Trading and Clearing in Modern Times
ISBN: 978 90 3610 489 0

© Wenqian Huang, 2017

All rights reserved. Save exceptions stated by the law, no part of this publication may be reproduced, stored in a retrieval system of any nature, or transmitted in any form or by any means, electronic, mechanical, photocopying, recording, or otherwise, included a complete or partial transcription, without the prior written permission of the author, application for which should be addressed to the author.

Cover design: Crasborn Graphic Designers bno, Valkenburg a.d. Geul

This book is no.700 of the Tinbergen Institute Research Series, established through cooperation between Thela Thesis and the Tinbergen Institute. A list of books which already appeared in the series can be found in the back.
TRADING AND CLEARING IN MODERN TIMES

ACADEMISCH PROEFSCHRIFT

ter verkrijging van de graad Doctor aan
de Vrije Universiteit Amsterdam,
op gezag van de rector magnificus
prof.dr. V. Subramaniam,
in het openbaar te verdedigen
ten overstaan van de promotiecommissie
van de School of Business and Economics
op maandag 18 september 2017 om 9.45 uur
in de aula van de universiteit
De Boelelaan 1105

door
Wenqian Huang

geboren te Guangdong, China
promotor: prof.dr. A. J. Menkveld

copromotor: dr. V. van Kervel
Acknowledgements

During my PhD, I had the extreme luck to work closely with many excellent people and to learn a lot from them. Their collective contributions were of great importance to the fulfillment of this thesis.

First and foremost, I would like to express my deepest gratitude to my supervisor, Albert J. Menkveld. Thank you for providing me an inspiring and challenging environment. You have been a great mentor, with your door always open for various types of discussions: brainstorming, exploring novel intuitions, addressing economic concepts, and providing career tips, etc. Your comments are always to the point and offered great guidance in addressing my questions.

I would also like to thank Evangelos Benos and Michalis Vasios in the Bank of England. Thank you for offering me a great opportunity to work in the Bank and have a first taste of the policy world. I have learned so much for both of you, not only via numerous discussions about the research project but also from the fun moments in our lunch breaks. I hope that I could be as lively, enthusiastic, and energetic as you two. I am also truly grateful to the other members of the Risk and Research team: Pedro Gurrola-Perez, Gerardo Ferrara, Mark Manning, Emmanouil Karimalis.

I have greatly benefited from the feedback of my Thesis Committee members Peter Boswijk, Jorge Cruz-Lopez, Ton Vorst and Sweder van Wijnbergen. I also benefited a lot from interactions with the finance faculty at VU Amsterdam: Anne Opschoor was always available for a fun chat; Jan Schnitzler, Tanja Artiga Gonzalez, and Norman
Seeger helped me improve my teaching skills; Teodor Dyakov and Liping Lu organized seminar series, from which I benefited a lot.

The Tinbergen Institute (TI) have provided a very nice work environment. I thank all staff members for their friendly support. In particular, I would like to thank Christina Månsson and Arianne de Jong for their assistance in my job market; Judith van Kronenburg and Ester van den Bragt helped me a lot since the moment I arrived at TI.

I was lucky to have friends around me which added lots of fun and colors in my PhD life. Especially, I would like to thank my “big brother” - Marius Zoican who are extremely knowledgable and super supportive. Your encouragement and support mean a lot for me. I am also tremendously grateful to Lucyna Górnicka, Istvan Barra, Janko Cizel, Marcin Zamojski, who offered me great suggestions for my PhD life; Kristian Støre, KY Lee, Hoeming Wong, who provided me many many cool advice about work-life balance; and Nicole Ciurila, Iulian Ciobica, Kimi Jiang, Dieter Wang, Eglé Jakučionytė, Sabina Albrecht, Oana Furtuna, Robin Döttling, Pascal Golec, Sándor Sóvágó, An-ndries van Vlodrop, with whom I had numerous friendly discussions and fun moments.

Of course, the “Chinese group” at TI always made me feel at home - Thank you, Bo Hu, Yuan Gu, Yajie Sun, Shihao Yu, Hao Fang, Shuo Xia, Xiao Xiao, Yang Liu, Tong Wang, Qi Lin, Hang Liu, Yiming Zhang! I will miss all the laughter we have together.

Finally, a really special “thank you!” goes to my family, without whom I will not be who I am today. Mom and Dad, thank you so much for giving me the freedom to pursue my dreams. I hope I make you proud of me; and please keep in mind that no matter how far I go, you are always in my heart. Dear Xiao, my beloved boyfriend and husband, you know my English is too dry to express my love and gratitude to you. I wish all my words could turn to be flowers, deeply planted in your heart and fragrancing your morning everyday. I love you all dearly.

Wenqian Huang
Amsterdam 2017
## Contents

1 Introduction 1

2 Intermediaries and Venues: Connecting End-Users through Time and Space 11

2.1 Introduction ........................................... 11

2.2 Intermediaries and end-users ............................ 18

2.3 Taxonomy of traders .................................... 21

2.4 Profitability of different groups ......................... 26

2.4.1 How profits are related to cross-market activity? ..... 26

2.4.2 How profits are distributed in different frequencies? 31

2.5 Volatile vs quiet periods ................................ 33

2.5.1 Profitability and cross-market trading ............... 34

2.5.2 Frequency decomposition of profitability ............. 37

2.6 Factor-based intermediaries: connecting end-users on the same factors across securities ....................... 38

2.6.1 Identification of risk factors ....................... 39
2.6.2 Intermediaries with mean-reverting positions on risk factors . . . 41

2.6.3 Profitability of factor-based intermediaries . . . . . . . . . . . 43

2.6.4 Comparison between stock- and factor-based intermediaries . . 45

2.7 Conclusion . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 46

2.A Appendix . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 48

2.A.1 Frequency decomposition . . . . . . . . . . . . . . . . . . . . . . 48

2.A.2 Robust check of frequency decomposition of profits . . . . . . . 50

3 Systemic Risk in Real Time: A Risk Dashboard for Central Counterparties 51

3.1 Introduction . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 51

3.2 Approach . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 56

3.2.1 Real-time CCP exposure: tail risk in aggregate losses . . . . . . 57

3.2.2 Decomposition: Root cause(s) of CCP exposure change . . . . 58

3.2.3 Simple example to illustrate the exposure-change decomposition . 62

3.3 Data . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 65

3.4 Application . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 67

3.4.1 Implementation details . . . . . . . . . . . . . . . . . . . . . . . . 67

3.4.2 Real-time CCP exposure . . . . . . . . . . . . . . . . . . . . . . . 70

3.4.3 Decomposition of CCP exposure changes . . . . . . . . . . . . . 73

3.4.4 Three largest exposure increases . . . . . . . . . . . . . . . . . . 75

3.5 Concluding remarks . . . . . . . . . . . . . . . . . . . . . . . . . . . . 85
4 Central Counterparty Capitalization and Misaligned Incentives

4.1 Introduction ......................................................... 91

4.2 Model and first best allocation ..................................... 98
  4.2.1 Model primitives ............................................ 98
  4.2.2 First best allocation ......................................... 103

4.3 Benevolent CCP ..................................................... 104
  4.3.1 Collateral .................................................... 104
  4.3.2 Optimal capital and collateral for a benevolent CCP ........... 107

4.4 Profit-driven CCP .................................................. 111
  4.4.1 Collateralized and mutualized financial resources .............. 112
  4.4.2 End of default waterfall .................................... 115
  4.4.3 Traders’ decision ............................................ 119
  4.4.4 Optimal collateral and capital for a profit-driven CCP .......... 123

4.5 Optimal capital requirement for a profit-driven CCP .............. 127

4.6 Conclusion .......................................................... 130

4.A Appendix ........................................................... 132
  4.A.1 Variable summary ............................................ 132
## Contents

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.A.2 Proof</td>
<td>132</td>
</tr>
<tr>
<td>Summary</td>
<td>143</td>
</tr>
<tr>
<td>Nederlandse samenvatting (Summary in Dutch)</td>
<td>145</td>
</tr>
<tr>
<td>Bibliography</td>
<td>147</td>
</tr>
</tbody>
</table>
A security transaction involves two major processes: trading and clearing. Trading is the process by which a buyer and a seller reach an agreement on price and volume; and clearing is the process of actual exchange of money and securities between the buyer and the seller (BIS, 2010).¹

During the last decade, both trading and clearing have experienced a large number of changes. On the trading side, the proliferation of trading venues, coupled with the rise of algorithmic trading, has greatly reshaped financial markets. On the one hand, financial regulations, such as the Regulation National Market System (Reg NMS) in the US and the Markets in Financial Instruments Directive (MiFID) in Europe, encourage competition between trading venues (see e.g., SEC, 2013; Gresse, 2014). The same securities can be traded in different venues simultaneously and security trading has become highly fragmented (Chao, Yao, and Ye, 2017). On the other hand, High Frequency Traders (HFTs) adopt algorithmic trading to arbitrage across venues and to supply immediacy, which become modern financial intermediaries (see e.g., Menkveld, 2013; O’Hara, 2015; Boehmer, Li, and Saar, 2016; Menkveld, 2016b).

On the clearing side, since the 2007-2008 financial crisis, global regulatory reforms (for instance, Dodd-Frank Act in the US and EMIR in Europe) introduce mandatory central

¹Clearing includes settlement in this context.
clearing to a large number of financial asset classes, which puts a spotlight on Central Counterparties (CCPs). Figure 1.1 illustrates a CCP’s role. Through the “novation” process, a contract between a buyer and a seller splits into two: one is between the buyer and the CCP; the other is between the CCP and the seller. Hence, the CCP provides insurance against counterparty risk. When a trader defaults, the CCP inherits the default loss.

**Figure 1.1: Bilateral clearing vs central clearing**

This figure illustrates bilateral clearing on the left and central clearing on the right. In bilateral clearing, a buyer pays $100 cash to a seller, in exchange for equal-valued security. Both the buyer and the seller are exposed to each other’s potential default. In central clearing, a CCP interposes itself between the buyer and the seller. The CCP is responsible for delivering $100 security to the buyer and $100 cash to the seller. The buyer and the seller are only exposed to the CCP’s potential default.

To prepare a CCP for potential default losses, there are pre-funded financial resources, which together are called “default waterfall.” Figure 1.2 shows a standard default waterfall (Elliott, 2013; Duffie, 2014). The default losses will first be covered by the collateral and default fund contributed by the traders who default. These two layers constitute the collateralized financial resources. The remaining losses will be covered by the skin-in-the-game (SITG) contributed by the CCP. If the CCP’s SITG is not enough, default fund contributed by other traders will be used, which is the last layer of the pre-funded financial resources.
Figure 1.2: Default waterfall

This figure shows a standard default waterfall. Defaulters refer to the traders who default and non-defaulters refer to the traders who do not default.

Nevertheless, CCPs do not eliminate counterparty risk. Instead, CCPs concentrate counterparty risk within themselves. Counterparty default may result in systemic consequences if it threatens CCP solvency, as CCP insolvency will affect all counterparties. As central clearing is introduced to a large amount of asset classes, CCPs become systemic nodes in financial market (Bernanke, 2011).

