T]}{r + \frac{S(T)}{1-R}}$$

(25)

From this and Equation (23b) we get the Risky-PV01 for period $T$ as

$$RPV01(T) = \frac{1 - \exp[-(r + \frac{S(T)}{1-R})T]}{r + \frac{S(T)}{1-R}}$$

(26)

Henceforward Equation (25) will be the main workhorse to evaluate JPMorgan’s single positions, derive according loss distributions and empirical properties. The simplifying assumptions made in this section as well as the utilization of the credit triangle for our risk management application are justifiable for not being far of the mark as shown in O’Kane (2008, p. 130).

A.2 Tranche Mechanics and Valuation

As mentioned above there exists a reasonably liquid market of standardized credit index tranche products. This OTC market is more accurately described as a market of single-tranche synthetic CDOs (STCDO). In this sense the trading is similar to the classical CDO with important differences being: no special purpose vehicle (SPV) but only a bilateral contract between two counterparties; a standardized reference portfolio that is linked to a credit index; the structure is unfunded and usually entered by paying an upfront payment; and there is no need to issue all tranches and thus there is the possibility that only some tranches are liquidly or at all traded (O’Kane, 2008).

The most considerable property of the STCDO is its mechanism of structural subordination which is often subsumed as STCDO waterfall. This is, of each tranche the pay-off function depends on the cumulative default losses on the underlying portfolio. Every tranche has two defining boundaries, namely, the attachment point $K_A$ and detachment point $K_D$. These are similar to strikes for an option, where the corresponding tranche is only influenced by cumulative default losses $L(t)$ at time $t$ that reach into the interval $[K_A, K_D]$. Between the limits of 0% and 100%, the percentage tranche loss $L(t, K_A, K_D)$ is the linear function:

$$L(t, K_A, K_D) = \max(L(t) - K_A, 0) - \max(L(t) - K_D, 0)$$

(27)

This shows that the cash flow and subsequently present value of a tranche is dependent on the portfolio loss $L(t)$ until $t$ which is defined, analogue to the credit index valuation above, by the defaults of the underlying entities $m = 1, ..., M$, ordered by the time of default $\tau_1, ..., \tau_M$. Hence,

$$L(t) = \frac{1}{M} \sum_{m=1}^{M} (1 - R_m) 1_{\{\tau_m \leq t\}}$$

(28)

17This is only precise for tranches with $K_D$ below the maximum portfolio loss. For the senior most tranches a notional adjustment of $R/M$, following every default in the underlying portfolio, resolves the impreciseness. Further reading on this problem in O’Kane (2008).
Therefore we can write the present value of the contingent leg for a given tranche as a function of the tranche loss change $\Delta L(T, K_A, K_D)$, which itself is simply a function of the portfolio loss $L(T)$. Therefore,

$$PV \text{ Contingent Leg} = \mathbb{E}_{Q} \left[ \sum_{m=1}^{M} D(\tau_m) \Delta L(\tau_m, K_A, K_D) \right]$$

(29a)

and for the premium leg with standardized tranche coupon $C(T, K_A, K_D)$

$$PV \text{ Premium Leg} = C(T, K_A, K_D) \sum_{t=1}^{T} D(t) \mathbb{E}_{Q}[1 - L(t, K_A, K_D)]$$

(29b)

Pricing the tranches gets more involved than plain vanilla CDSs or indices. A viable option that yields computationally efficient closed form solutions is the Gaussian copula model, where we assume a large homogeneous portfolio\(^{18}\) (LHP) for pricing and risk applications of tranches. Market data for standardized tranches is however available in upfront payment format. Thus, there is no requirement for our application to convert a spread to its resulting present value.

### A.3 Details on Selected Credit Indices

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</tbody>
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Source: Markit (2008)

\(^{18}\)Further reading in Vasicek (1987) and (2002).
A.4 CIO Personnel and Reporting Lines

Source: United-States-Senate (2013a, Exhibit 2)
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