To safeguard financial stability, it is critical to understand CCP systemic risk, especially in the context of the fast-paced electronic markets. Furthermore, although CCPs are too-systemic-to-fail, many of them operate as profit-driven financial firms protected by limited liability. It leads to a conflict between private incentives and public interest, which underscores the importance of proper incentive regulations.

In my thesis, I study these new features of trading and clearing. Chapter 2 studies trades of modern financial intermediaries; and Chapter 3 and 4 analyze systemic risk and incentive problems of CCPs. Although the chapters of this thesis are self-contained and can thus be read independently, the remainder of the introductory chapter serves as a “road map” for the thesis.

Trades of modern financial intermediaries

Chapter 2 studies how modern financial intermediaries supply immediacy along both the time dimension and the space dimension. Traditionally, intermediaries are modeled as
liquidity providers that link buyers and sellers along the time. But the proliferation of trading venues and the rise of algorithmic trading change the landscape of financial intermediation in security markets. Modern financial intermediaries also actively trade across venues and supply immediacy along the space dimension (Menkveld, 2013).

We develop a taxonomy of intermediaries depending on the dimension(s) they connect end-users: time (TimeOnlyInt), space (SpaceOnlyInt), or both (TimeSpaceInt). Furthermore, frequency domain analysis is applied to study the frequency patterns of trades and profits for different types of intermediaries. With a unique dataset of trades in Nordic equity markets on eight trading venues, our analysis provides empirical evidence on cross-market activity and profitability of intermediaries. 15 intermediaries (out of 226 trading accounts) are identified based on their mean-reverting positions on stocks (Kirilenko et al., 2016; Korajczyk and Murphy, 2015). They are more active in trading at multiple venues than end-users. Moreover, intermediaries make an average daily profit of 3.2 million euro from end-users. In addition, decomposition of profits into different frequency bins shows that intermediaries make profits in all different frequency bins. For the ultrahigh frequency bins with reverting periods shorter than one minute, the profits of intermediaries are statistically significant at 99% confidence level. Our analysis suggests that the physically fragmented markets are virtually integrated by intermediaries.

Frequency domain analysis reveals that different types of intermediaries profit in different frequency patterns. A TimeOnlyInt makes profits mostly in high frequency bins with reverting periods between one minute and five minutes. A SpaceOnlyInt has significant profits in ultrahigh frequency bins with reverting periods less than one minute. As a combination of both a TimeOnlyInt and a SpaceOnlyInt, a TimeSpaceInt make profits in both ultrahigh and high frequency bins.

Further analysis on volatile periods and quiet periods shows that intermediaries profit tremendously from volatile periods. Intermediaries have an average daily profit of 18.2 million euro during volatile periods, which is much higher than during quiet periods. When markets are volatile, intermediaries make profits no matter whether or how they trade across markets. But during the quiet periods, intermediaries do not always make
profits. Instead, intermediaries need to coordinate their trading in different venues to secure profits.

We also extend the analysis of cross-market arbitrage to statistical arbitrage across securities. In cross-security arbitrage, intermediaries connect end-users trading on the same risk factors across securities. In this case, intermediaries have risky arbitrage instead of deterministic arbitrage. Based on mean-reverting positions on risk factors, there are 12 intermediaries. They have an average daily profit of 11.7 million euro, much higher than that of the intermediaries who have mean-reverting positions on stocks. Moreover, the factor-based intermediaries with large position variance on risk factors have high profits. Frequency decomposition on profits shows that they profit from a longer holding period. The results indicate that factor-based intermediaries are compensated for bearing the risk of statistical arbitrage.

This chapter contributes to the empirical literature of trades and profits of intermediaries. The taxonomy of intermediaries proposed in this chapter provides a new perspective on intermediaries’ roles in modern financial markets featured with substantial security fragmentation and algorithmic trading. Our empirical findings show that modern intermediaries could connect buyers and sellers along both the time dimension and the space dimension.

**Systemic risk management of Central Counterparties (CCPs)**

Chapter 3 turns to the clearing side and develops a tool to monitor systemic risk of CCPs in real time. Electronic markets can change rapidly. High Frequency Traders (HFTs), for example, can build large positions within a millisecond. Recent market turmoils highlight the importance of real-time monitoring on CCP exposure. On October 7, 2016, the pound dropped more than 8% from 1.26 to 1.1491 in just eight minutes. On January 15, 2015, Swiss franc rose by 20% against the euro within five minutes after the central bank shocked global markets by abandoning its peg against the euro. On October 15, 2014, 10-year US bond moved 40 basis points, a huge plunge in a market where a single basis point matters. Such large price variations, coupled with substantial outstand-
ing positions, constitute real economic risk for CCPs. It is therefore not surprising that the CPMI-IOSCO, an international authoritative body of central bankers and regulators, recently formally recommended that CCPs should monitor their exposures in real time (CPMI-IOSCO, 2016a).

We measure CCP exposure as the tail risk of losses in an oncoming period, aggregated across all clearing members (Duffie and Zhu, 2011; Menkveld, 2016a). CCP exposure changes are decomposed into two types of risk factors: price-change risk and trade-change risk. For price-change risk, we disentangle three different risk channels through security price variations: volatility changes, correlation changes, and price level changes. For trade-change risk, we decompose it into position risk and crowding risk. Position risk reflects whether a new trade extends or reverses existing positions, while crowding risk captures the impact of a new trade on the interdependence between traders’ portfolio returns. To pin down whose trades lead to CCP exposure increases, we further decompose position and crowding risk into risk components from house accounts and client accounts. A house account is a clearing account for the clearing member’s own trading. A client account is a clearing account that the member uses for client trades.

We implement the tool with transactional data of the Nordic equity markets. We find extreme right-skewness of CCP exposure changes during the sample periods, implying extreme market stress periods. As we are interested in large CCP exposure increases, we compare the decomposition of CCP exposure changes in normal times and in turbulent periods. In normal times, the three most important factors are position risk from house-house trades, house-client trades, and client-client trades. Together they capture virtually all CCP exposure changes, accounting for 45.9%, 44.6%, and 10.8% of CCP exposure changes, respectively. However, these three factors capture only 70% of the 10 largest increases. It shows that position risk is the only cause for CCP exposure changes in normal times, but not in turbulent periods.

In turbulent periods, volatility changes and crowding risk play an important role in increasing CCP exposure. For the 10 largest CCP exposure increases, the three most important factors are position risk from house-house trades, risk due to volatility changes,
and crowding risk from trading. They capture 47.1%, 20.1% and 17.2% of the 10 largest CCP exposure increases. Moreover, half of the crowding risk in the top 10 increases is from house-house trades. In other words, trade crowdedness of house accounts gives rise to 9.3% for the 10 largest increases, signaling substantial concentration risk among clearing members. The real-time monitoring tool suggests that the CCP should keep track on volatility changes and crowding risk during market stress periods.

This chapter contributes to a rapidly growing literature of CCP systemic risk by providing a useful tool to diagnose quick build-ups in CCP exposure. The tool also has several appealing features. First, it has analytical solutions, which avoids the costly simulations that prohibit real-time implementation. Second, the methodology of delta-normal Value-at-Risk (VaR) is firmly grounded in standard industry practice. Third, the tool accounts for correlations across member portfolios, and thus for the additional risk that crowded positions impose on a CCP.

**Incentive problems of Central Counterparties (CCPs)**

Chapter 4 studies incentive problems of CCPs. Although CCPs are systemically important, many CCPs operate as profit-driven financial firms with limited liability, such as CME in the US and Eurex in Europe. There are potential conflicts between CCPs’ systemic role and their private incentives. Moreover, CCPs in general have a thin layer of skin-in-the-game (SITG), compared to the overall pre-funded financial resources. Figure 1.3 report CCPs’ SITG and default fund, based on the 2016 quantitative disclosure results. Most of the CCPs’ SITG is less than 1% of their default fund.
In this chapter, I construct a static partial equilibrium model to study the incentive problems of a profit-driven CCP with limited liability. The trading environment is similar to the settings of Biais, Heider, and Hoerova (2015) and Perez Saiz, Fontaine, and Slive (2013). There are two dates ($t = 0, 1$), a mass-one continuum of risk-averse protection buyers, a mass-one continuum of heterogeneous risk-neutral protection sellers and a risk-neutral profit-driven CCP. Buyers and sellers are randomly matched and trade a standardized protection contract. Such a contract can be implemented as a Credit Default Swap (CDS). In case of some sellers’ defaults, the losses will be covered first by the collateralized financial resources, then by the CCP’s SITG, and finally by the default fund contributed by other sellers that do not default. Conditional on available capital, the CCP fine-tunes collateral requirements to balance fee incomes against counterparty risk. High collateral reduces potential default losses, but leads to foregone profitable trades.
There are several key results from the model. First, without capital requirement for CCPs, a profit-driven CCP chooses the minimum capital, whereas a benevolent CCP will favor high capital when capital cost is low. The low SITG chosen by a profit-driven CCP leads to insolvency problems. A profit-driven CCP here refers to a CCP that maximizes the CCP’s own value and has limited liability. On the contrary, a benevolent CCP is a CCP that maximizes total welfare surplus, including the utility improvement of traders and the CCP value, and will not default. These two types of CCPs reflect the reality of non-user-owned CCPs and user-owned CCPs (see, e.g., Cox and Steigerwald, 2016). My model suggests different capital regulations for different types of CCPs.

Second, a higher SITG gives rise to a higher collateral requirement, increasing trading cost. This is the general argument used by profit-driven CCPs against high SITG. My model, however, suggests that a higher SITG still could increase social welfare when the benefits of a safe CCP overweight the cost of high collateral cost.

Third, profit-maximization and limited liability create a wedge between the profit-driven CCP’s collateral policy and the socially optimal collateral level. However, regulators can use capital requirements to close the wedge, unless clearing fees exceed a threshold. Hence, the optimal capital requirement for a profit-driven CCP depends on the profitability of the volume-based fee charged by the CCP. It suggests that clearing fee could be an informative variable when regulators consider optimal capital requirements.

To the best of my knowledge, this model is the first in the literature that studies CCP insolvency from the perspective of CCP’s incentives. In the literature of central clearing, CCPs are modeled as benevolent institutions (see, e.g., Koepl, Monnet, and Temzelides, 2012; Biais, Heider, and Hoerova, 2015). My model contributes to the literature by analyzing CCP’s incentive problems explicitly, which sheds light on the policy discussions about CCP resilience.
Chapter 2

Intermediaries and Venues: Connecting End-Users through Time and Space

This chapter is based on Huang and Menkveld (2017). Apart from the collaboration with Albert Menkveld, the research greatly benefits from discussion with Harald Hau.

2.1 Introduction

Competition between trading venues leads to fragmented security trading. The enforcement of financial regulations, such as the Regulation National Market System (Reg NMS) in the US and the Markets in Financial Instruments Directive (MiFID) in Europe, encourages competition between trading venues (see e.g., SEC, 2013; Gresse, 2014). The same securities can be traded in different venues simultaneously. For instance, US stocks are traded simultaneously in 13 stock exchanges in 2017 (Chao, Yao, and Ye, 2017).

But not every trader is trading actively in multiple markets; arguably because multi-market trading is costly. As traders seek liquidity across venues, smart order routers (SORs) are developed to access and compare quotes in different trading venues. Due to the techno-
logical complexity of SORs, many small- and mid-sized brokers will not be able to afford them.¹

**Figure 2.1: Histogram of numbers of trading venues for each trader**

This figure shows the histogram of numbers of trading venues for each trader in Nordic equity markets from Oct 2009 to Sep 2010. The y-axis on the left hand side shows the number of traders and the one on the right hand side shows the relative proportion.

Figure 3.3 shows the number of traders that trade in different numbers of markets in Nordic equity markets from Oct 2009 to Sep 2010. It turns out that around 40% of traders trade only in single venue and less than 10% of traders trade in more than five venues. It underscores the role of intermediaries that bridge across trading venues.

Traditionally, intermediaries are modeled as liquidity providers that link buyers and sellers along the time. Intermediaries “supply immediacy by their continuous presence and willingness to bear risk during the time period between the arrival of final buyers and sellers” (Grossman and Miller, 1988). Empirical evidence supports the theoretical predictions and shows that market liquidity is sensitive to intermediaries’ inventory positions (see e.g., Hendershott and Seasholes, 2006; Comerton-Forde et al., 2010).

¹There is anecdotal evidence for the complexity and cost of SORs. Industry practitioners argue that SORs are too difficult and too expensive to be implemented in Europe. (“Smart routing and proprietary trading – an uneasy marriage?” The Trade magazine, August 06, 2010)
This paper studies intermediaries along both the space dimension and the time dimension. Intermediaries are distinguished from end-users based on whether their net positions mean-revert within the day (see e.g., Kirilenko et al., 2016; Korajczyk and Murphy, 2015). More importantly, intermediaries are categorized into three groups based on their trading patterns. Figure 2.2 shows how intermediaries and venues could connect end-users in three different ways. Suppose there is a seller $S$ at market A at time $t$. The taxonomy of intermediaries is as follows.

**Figure 2.2: Connecting end-users through time and space**

This figure illustrates the taxonomy of intermediaries. There are two trading venues: A and B. There are two time periods: $t$ and $t+1$. $S$ stands for seller and $B$ stands for buyer.

- The first type is **TimeOnlyInt** that connects the seller $S$ with a buyer $B_1$ along the time dimension. The intermediary buys the asset from $S$, holds it for one period, and sells the asset to $B_1$. The intermediary carries the price risk and needs to be compensated (Grossman and Miller, 1988).

- The second type is **SpaceOnlyInt** who connects the seller $S$ with a buyer $B_2$ along the space dimension through cross-market arbitrage. A SpaceOnlyInt trades in multiple markets. Since he arbitrages across markets, a SpaceOnlyInt should have negative covariance between positions in different markets. Furthermore, since a SpaceOnlyInt does not hold securities along the time dimension, his positions should revert in high frequencies.
The third type of intermediaries is **TimeSpaceInt** who connects the seller $S$ with a buyer $B3$ along both the time dimension and the space dimension. A TimeSpaceInt combines Grossman-Miller type market-making and cross-market arbitrage. A TimeSpaceInt trades in multiple markets and holds securities along the time dimension.

Our analysis yields a number of results. We provide empirical evidence on cross-market activity and profitability of intermediaries. Intermediaries are identified based on their mean-reverting positions on stocks. They are more active in trading at multiple venues than end-users do. On average, intermediaries trade in 3.4 venues and end-users trade in 2.5 venues. The average Herfindal index of trading volume and outstanding position\(^2\) across venues for intermediaries are 63% and 55%, which are lower than those for for end-users. Also, intermediaries make an average daily profit of 3.2 million euro from end-users. Moreover, decomposition of profits into different frequency bins shows that intermediaries make profits in all different frequency bins. For the ultrahigh frequency bins with reverting periods shorter than one minute, the profits of intermediaries are statistically significant at 99% confidence level.

The taxonomy of intermediaries leads to different profitability patterns. There are 1 Time-OnlyInt, 3 SpaceOnlyInts and 11 TimeSpaceInts in our sample. First, the TimeOnlyInt on average earns 1000 euro per day. He has most of the profit from high frequency bins, with reverting cycles between one and five minutes. The average daily profit from high frequency bins is statistically significant at 99% confidence level based on the z-test. But the TimeOnlyInt’s profits from other frequency bins are negligible. It means that the TimeOnlyInt profits by intermediating in high frequencies. Second, the SpaceOnlyInts have an average daily profit of 2.2 million euro. They earn significant profits (at 99% confidence level) from the ultrahigh frequency bins, with cycles shorter than one minute. The profits from the ultrahigh frequency bins imply that SpaceOnlyInts profit from cross-market arbitrage. Third, the TimeSpaceInts earn an average daily profit of 1.0 million euro.

---

\(^2\)Each trader’s position is calculated as the cumulation of his trades, based on the assumption of zero position at the beginning of the day.
have significant profits from both the high frequency bins and the ultrahigh frequency bins, suggesting that they are a combination of TimeOnlyInt and SpaceOnlyInt.

Intermediaries have larger profits in volatile periods than in quiet periods. Volatile periods are defined as periods with top quartile VIX, while the rest of the sample periods are defined as quiet periods (Clarida, Davis, and Pedersen, 2009). During the volatile periods, intermediaries have a large daily profit of 18.2 million euro, mainly due to the large profits of TimeSpaceInts. Polynomial regressions show that intermediaries in quiet periods have a U-shape relationship between profit and position covariance across markets. In other words, during the quiet periods, the more correlatively (either positively or negatively) intermediaries trade in different venues, the larger profits they have. It suggests that intermediaries need to coordinate their positions across markets so that they can make money during the quiet periods. But such relationship does not exist in volatile periods. For volatile periods, it turns out that intermediaries in general make profits, no matter whether they trade in different venues correlatively or not.

Relationship between profitability and cross-market activity is different for intermediaries and end-users. There is a significant U-shape relationship between end-users’ profitability and cross-market activity. End-users trade in single market make large losses while those trade in multiple markets make profits, indicating that the latter is more sophisticated.

The analysis on cross-market arbitrage could be extended to statistical arbitrage, in which intermediaries connect end-users that trade on the same risk factors but in different securities.\(^3\) In statistical arbitrage, risk factors are traded in different securities simultaneously, which leads to “cross-security fragmentation.” In this case, intermediaries are identified based on their mean-reverting positions on risk factors instead of that on stocks. Our analysis shows three interesting findings. First, “factor-based” intermediaries have a better profitability than “stock-based” intermediaries, with an average daily profit of 11.7 mil-

\(^3\)A simple example of statistical arbitrage is “pair trading” in which securities are paired based on some statistical characteristics such as high correlation or cointegration. For instance, both Pepsi and Coca Cola produce similar products and are exposed to the same risk factors of soda market. If the stock price of Pepsi undergoes strong (but transitory) buying pressure from end-users so that the statistical relationship between stock prices of Pepsi and Coca Cola breaks down, intermediaries can arbitrage across these two securities and re-establish the statistical relationship. In this way, intermediaries supply immediacy for end-users that trade on the same risk factor.
lion euro. Second, the factor-based intermediaries with large position variance on risk factors make large profits. Third, factor-based intermediaries profits from a longer reverting period than stock-based intermediaries do. All these findings suggest that factor-based intermediaries bear high risk, through the large position variance and long holding period, and are compensated for it with large profits.

This paper contributes to the empirical literature on trades and profitability of intermediaries. Hasbrouck and Sofianos (1993) investigate the trades of NYSE specialists and apply a frequency domain decomposition of the estimated profits. Their results indicate that intermediaries mainly profit from short-term horizons. In other words, their profits are mainly from high frequency bins. Hau (2001) studies the links between location and profits of traders. The frequency domain decomposition of traders’ profits suggest that local proximity enhances profitabilities in high frequency bins, but not in other frequency bins. Coughenour and Harris (2004) analyze the impact of lowering the tick size on the profits of NYSE specialists. They find that profits in high frequency bins are larger for stocks with the larger drop in the relative tick size. Menkveld (2013) focuses on a large high-frequency trader (HFT) that intermediates across two markets. The frequency decomposition results show that the intermediary earns money in high frequency bins but loses money in other lower frequency bins. This paper is also an application of frequency domain analysis on security market data. What distinguishes our paper from the others is that we decompose the profits of different types of intermediaries, depending on how they link buyers and sellers. Hence, our study reveals the frequency patterns of profits for different types of intermediaries.

The paper further contributes to the strand of literature on market fragmentation. O’Hara and Ye (2011) examine the impact of market fragmentation on market quality. Their cross-sectional analyses show that highly-fragmented stocks have lower transaction costs than less-fragmented stocks, suggesting that the physically fragmented markets are virtually integrated as one single markets. Madhavan (2012) studies how quote and volume fragmentation on the US stock markets are associated with the “Flash Crash” on May 6, 2010. The author finds that stocks with higher quote fragmentation on the day before the “Flash Crash” have larger price decline during the “Flash Crash”, suggesting that quote
2.1 Introduction

Fragmentation is an important risk factor in amplifying liquidity shocks. Menkveld and Yueshen (2016) provide a more direct empirical evidence on how market fragmentation may contribute to the “Flash Crash.” Their results suggest that the broken cross-market arbitrage between E-mini and SPY market leads to extreme illiquidity that triggers the “Flash Crash.” All these are very important features of market fragmentation. But our paper is the first in the literature that provides empirical evidence on market fragmentation through the perspective of activity and profitability of intermediaries when market is fragmented.

Last but not least, the paper is also linked to the empirical literature on arbitrage pricing theory (APT). There are many different ways to identify the risk factors in the context of APT. One can use maximum likelihood factor analysis to estimate the number of factors and the factor loadings (see e.g., Roll and Ross, 1980; CHEN, 1983; Chamberlain, 1983). One can choose the risk factors based on intuition and economic insights. For instance, Chen, Roll, and Ross (1986) use financial and macroeconomic variables as risk factors. Fama and French (1993) use the spread between stock returns of small and large firms as a risk factor (SML) and the spread between stock returns of value and growth firms as another risk factor (HML). One can also choose the risk factors based on statistical properties of the estimated covariance matrix. Chamberlain (1983) and Connor and Korajczyk (1986) propose (asymptotic) principal component analysis to identify risk factors. In this paper, we choose asymptotic principal component analysis. Because it does not require specific judgement and has a better performance than the maximum likelihood factor analysis (Shukla and Trzcinka, 1990). Our estimates and regression results are consistent with the findings in Connor and Korajczyk (1986).

The rest of the paper is organized as follows. Section 2.2 identifies intermediaries based on their mean-reverting positions on stocks. Section 2.3 develops the taxonomy of traders and reports summary statistics. Section 2.4 studies the profitability patterns of different groups of intermediaries. Section 2.5 zooms into the profits of intermediaries during the volatile periods and quiet periods. Section 2.6 extends the analysis to intermediaries with mean-reverting positions on risk factors. Section 3.5 concludes.
2.2 Intermediaries and end-users

The data we used is from the European Multilateral Clearing Facility (EMCF), the Central Counterparty (CCP) of the Nordic stock markets (based on Copenhagen, Stockholm and Helsinki). There are eight trading platforms in our sample: Nasdaq OMX Copenhagen, Nasdaq OMX Stockholm, Nasdaq OMX Helsinki, Chi-X, BATS Europe, Burgundy, Nasdaq Europe and Quote MTF.\(^4\) The sample starts from October 19, 2009 when clearing through EMCF became mandatory for all eight trading platforms, and ends on September 10, 2010. There are in total 228 trading days, 226 trader accounts and 242 stocks in the sample.

Intermediaries are identified based on their empirical features of intraday mean-reversion in stock positions and relatively high trading volume (see e.g., Hasbrouck and Sofianos, 1993; Madhavan and Smidt, 1993). Kirilenko et al. (2016) identifies high frequency traders (HFTs), which is an important type of modern intermediaries, by establishing three statistical criteria based on trade information. They employ the criteria in analyzing the “Flash Crash” in 2010. But their criteria is only applicable for single financial asset. In their case, that is the E-mini futures. Korajczyk and Murphy (2015) study HFTs in the Canadian stocks market. They propose a different set of criteria based on both trade and quote data to identify intermediaries in two steps when there are multiple stocks.

Since we have only trade information and we study the intermediaries in the settings with multiple stocks, we literally follow Kirilenko et al. (2016) and Korajczyk and Murphy (2015) to identify intermediaries with the following two steps.\(^5\)

1. We first identify a trader as an intermediary for a given stock-day if the following three criteria holds.
   - The trader trades more than 10 shares for a given stock-day;

\(^4\)The only venue that is out of our sample is Turquoise. Turquoise, however, has a market share of less than 1\% during our sample window.

\(^5\)All the cut-off values are directly from Kirilenko et al. (2016) and Korajczyk and Murphy (2015).
2.2 Intermediaries and end-users

- The trader’s end-of-day position is relatively low such that
  \[
  \frac{\text{End-of-day position}}{\text{Trading volume}} \leq 5\%; \quad (2.1)
  \]

- The traders has relatively low intraday position deviation such that
  \[
  \sqrt{\sum_{t=1}^{450} \left( \frac{\text{Position}_t - \text{Position}_{450}}{\text{Trading volume}} \right)^2} \leq 1.5\% \quad (2.2)
  \]

where there are in total 450 (= 7.5 \times 60) minutes in one trading day and \text{Position}, is the net position of the trader at the end of minute \( t \).

2. Then a trader is identified as an intermediary throughout different stocks if the following two criteria holds.

- The trader is identified as an intermediary for at least 75\% of stock-days in which he trades at least once;
- The trader is identified as an intermediary for at least 20 stock-days.

With these criteria, 15 intermediaries are identified in our sample. Intermediaries’ proportion of trades is 14.7\%, with a total trading volume of 163.5 billion euro and an average daily profit of 3.2 million euro. Table 2.1 reports summary statistics on intermediaries and end-users.

The main message from the table is that intermediaries are more active in multi-market trading. On average, intermediaries trade at 3.4 markets while end-users trade at 2.5 markets. We also calculate the Herfindal index (HHI), a standard measure of concentration, of both trading volume and end-of-day position. The HHI of trading volume and end-of-day position for intermediaries are 63\% and 55\% on average, much lower than those for end-users. It means that trades of intermediaries are less concentrated than those of end-users.

\footnote{The end-of-day position is calculated as the cumulation of intraday trades. In other words, we assume the start-of-day position is zero.}
In addition, intermediaries in general are more active than end-users. The average trading volume of intermediaries is 10.9 billion euro, two times as large as that of end-users. The median trading volume of intermediaries is 2.03 billion euro, while that of end-users is only 0.39 billion euro.

**Table 2.1: Summary statistics**

This table shows summary statistics of intermediaries and end-users. Panel A is a general description. Panel B and C present the cross-market activity of intermediaries and end-users, respectively. HHI\_vlm is the Herfindal index of trading volume in different venues. HHI\_position is that of end-of-day position which is calculated as the cumulation of intraday trades. In other words, we assume the start-of-day position is zero.

<table>
<thead>
<tr>
<th>Panel A Intermediaries and end-users</th>
<th>Intermediary</th>
<th>End-user</th>
</tr>
</thead>
<tbody>
<tr>
<td>NumTraders</td>
<td>15</td>
<td>211</td>
</tr>
<tr>
<td>TotalVolume (bln. euro)</td>
<td>163.5</td>
<td>1046.1</td>
</tr>
<tr>
<td>NumTrades (mln.)</td>
<td>17.5</td>
<td>119.0</td>
</tr>
<tr>
<td>MarketShare</td>
<td>14.7%</td>
<td>85.3%</td>
</tr>
<tr>
<td>DailyProfit (mln. euro)</td>
<td>3.2</td>
<td>-3.2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B Cross-market activity of intermediaries</th>
<th>HHI_vlm</th>
<th>HHI_position</th>
<th>NumMarket</th>
<th>Volume (bln. euro)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>63%</td>
<td>55%</td>
<td>3.4</td>
<td>10.90</td>
</tr>
<tr>
<td>Std</td>
<td>23%</td>
<td>21%</td>
<td>1.3</td>
<td>14.96</td>
</tr>
<tr>
<td>Min</td>
<td>33%</td>
<td>25%</td>
<td>1</td>
<td>0.02</td>
</tr>
<tr>
<td>25%</td>
<td>50%</td>
<td>38%</td>
<td>3</td>
<td>0.55</td>
</tr>
<tr>
<td>50%</td>
<td>54%</td>
<td>54%</td>
<td>3</td>
<td>2.03</td>
</tr>
<tr>
<td>75%</td>
<td>77%</td>
<td>60%</td>
<td>4</td>
<td>14.37</td>
</tr>
<tr>
<td>Max</td>
<td>100%</td>
<td>100%</td>
<td>6</td>
<td>54.55</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C Cross-market activity of end-users</th>
<th>HHI_vlm</th>
<th>HHI_position</th>
<th>NumMarket</th>
<th>Volume (bln. euro)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>75%</td>
<td>71%</td>
<td>2.5</td>
<td>4.98</td>
</tr>
<tr>
<td>Std</td>
<td>27%</td>
<td>29%</td>
<td>1.6</td>
<td>10.81</td>
</tr>
<tr>
<td>Min</td>
<td>22%</td>
<td>21%</td>
<td>1</td>
<td>0.00</td>
</tr>
<tr>
<td>25%</td>
<td>47%</td>
<td>42%</td>
<td>1</td>
<td>0.03</td>
</tr>
<tr>
<td>50%</td>
<td>89%</td>
<td>79%</td>
<td>2</td>
<td>0.39</td>
</tr>
<tr>
<td>75%</td>
<td>100%</td>
<td>100%</td>
<td>3</td>
<td>3.61</td>
</tr>
<tr>
<td>Max</td>
<td>100%</td>
<td>100%</td>
<td>8</td>
<td>80.02</td>
</tr>
</tbody>
</table>


2.3 Taxonomy of traders

Intermediaries. Figure 2.3 shows simple examples on three different groups of intermediaries, which correspond to the different concepts in Figure 2.2.

- A TimeOnlyInt trades in only one market. He buys from a seller in period $t$ and offloads the position to a buyer in period $t + 1$ within the day. In this way, he maintains a relatively flat end-of-day position. The criterium to identify a TimeOnlyInt from the group of intermediaries is straightforward.
  
  - Number of active market is one.

- A SpaceOnlyInt connects end-users through cross-market arbitrage. He buys in market A and sells in market B at the same time. Hence, his positions between markets should be negatively correlated. Furthermore, since the SpaceOnlyInt does not hold the asset along the time dimension, his positions should revert in high frequencies. In order to study the frequency pattern of intermediaries’ positions, we apply frequency domain decomposition as Hasbrouck and Sofianos (1993) and Menkveld (2013) do, since it is a natural way of looking at the frequency patterns of trading activity. Appendix 2.A.1 presents the details of frequency decomposition. A SpaceOnlyInt is defined as an intermediary that meets the following criteria.

  - Number of active market is larger than one.
  - On average, covariance of positions between markets is negative.
  - On average, position variance of high frequency bins is larger than that for white noise. We take white noise process as benchmark because of the mean-reverting behavior of intermediaries.

- A TimeSpaceInt is a combination of both TimeOnlyInt and SpaceOnlyInt. He buys in market A at period $t$ and offloads the position in market B at period $t + 1$. He connects end-users through both time dimension and space dimension. The rest of intermediaries satisfy the definition of TimeSpaceInt. Hence, they are categorized as TimeSpaceInts.
**End-users.** Different from intermediaries, end-users do not make markets, neither along the time dimension nor along the space dimension. For the end-users, they are classified into two groups based on the number of active market(s): a **SiMEndUser** trades only in Single Market while a **MuMEndUser** trades in Multiple Markets.

**Figure 2.3: Taxonomy of intermediaries**

Suppose there are two trading venues. The three subplots below show the time series of positions in two different venues for three groups of intermediaries. TimeOnlyInt is the intermediary that trades in only one venue. SpaceOnlyInt is the intermediary that arbitrages across two venues and holds zero inventory along the time. TimeSpaceInt is the intermediary that is active in two venues and holds inventory within the day.

Out of the 15 intermediaries in our sample, there are 1 TimeOnlyInt, 3 SpaceOnlyInts and 11 TimeSpaceInts. As to the 211 end-users, there are 80 SiMEndUsers, accounting for 40% of the total number of end-users. Table 2.2 presents some descriptive statistics for different groups, which lead to several interesting observations.

First and foremost, all three groups of intermediaries make money. The TimeOnlyInt has an average daily profit of 1000 euro. The three SpaceOnlyInts make an average daily profit of 2.2 million euro. The 11 TimeSpaceInts earn on average a daily profit of 1.0 million euro. The median traders in all the three groups of intermediaries have positive profits as well, suggesting that the majority of intermediaries make profits. Moreover, as indicated in Table 2.1, intermediaries in general trade very actively. Hence, the relative
daily profit, which is the ratio between daily profit and daily volume, is also calculated to evaluate the profitability of intermediaries. In terms of the relative daily profit, the SpaceOnlyInts are the most profitable ones, with a profit of 0.6 cent per euro traded.

Second, the three SpaceOnlyInts trade very actively with an average daily trading volume of 344 million euro, accounting for about 50% of trading volume of all intermediaries. But the SpaceOnlyInts manage to keep the position variance low, which is only 0.4% of the total position variance of intermediaries. It means that the SpaceOnlyInts are capable of controlling their overall inventories while trading a lot in different venues, which is also cross-checked with the large but negative position covariance across markets. All these numbers confirm that the SpaceOnlyInts selected by our criteria are those intermediaries that connect end-users only along the space dimension.
Table 2.2: Activities of different groups

This table reports the activities of different groups. Panel A is for intermediaries and panel B is for end-users. DailyProfitMedian is the daily profit for the median trader in the group, while DailyProfitGroup is the overall daily profit for the group. RelativeProfitGroup is the relative daily profit, which is the ratio between daily profit and daily volume, of the group. PositionVar is the average variance of positions across days. CovCrossMarket is the average covariance of positions between trading venues across days.

<table>
<thead>
<tr>
<th>Panel A Intermediaries</th>
<th>Total</th>
<th>TimeOnly</th>
<th>SpaceOnly</th>
<th>TimeSpace</th>
</tr>
</thead>
<tbody>
<tr>
<td>NumTraders</td>
<td>15</td>
<td>1</td>
<td>3</td>
<td>11</td>
</tr>
<tr>
<td>NumStocks</td>
<td>219</td>
<td>24</td>
<td>111</td>
<td>219</td>
</tr>
<tr>
<td>NumDays</td>
<td>228</td>
<td>59</td>
<td>228</td>
<td>228</td>
</tr>
<tr>
<td>DailyVolume (mln. euro)</td>
<td>717</td>
<td>6</td>
<td>344</td>
<td>368</td>
</tr>
<tr>
<td>PositionVar (sq. mln. euro)</td>
<td>27562</td>
<td>0.29</td>
<td>114</td>
<td>27447</td>
</tr>
<tr>
<td>CovCrossMarket (sq. mln. euro)</td>
<td>436</td>
<td>0</td>
<td>-535</td>
<td>971</td>
</tr>
<tr>
<td>DailyProfitMedian (1000 euro)</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>DailyProfitGroup (mln. euro)</td>
<td>3.2</td>
<td>0.001</td>
<td>2.2</td>
<td>1.0</td>
</tr>
<tr>
<td>RelativeProfitGroup</td>
<td>0.004</td>
<td>0.000</td>
<td>0.006</td>
<td>0.003</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B End-users</th>
<th>Total</th>
<th>SiMEndUser</th>
<th>MuMEndUser</th>
</tr>
</thead>
<tbody>
<tr>
<td>NumTraders</td>
<td>211</td>
<td>80</td>
<td>131</td>
</tr>
<tr>
<td>NumStocks</td>
<td>242</td>
<td>217</td>
<td>242</td>
</tr>
<tr>
<td>NumDays</td>
<td>228</td>
<td>228</td>
<td>228</td>
</tr>
<tr>
<td>DailyVolume (mln. euro)</td>
<td>4588</td>
<td>129</td>
<td>4459</td>
</tr>
<tr>
<td>PositionVar (sq. mln. euro)</td>
<td>221900</td>
<td>4739</td>
<td>217160</td>
</tr>
<tr>
<td>CovCrossMarket (sq. mln. euro)</td>
<td>463</td>
<td>0</td>
<td>463</td>
</tr>
<tr>
<td>DailyProfitMedian (1000 euro)</td>
<td>-0.02</td>
<td>-0.02</td>
<td>-0.01</td>
</tr>
<tr>
<td>DailyProfitGroup (mln. euro)</td>
<td>-3.2</td>
<td>-31.3</td>
<td>28.2</td>
</tr>
<tr>
<td>RelativeProfitGroup</td>
<td>-0.004</td>
<td>-0.24</td>
<td>0.006</td>
</tr>
</tbody>
</table>

Third, the majority of the end-users make losses, as the median traders in both SiMEndUsers and MuMEndUsers lose money. The SiMEndUsers trade very little but make large losses. Although SiMEndUsers account for 40% of the end-users in terms of number of traders, their trading volume is less than 3% of the total trading volume of end-users. Yet, they on average lose 31.3 million euro each day. In other words, for each euro they trade, they make a loss of 24 cents. Such large losses could imply that SiMEndUsers are not sophisticated. But it could also be the case that they are trading for reasons out of the stock markets, hedging for instance.
Table 2.3: Frequency decomposition of position variance

This table shows frequency decomposition for average daily positions. Panel A and B report results for intermediaries and end-users, respectively. The unit is squared million euro. The numbers in the brackets are the proportions.

<table>
<thead>
<tr>
<th></th>
<th>Panel A Intermediaries</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
<td>TimeOnly</td>
<td>SpaceOnly</td>
<td>TimeSpace</td>
</tr>
<tr>
<td>High (1min-5min)</td>
<td>361</td>
<td>0.04</td>
<td>8</td>
<td>353</td>
</tr>
<tr>
<td></td>
<td>(1%)</td>
<td>(14%)</td>
<td>(7%)</td>
<td>(1%)</td>
</tr>
<tr>
<td>Medium (5min-1hour)</td>
<td>4465</td>
<td>0.16</td>
<td>53</td>
<td>4412</td>
</tr>
<tr>
<td></td>
<td>(17%)</td>
<td>(56%)</td>
<td>(46%)</td>
<td>(16%)</td>
</tr>
<tr>
<td>Low (1hour-1day)</td>
<td>22736</td>
<td>0.09</td>
<td>53</td>
<td>22682</td>
</tr>
<tr>
<td></td>
<td>(82%)</td>
<td>(30%)</td>
<td>(46%)</td>
<td>(83%)</td>
</tr>
<tr>
<td>Variance</td>
<td>27562</td>
<td>0.29</td>
<td>114</td>
<td>27447</td>
</tr>
<tr>
<td></td>
<td>(100%)</td>
<td>(100%)</td>
<td>(100%)</td>
<td>(100%)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Panel B End-users</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
<td>SiMEndUser</td>
<td>MuMEndUser</td>
<td></td>
</tr>
<tr>
<td>High (1min-5min)</td>
<td>3093</td>
<td>57</td>
<td>3036</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1%)</td>
<td>(1%)</td>
<td>(1%)</td>
<td></td>
</tr>
<tr>
<td>Medium (5min-1hour)</td>
<td>35300</td>
<td>756</td>
<td>34544</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(16%)</td>
<td>(16%)</td>
<td>(16%)</td>
<td></td>
</tr>
<tr>
<td>Low (1hour-1day)</td>
<td>183506</td>
<td>3927</td>
<td>179580</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(83%)</td>
<td>(83%)</td>
<td>(83%)</td>
<td></td>
</tr>
<tr>
<td>Variance</td>
<td>221900</td>
<td>4739</td>
<td>217160</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(100%)</td>
<td>(100%)</td>
<td>(100%)</td>
<td></td>
</tr>
</tbody>
</table>

Table 2.3 decomposes position variance into different frequency bins. Equation 2.A.6 in Appendix 2.A.1 presents the details of the frequency decomposition approach. It is interesting that the taxonomy of intermediaries leads to different frequency patterns of position variance. First, among the three groups, TimeOnlyInt has the highest proportions in both high frequency bins and medium bins, accounting for 14% and 56% of the overall position variance. It suggests that the TimeOnlyInt that trades in single market has reverting-position with the highest frequency pattern among the three different groups.

Second, although the SpaceOnlyInts have less mass from the high frequency bins than TimeOnlyInt, they have larger proportion in high frequency bins than white noise by definition. As a benchmark for mean-reverting process, white noise has 1% in high frequency bins, 11% in medium frequency bins and 88% in low frequency bins. Compared to white
noise process, the SpaceOnlyInts have their positions revert in a rather high frequency pattern. To some extent, they are “whiter” than white noise.\footnote{In the literature of engineering, the color of noise refers to the power spectrum of a noise signal. White noise has a flat frequency spectrum, with equal power in every frequency. Pink noise has less high frequency components than white noise. Red noise is also called Brownian noise, meaning that it is a Brownian motion. The criterium that a SpaceOnlyInt should have larger proportion of position variance in high frequency bins actually requires a SpaceOnlyInt to be “whiter” than white noise.}

Third, for the end-users, trading in single markets or multiple markets does not give rise to different frequency patterns of position variance, although the size of position variance for these two groups is rather different. Both SiMEndUsers and MuMEndUsers have 1%, 16%, and 83% in the high, medium, and low frequency bins.

## 2.4 Profitability of different groups

In this section, we study the profitability of different groups in details. Profits are measured on a mark-to-market basis (Hasbrouck and Sofianos, 1993; Menkveld, 2013). Let $p_t$ denote the security price at time $t$ and $n_t$ the number of shares held at time $t$. The mark-to-market profit $\pi_t$ could be expressed as the product of existing position and future price change.

$$\pi_t = n_{t-1}(p_t - p_{t-1}).$$

We first investigate the relationship between traders’ profitability and cross-market activity. Then we apply frequency domain analysis to decompose traders’ profits into different frequency bins.

### 2.4.1 How profits are related to cross-market activity?

To better understand the relationship between profits and cross-market activity, we run a polynomial regression based on Kendall et al. (1946) and Edwards, Drasgow, and Schmitt...
2.4 Profitability of different groups

Polynomial regression is one type of linear regression in which the relationship between the independent variables and the dependent variable is modeled as $n$th degree polynomial. The benefit of polynomial regression is that it can capture non-linear relationship between the independent variables and the dependent variables, although the estimation method itself is linear.

We use position variance and position covariance between trading venues to measure cross-market activity. A log-scale transformation for the variables is introduced to reduce the differences in scales. Since profit and position covariance between trading venues can be both positive and negative, the log-scale transformation strives to maintain the signs of the variables. Let $x$ denote the original variable, $x'$ is the log-transformed variable.

$$x' = \frac{|x|}{x} \log(|x|) \quad (2.4)$$

Let $X$ denote the log-transformed position variance, $Y$ the log-transformed position covariance between trading venues, and $Z$ the log-transformed profit. The idea is to find the least-square solution to the following equations.

$$Z = \begin{cases} 
\beta_0 + \beta_1 X + \beta_2 Y, & \text{Linear model} \\
\beta_0 + \beta_1 X + \beta_2 Y + \beta_3 X^2 + \beta_4 Y^2 + \beta_5 XY, & \text{Quadratic model} \\
\beta_0 + \beta_1 X + \beta_2 Y + \beta_3 X^2 + \beta_4 Y^2 + \beta_5 XY + \beta_6 X^3 + \beta_7 Y^3 + \beta_8 X^2 Y + \beta_9 XY^2, & \text{Cubic model} 
\end{cases} \quad (2.5)$$

In other words, we run an OLS regression of $Z$ on the polynomial forms of $X$ and $Y$. For the 1st order polynomial form, it is a simple linear regression of $Z$ on $X$ and $Y$. On top of that, the 2nd order polynomial form captures both the linear terms and the quadratic terms. Similarly, the 3rd order polynomial regression picks up the additional cubic terms.

In order to choose the optimal order of polynomial regression, F-statistic is used to test the differences in $R^2$ between two regression models. Let subscript $U$ denote the uncon-
strained models (the bigger models) and \( C \) denote the constrained models (the smaller models). The general formula to calculate F-statistic is as follows.

\[
F\text{-stat} = \frac{(R^2_U - R^2_C)/(df_U - df_C)}{(1 - R^2_U)/df_U}.
\] (2.6)

Based on the F-statistic and degrees of freedom, p-value can be determined. When a p-value is less than 0.05, the unconstrained model fits the data significantly better than the constrained model.
Table 2.4: Polynomial regression results

This table shows the polynomial regression results for intermediaries and end-users. The numbers in the brackets represent t-statistics and the stars indicate the statistical significance based on p-values.

<table>
<thead>
<tr>
<th></th>
<th>Intermediaries</th>
<th>End-users</th>
<th>Intermediaries</th>
<th>End-users</th>
</tr>
</thead>
<tbody>
<tr>
<td>β₀</td>
<td>Linear</td>
<td>Quadratic</td>
<td>Cubic</td>
<td>Linear</td>
</tr>
<tr>
<td></td>
<td>−0.06</td>
<td>−0.21</td>
<td>0.04</td>
<td>−0.06</td>
</tr>
<tr>
<td></td>
<td>(−0.52)</td>
<td>(−1.09)</td>
<td>(0.13)</td>
<td>(−1.32)</td>
</tr>
<tr>
<td>β₁</td>
<td>0.06</td>
<td>0.36</td>
<td>−0.27</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>(1.15)</td>
<td>(1.47)</td>
<td>(−0.37)</td>
<td>(1.39)</td>
</tr>
<tr>
<td>β₂</td>
<td>−0.03</td>
<td>−0.37</td>
<td>−0.19</td>
<td>−0.01</td>
</tr>
<tr>
<td></td>
<td>(−0.92)</td>
<td>(−1.54)</td>
<td>(−0.18)</td>
<td>(−0.10)</td>
</tr>
<tr>
<td>β₃</td>
<td>−0.07</td>
<td>0.29</td>
<td>0.04*</td>
<td>−0.05</td>
</tr>
<tr>
<td></td>
<td>(−1.00)</td>
<td>(0.49)</td>
<td>(1.90)</td>
<td>(−0.40)</td>
</tr>
<tr>
<td>β₄</td>
<td>−0.04</td>
<td>0.03</td>
<td>0.22***</td>
<td>−0.57</td>
</tr>
<tr>
<td></td>
<td>(−1.01)</td>
<td>(0.08)</td>
<td>(4.43)</td>
<td>(−1.49)</td>
</tr>
<tr>
<td>β₅</td>
<td>0.12</td>
<td>−0.12</td>
<td>−0.09</td>
<td>−0.16</td>
</tr>
<tr>
<td></td>
<td>(1.41)</td>
<td>(−0.15)</td>
<td>(−1.11)</td>
<td>(−0.31)</td>
</tr>
<tr>
<td>β₆</td>
<td>−0.06</td>
<td>0.01</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(−0.42)</td>
<td></td>
<td>(0.58)</td>
<td></td>
</tr>
<tr>
<td>β₇</td>
<td>0.04</td>
<td></td>
<td>−0.12***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.89)</td>
<td></td>
<td>(−2.62)</td>
<td></td>
</tr>
<tr>
<td>β₈</td>
<td>0.04</td>
<td></td>
<td>−0.01</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.22)</td>
<td></td>
<td>(−0.05)</td>
<td></td>
</tr>
<tr>
<td>β₉</td>
<td>−0.03</td>
<td></td>
<td>0.27**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(−0.20)</td>
<td></td>
<td>(2.20)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Intermediaries</th>
<th>End-users</th>
<th>Intermediaries</th>
<th>End-users</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. Observation</td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>211</td>
</tr>
<tr>
<td>R²</td>
<td>12.9%</td>
<td>34.3%</td>
<td>62.3%</td>
<td>1.0%</td>
</tr>
<tr>
<td>F-stat</td>
<td>0.89</td>
<td>1.09</td>
<td>0.93</td>
<td>1.05</td>
</tr>
<tr>
<td>p-value</td>
<td>0.44</td>
<td>0.41</td>
<td>0.51</td>
<td>0.35</td>
</tr>
</tbody>
</table>

Table 2.4 reports the polynomial regression results for intermediaries and end-users. On the one hand, for the intermediaries, there is no significant relationship between their profitability and cross-market activity. Neither the linear terms, quadratic terms, nor cubic terms of cross-market activity are significant since the p-values are always larger than 0.05. Hence, although the intermediaries trade actively in multiple markets and make
profits from the end-users, cross-sectional analysis of intermediaries shows no significant correlation between profitability and cross-market activity.

On the other hand, for the end-users, the quadratic terms of cross-market activity contribute significantly in explaining the variation of profitability, as shown by the small p-value (0.00) of the quadratic regression. It shows a non-linear relationship between profitability and cross-market activity. From the OLS estimates of the quadratic regression, profitability ($Z$) is positively correlated with the quadratic term of position covariance ($Y^2$), meaning that profits of end-users exhibit a U-shape relationship with position covariance. In other words, end-users with zero position covariance make losses, which echoes the finding in Table 2.2 that SiMEndUsers make large losses.

**Figure 2.4: Best-fit surfaces based on the polynomial regressions**

This graph presents the best-fit surfaces based on the polynomial regression estimates. The x-axis is position variance, the y-axis is position covariance across markets, and the z-axis is profit. Profit, position variance and position covariance are in log transformation ($x' = \frac{|x|}{2}\log(|x|)$). Red in the colormap refers to loss and blue refers to profit.

To visualize the relationship between profitability and cross-market activity, Figure 2.4 plots the best-fit surfaces based on the polynomial regression estimates. As shown in Table 2.4, the relationship between profits and cross-market activity is different for intermediaries and end-users. The profitability of intermediaries does not vary a lot when the nature of cross-market activity changes, while the profitability of end-users shows a U-
shape relationship with cross-market activity. Furthermore, the deep red of the area with zero covariance shows that SiMEndUsers are the ones that incur great losses.

### 2.4.2 How profits are distributed in different frequencies?

We apply frequency domain analysis to decompose profits into different frequency bins. Equation 2.A.4 in Appendix 2.A.1 shows how frequency domain analysis decomposes the mark-to-market profits. Note that the highest frequency in frequency domain analysis is the sampling frequency. Hence, frequency domain analysis does not capture the profits due to the price changes within the sampling interval. Hence, the realized gross profit should consist of two parts: the within-interval profit and the frequency domain profit estimate. To be consistent with the frequency domain study, the within-interval profit is labeled as profit from ultrahigh frequency bins. Note that the ultrahigh frequency bins are only valid for profit decomposition because of the within interval price changes. They do NOT exist in frequency decomposition on position variance in Table 2.3.

In our analysis, we sample at the frequency of one minute.\(^8\) Thus, ultrahigh frequency bins are bins with reverting periods within one minute. For the frequency domain decomposition, profits are decomposed into frequency bins of reverting periods with boundaries at 5 minutes, 1 hour, and 1 day. In other words, high frequency bins are bins with cycles between one minute and five minutes; medium frequency bins are bins with cycles between five minutes and one hour; low frequency bins are bins with cycles between one hour and the full trading day. Finally, since profit is viewed as the product of position and future price changes, there is also a level bin that collects the profit due to the aver-

---

\(^8\)The analysis could also be done with sampling frequency of one second, which is the highest frequency of the timestamp in our sample. However, it is always a trade-off between decomposition accuracy and calculation efficiency. From the literature of frequency analysis on stock markets, Hasbrouck and Sofianos (1993) use frequency analysis with a volume clock. The highest frequency in their analysis is with reverting periods of 10 transactions for each stock. For our sample, that corresponds to 1.8 minutes on average across stocks and days. Because we have in total 137 million trades on 242 stocks and 228 trading days, each day with 450 minutes. Menkveld (2013) has a sampling frequency of one second. But from the results of Table 3 in Menkveld (2013), the position variance of frequency bins with reverting periods within one minute accounts for 3% of total position variance. Hence, for current analysis, we adopt a sampling frequency of one minute because the calculation burden of a higher sampling frequency overweights the potential benefit of that. A further detailed analysis with a higher sampling frequency remains for future studies.
age position and average price changes. The level bin is the lowest frequency bin in the decomposition.

Table 2.5 shows frequency decomposition results of profits. First, the average daily profit of intermediaries from the ultrahigh frequency bins is significant at 99% confidence level based on the z-test. On average, they have a daily profit of 25,000 euro in the ultrahigh frequency bins. It indicates that intermediaries as a group earn profits from end-users in the highest frequencies.

Second, the TimeOnlyInt makes an average daily profit of 1000 euro in the high frequency bins, which is significant at 99% confidence level. But the profits from other frequency bins are negligible. It fits the model prediction that an intermediary supplies immediacy along the time dimension should be compensated for carrying price risk (Grossman and Miller, 1988). Also, it is consistent with the literature that modern intermediaries profit from high frequency bins (Menkveld, 2013).

Third, the SpaceOnlyInts have an average daily profit of 2.2 million euro, with significant profits at 99% confidence level from the ultrahigh frequency bins and the medium frequency bins. Coupled with the results in Table 2.3, the statistically significant profit from the ultrahigh frequency bins shows that the SpaceOnlyInts probably arbitrage across markets, connects end-users across venues, and make stable profits out of it. Also, their profit from the medium frequency bins suggests that, apart from deterministic arbitrage across markets, they may also have other trading strategies that lead to profits in lower frequencies.

Fourth, the TimeSpaceInts have significant profits from both the ultrahigh frequency bins and the high frequency bins. The frequency pattern of their profitability is a combination of that of the TimeOnlyInt and the SpaceOnlyInt, suggesting that the TimeSpaceInts profits from multi-market trading and from holding inventories along the time.

Last, most of the profits/losses of end-users are from the level bin. SiMEndUsers make a loss of 44.5 million euro and MuMEndUsers make a profit of 43.0 million euro in the level
2.5 Volatile vs quiet periods

In this session, we split the sample into two subsamples: (i) volatile periods and (ii) quiet periods. The volatile periods are defined as the days with top quartile VIX (Clarida, Davis, and Pedersen, 2009). The rest of the sample periods are quiet periods.

Figure 2.5 shows the time series of the S&P 500 VIX. To make sure that the volatility measure is forward looking, the time series shows the start-of-day VIX. The threshold to distinguish volatile periods and quiet periods is 26. Out of 228 days in the full sample, the volatile periods consist of 57 days, covering several periods of market stress.
Figure 2.5: VIX

This graph is a time series of start-of-day S&P 500 VIX. The black dash line is the threshold that is used to distinguish volatile period and quiet period. The volatile days have high VIX (top quartile) and marked with red stars.

2.5.1 Profitability and cross-market trading

We redo the polynomial regressions for the subsamples. Table 2.6 reports the selected models based on the F-test outlined in equation 2.6: linear model for intermediaries in volatile periods, and quadratic models for other subsamples.

The OLS estimates in the linear regression model suggest no significant relationship between profitability and cross-market activity for intermediaries during the volatile periods. However, for intermediaries during the quiet periods, the quadratic model suggests a significant U-shape relationship between profitability and position covariance across markets.

For the end-users, the U-shape relationship between profitability and covariance is preserved in both volatile and quiet periods. Moreover, for end-users in the quiet periods, the significant negative relationship between profitability (Z) and the quadratic term of po-
sition variance ($X^2$) indicates that end-users’ profits decrease as their variance increases. The underlying reason could be that the end-users with larger variance of positions will create higher price pressure, which translates to higher execution costs for the end-users.

**Table 2.6: Polynomial regression results for volatile and quiet periods**

This table shows the polynomial regression results for intermediaries and end-users during the volatile and quiet periods. The numbers in the brackets represent t-statistics and the stars indicate the statistical significance based on p-values.

<table>
<thead>
<tr>
<th></th>
<th>Intermediaries</th>
<th>End-users</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Volatile</td>
<td>Quiet</td>
</tr>
<tr>
<td>$\hat{\beta}_0$</td>
<td>-0.12</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>(-0.52)</td>
<td>(0.25)</td>
</tr>
<tr>
<td>$\hat{\beta}_1$</td>
<td>0.10</td>
<td>0.08</td>
</tr>
<tr>
<td></td>
<td>(1.01)</td>
<td>(0.40)</td>
</tr>
<tr>
<td>$\hat{\beta}_2$</td>
<td>-0.05</td>
<td>-0.34</td>
</tr>
<tr>
<td></td>
<td>(-0.64)</td>
<td>(-1.71)</td>
</tr>
<tr>
<td>$\hat{\beta}_3$</td>
<td>-0.10*</td>
<td>0.13</td>
</tr>
<tr>
<td></td>
<td>(-1.86)</td>
<td></td>
</tr>
<tr>
<td>$\hat{\beta}_4$</td>
<td>0.10***-2.02</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.72)</td>
<td></td>
</tr>
<tr>
<td>$\hat{\beta}_5$</td>
<td>0.14**-0.13</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.97)</td>
<td></td>
</tr>
<tr>
<td>No. Observation</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>$R^2$</td>
<td>9.5%</td>
<td>61.4%</td>
</tr>
</tbody>
</table>

According to Clogg, Petkova, and Haritou (1995), the following Z-statistic is used to test whether the differences in the OLS estimates of the volatile periods and the quiet periods are significantly different. Let $V$ denote volatile periods, $Q$ denote quiet periods, and SE denote the standard errors.

$$Z\text{-stat} = \frac{\hat{\beta}_V - \hat{\beta}_Q}{\sqrt{(SE_{\hat{\beta}_V})^2 + (SE_{\hat{\beta}_Q})^2}}. \quad (2.7)$$

The differences between model estimates in the volatile periods and the quiet periods are tested through the $z$-statistic. For intermediaries, the $z$-statistic for $\hat{\beta}_4$ is significant at 95% confidence level, indicating that the U-shape relationship between profitability
and covariance in the quiet periods is significantly different from the relationship in the volatile periods. For end-users, the z-statistic for $\hat{\beta}_4$ is not significant, which means that the U-shape relationship does not change in the two different subsamples.

**Figure 2.6: Best-fit surface plots for volatile and quiet periods**

This graph presents the best-fit surface plots for volatile and quiet periods. The x-axis is position variance, the y-axis is position covariance across markets, and the z-axis is profit. Profit, variance and covariance are in log-scale ($x' = \frac{1}{2} \log(|x|)$). The left hand side plots are for volatile periods and the right hand side plots are for quiet periods. Red in the colormap refers to loss and blue refers to profit. Panel A and B shows the plots for intermediaries and end-users, respectively.

**Panel A: Intermediaries**

**Panel B: End users**

Figure 2.6 shows the best-fit surface plots based on the polynomial regression results for both volatile and quiet periods. Coupled with the results in Table 2.6, Figure 2.6 shows that intermediaries love volatility. It is striking that end-users are deep in red in volatile periods, which means that they are making large losses when markets are volatile. Hence,
intermediaries, no matter whether and how they trade in multiple venues, always make profits from end-users during the volatile periods.

For the quiet periods, the situation changes. Intermediaries do not always make profits, especially for those with small position covariance and large position variance. It could be the case that, during the quiet periods, intermediaries who trade in single markets and create high price pressures have to “time” the market correctly to provide liquidity. Otherwise, such intermediaries will make losses as well.

### 2.5.2 Frequency decomposition of profitability

**Table 2.7: Frequency decomposition of intermediaries’ profits**

This table shows frequency decomposition for average daily profits of intermediaries. Panel A and B report results for volatile and quiet periods, respectively. The unit is million euro. The stars indicate the statistical significance of z-test on the average daily profits. There are in total 57 trading days for the volatile periods and 171 days for the quiet periods.

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>TimeOnly</th>
<th>SpaceOnly</th>
<th>TimeSpace</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Volatile periods</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ultrahigh (&lt;1min)</td>
<td>0.006*</td>
<td>0.000</td>
<td>0.005***</td>
<td>0.001</td>
</tr>
<tr>
<td>High (1min-5min)</td>
<td>−0.4</td>
<td>0.002***</td>
<td>1.5***</td>
<td>−2.0***</td>
</tr>
<tr>
<td>Medium (5min-1hour)</td>
<td>−2.6</td>
<td>0.001**</td>
<td>2.1***</td>
<td>−4.7***</td>
</tr>
<tr>
<td>Low (1hour-1day)</td>
<td>11.0*</td>
<td>0.000</td>
<td>0.2</td>
<td>10.8*</td>
</tr>
<tr>
<td>Level</td>
<td>10.2</td>
<td>−0.001</td>
<td>−0.5**</td>
<td>10.8*</td>
</tr>
<tr>
<td>Gross profit</td>
<td>18.2</td>
<td>0.002**</td>
<td>3.3***</td>
<td>14.9*</td>
</tr>
<tr>
<td><strong>Panel B: Quiet periods</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ultrahigh (&lt;1min)</td>
<td>0.031***</td>
<td>0.000</td>
<td>0.008***</td>
<td>0.023**</td>
</tr>
<tr>
<td>High (1min-5min)</td>
<td>−1.9</td>
<td>0.000</td>
<td>−4.3</td>
<td>2.4</td>
</tr>
<tr>
<td>Medium (5min-1hour)</td>
<td>4.0</td>
<td>0.001</td>
<td>6.8</td>
<td>−2.8**</td>
</tr>
<tr>
<td>Low (1hour-1day)</td>
<td>−2.5*</td>
<td>0.000</td>
<td>−0.5</td>
<td>−1.9***</td>
</tr>
<tr>
<td>Level</td>
<td>−1.4</td>
<td>0.000</td>
<td>0.0</td>
<td>−1.3</td>
</tr>
<tr>
<td>Gross profit</td>
<td>−1.7</td>
<td>0.001*</td>
<td>2.0***</td>
<td>−3.6</td>
</tr>
</tbody>
</table>

Table 2.7 reports the frequency decomposition results of intermediaries’ profits in volatile and quiet periods. First, it shows that intermediaries make most of their profits from the volatile periods. Intermediaries make an average daily profit of 18.2 million euro in the
volatile periods and an average daily loss of 1.7 million euro in the quiet periods. In
individual groups of intermediaries, the profitability in the volatile periods is much better
than that in the quiet periods. The finding is also consistent with the observation in Figure
2.6 that end-users lose a lot of money in volatile periods.

Second, TimeSpaceInts are the most profitable intermediaries when markets are volatile.
They make a large daily profit of 14.9 million euro in volatile periods, out of which 21.6
million euro is from the low frequency bins and the level bin. It means that they make
profits mainly from holding assets for a relatively long period.

Third, SpaceOnlyInts have a significant daily profit from the ultrahigh frequency bins,
both in volatile periods and in quiet periods. It is consistent with the idea that the cross-
market arbitrage of SpaceOnlyInts should always yield positive profits.

2.6 Factor-based intermediaries: connecting end-users on
the same factors across securities

Our analysis on cross-market arbitrage could be extended to statistical arbitrage on the
common risk factors across securities. A simple example of such statistical arbitrage
across securities is “pair trading” where a pair of securities are exposed to the same risk
factors. For instance, Pepsi and Coca Cola, both of which have similar products and are
exposed to the same risk factors. Hence, the returns of these two stocks will share some
statistical characteristics such as high correlation or cointegration (Engle and Granger,
1987; Brenner and Kroner, 1995). When Pepsi undergoes strong (but transitory) buying
pressure from end-users so that the statistical relationship between Pepsi and Coca Cola
breaks down, intermediaries can arbitrage across these two securities and re-establish the
statistical relationship. In this way, intermediaries supply immediacy to end-users that
trade on the same risk factors.

Arbitrage pricing theory (APT) assumes that security returns follow a factor model (Ross,
1976; Roll and Ross, 1980). Let $f$ denote the $k$-vector of random factors, $\beta$ the $n \times k$ matrix
2.6 Factor-based intermediaries: connecting end-users on the same factors across securities

of factor loadings, and $\epsilon$ the $n$-vector of idiosyncratic returns. The $n$-vector of returns $r$ could be return as

$$ r = E(r) + \beta f + \epsilon, $$

(2.8)

where $E(f) = 0$, $E(\epsilon) = 0$, and $E(\epsilon \epsilon') = 0$. In the APT context, the common risk factors are “fragmented” by securities. Intermediaries that supply immediacy can also be viewed as connecting end-users that trade the same risk factors but through different securities. In this case, intermediaries do statistical arbitrage across securities instead of deterministic arbitrage across venues.

### 2.6.1 Identification of risk factors

Following Connor and Korajczyk (1986) and Connor and Korajczyk (1988), the underlying risk factors assumed by the APT are statistically identified by the asymptotic principal components analysis. From Equation 2.8, the covariance of security returns $\Sigma$ can be written as

$$ \Sigma = \beta \beta' + V, $$

(2.9)

where $V = \epsilon \epsilon'$, which is a diagonal matrix under the assumption of strict factor model. Assuming that $V$ is nonsingular, Equation 2.9 can be rewritten by pre- and post-multiplying $V^{-1/2}$ as

$$ \Sigma^* = \beta^* \beta^{*'} + I, $$

(2.10)

where $\beta^* = V^{-1/2} \beta$ and $\Sigma^* = V^{-1/2} \Sigma V^{-1/2}$, which is the covariance matrix of the transformed return $r^* = V^{-1/2} r$. Since the principal components of Equation 2.10 are the same as the factor loadings of Equation 2.9 as long as there is a nonsingular $k \times k$ transforma-
tion. In other words, when the security returns are scaled by the standard deviations of the idiosyncratic returns, the principal components are identical to the factor loadings.

We use weekly stock returns in our sample to identify the underlying common risk factors. The weekly market index returns are volume-weighted portfolio of all stocks. The risk-free rate is the 1-month US Treasury bill rate. Let $R_t$ denote the excess return at week $t$. First, we estimate the factor(s) $G$ by asymptotic principal component analysis.\(^9\)

$$R_t = \begin{cases} \alpha + \beta_1 G_{1,t} + \epsilon_t, & \text{One-factor} \\ \alpha + \beta_1 G_{1,t} + \beta_2 G_{2,t} + \ldots + \beta_5 G_{5,t} + \epsilon_t, & \text{Five-factor} \\ \alpha + \beta_1 G_{1,t} + \beta_2 G_{2,t} + \ldots + \beta_{10} G_{10,t} + \epsilon_t, & \text{Ten-factor} \end{cases} \quad (2.11)$$

Then, we regress the excess return on the first one, five, and ten factors. Following Connor and Korajczyk (1988), we further test the one-factor, five-factor and ten-factor models based on F-statistic in Equation 2.6. Table 2.8 reports the regression results of one-factor, five-factor and ten-factor models. Similar with the results in Connor and Korajczyk (1988), the first factor explains 37.3% of the covariance of the weekly returns in the principal component analysis. The remaining factors in the five-factor model have statistically significant explanatory power, with a small p-value of 0.00. But they obviously explain much less of the variance. The first five factors in total explain 56.0% of the covariance. The additional factors in the ten-factor model do not improve the explanatory power much, with a p-value of 0.08. Based on the test results, we use the five factors as the “true” factors.

\(^9\)Following Connor and Korajczyk (1988), the factor estimates $G$ are scaled so that the equal-weighted portfolio has a unit beta for each factor. The scaling has no effect on the estimates of $\alpha$ and $R^2$. 
2.6 Factor-based intermediaries: connecting end-users on the same factors across securities

2.6.2 Intermediaries with mean-reverting positions on risk factors

With the five common risk factors estimated by asymptotic principal components analysis, intermediaries are identified based on their mean-reverting positions on risk factors, which are called “factor-based” intermediaries. In this case, a trader’s positions on the five risk factors are calculated based on the eigenvectors of the first five components. With the positions on the five factors, an intermediary is identified by the two steps outlined in Sec-

Table 2.8: Regression results on factor models

This table shows the regression results of one-factor, five-factor and ten-factor models. The numbers in the brackets are t-statistics and the stars indicate the statistical significance based on p-values.

<table>
<thead>
<tr>
<th></th>
<th>One-factor</th>
<th>Five-factor</th>
<th>Ten-factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>-0.00</td>
<td>-0.00</td>
<td>-0.00</td>
</tr>
<tr>
<td></td>
<td>(-1.22)</td>
<td>(-1.37)</td>
<td>(-1.22)</td>
</tr>
<tr>
<td>( \beta_1 )</td>
<td>0.53***</td>
<td>0.53***</td>
<td>0.53***</td>
</tr>
<tr>
<td></td>
<td>(86.13)</td>
<td>(99.55)</td>
<td>(111.36)</td>
</tr>
<tr>
<td>( \beta_2 )</td>
<td>-0.04**</td>
<td>-0.04***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.56)</td>
<td>(-2.86)</td>
<td></td>
</tr>
<tr>
<td>( \beta_3 )</td>
<td>0.04***</td>
<td>0.04***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.73)</td>
<td>(3.06)</td>
<td></td>
</tr>
<tr>
<td>( \beta_4 )</td>
<td>0.03*</td>
<td>0.03**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.90)</td>
<td>(2.12)</td>
<td></td>
</tr>
<tr>
<td>( \beta_5 )</td>
<td>-0.01</td>
<td>-0.01</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.70)</td>
<td>(-0.79)</td>
<td></td>
</tr>
<tr>
<td>( \beta_6 )</td>
<td>0.00</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.19)</td>
<td>(0.19)</td>
<td></td>
</tr>
<tr>
<td>( \beta_7 )</td>
<td>0.06***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.38)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \beta_8 )</td>
<td>0.02</td>
<td>0.02</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.34)</td>
<td>(1.34)</td>
<td></td>
</tr>
<tr>
<td>( \beta_9 )</td>
<td>0.00</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.19)</td>
<td>(0.19)</td>
<td></td>
</tr>
<tr>
<td>( \beta_{10} )</td>
<td>0.02</td>
<td>0.02</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.13)</td>
<td>(1.13)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>No. Observation</th>
<th>44</th>
<th>44</th>
<th>44</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proportion in covariance</td>
<td>37.3%</td>
<td>56.0%</td>
<td>69.6%</td>
</tr>
<tr>
<td>p-value</td>
<td>–</td>
<td>0.00</td>
<td>0.08</td>
</tr>
</tbody>
</table>

No. Observation 44 44 44
Proportion in covariance 37.3% 56.0% 69.6%
p-value – 0.00 0.08
The intermediaries who were identified based on their mean-reverting positions on stocks are called “stock-based” intermediaries.

The factor-based intermediaries are also categorized into three groups based on the same taxonomy in Section 2.3. In the case of stock-based intermediaries, there is physical fragmentation that one stock could be traded in several venues simultaneously. The space dimension refers to trading across venues. In the case of factor-based intermediaries, there is “cross-security fragmentation” that one risk factor could be traded in several securities simultaneously. Hence, the “space” dimension refers to trading across securities.

**Table 2.9: Description of factor-based intermediaries**

This table reports statistics on factor-based intermediaries. Factor-based intermediaries are identified based on their mean-reverting positions on risk factors, with the same taxonomy of intermediaries as in Section 2.3. Panel A describes the different types of factor-based intermediaries. Panel B decomposes the position variance. The numbers in the brackets of Panel B are the proportions.

<table>
<thead>
<tr>
<th></th>
<th>Total</th>
<th>SpaceOnly</th>
<th>TimeSpace</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A Descriptive Statistics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NumTraders</td>
<td>12</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td>NumStocks</td>
<td>211</td>
<td>111</td>
<td>211</td>
</tr>
<tr>
<td>NumDays</td>
<td>228</td>
<td>228</td>
<td>228</td>
</tr>
<tr>
<td>DailyVolume (mln. euro)</td>
<td>806</td>
<td>296</td>
<td>510</td>
</tr>
<tr>
<td>PositionVar (sq. mln. euro)</td>
<td>8618</td>
<td>114</td>
<td>8503</td>
</tr>
<tr>
<td><strong>Panel B Position variance decomposition (sq. mln. euro)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High (1min-5min)</td>
<td>114</td>
<td>8</td>
<td>106</td>
</tr>
<tr>
<td></td>
<td>(1%)</td>
<td>(7%)</td>
<td>(1%)</td>
</tr>
<tr>
<td>Medium (5min-1hour)</td>
<td>1386</td>
<td>53</td>
<td>1333</td>
</tr>
<tr>
<td></td>
<td>(16%)</td>
<td>(46%)</td>
<td>(16%)</td>
</tr>
<tr>
<td>Low (1hour-1day)</td>
<td>7118</td>
<td>53</td>
<td>7065</td>
</tr>
<tr>
<td></td>
<td>(83%)</td>
<td>(47%)</td>
<td>(83%)</td>
</tr>
<tr>
<td>Variance</td>
<td>8618</td>
<td>114</td>
<td>8503</td>
</tr>
<tr>
<td></td>
<td>(100%)</td>
<td>(100%)</td>
<td>(100%)</td>
</tr>
</tbody>
</table>

In our sample, there are in total 12 factor-based intermediaries, out of which two are SpaceOnlyInts and ten are TimeSpaceInts. It turns out that, in our sample, no factor-based intermediary trades in only one security. Hence, there is no TimeOnlyInts in the case of factor-based intermediaries. Table 2.9 reports statistics of different types of factor-based intermediaries. Both SpaceOnlyInts and TimeSpaceInts are active in every trading
2.6 Factor-based intermediaries: connecting end-users on the same factors across securities

day. But SpaceOnlyInts trade in 111 stocks, much lesser than TimeSpaceInts do. In terms of trading volume, SpaceOnlyInts have a daily average of 296 million euro, 36.7% of the trading volume of all intermediaries. But SpaceOnlyInts only accounts for 1.3% of the position variance of all intermediaries. It shows that SpaceOnlyInts manage to keep the variance low while trading a lot. The decomposition of position variance shows that SpaceOnlyInts have a larger proportion in high frequency bins than TimeSpaceInts, which means that SpaceOnlyInts in general have a shorter reverting period than TimeSpaceInts do.

2.6.3 Profitability of factor-based intermediaries

Table 2.10 shows results on the profitability of factor-based intermediaries. We run the polynomial regressions outlined in Equation 2.5. The log-transformed position variance $X$ is the log-scale transformation of the variance of an intermediary’s position on the risk factors. The log-transformed position covariance between securities $Y$ is the log-scale transformation of the position covariance between securities. The log-transformed profit $Z$ is the log-scale transformation of the profit. Panel A of Table 2.10 shows the polynomial regression results for linear model, quadratic model and cubic model. It shows that the linear terms and the cubic terms have statistical significant explanatory power on intermediaries’ profits. The large coefficients for $X$ and $X^3$ show that profit increases when position variance (on factors) increases. It suggests that factor-based intermediaries who bear higher risk, in terms of position variance, are compensated with larger profits.

Panel B of Table 2.10 decomposes the profits for factor-based intermediaries. Factor-based intermediaries have an average daily profit of 11.7 million euro, which is significant at 99% confidence level. Frequency decomposition shows that the profits from the ultrahigh frequency bins and the level bin are significant, with average daily profits of 45,000 euro and 7.3 million euro respectively. Moreover, TimeSpaceInts have an average daily profit of 9.5 million euro, much larger than that of SpaceOnlyInts. SpaceOnlyInts on average make a daily profit of 2.2 million euro. Both are significant at 99% confidence level.
Table 2.10: Profitability of factor-based intermediaries

This table reports the profitability of factor-based intermediaries. Panel A shows the polynomial regression results. The numbers in the brackets are t-statistics. There are in total 12 factor-based intermediaries. Panel B decomposes the average daily profits into different frequency bins. The stars indicate the statistical significance of z-test on the average daily profits. There are in total 228 trading days.

<table>
<thead>
<tr>
<th>Panel A Polynomial regressions</th>
<th>Linear</th>
<th>Quadratic</th>
<th>Cubic</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta_0 )</td>
<td>-0.61</td>
<td>1.07</td>
<td>-9.17***</td>
</tr>
<tr>
<td></td>
<td>(-1.74)</td>
<td>(1.17)</td>
<td>(-14.38)</td>
</tr>
<tr>
<td>( \beta_1 )</td>
<td>0.26*</td>
<td>-1.29</td>
<td>15.19***</td>
</tr>
<tr>
<td></td>
<td>(1.80)</td>
<td>(-1.48)</td>
<td>(15.28)</td>
</tr>
<tr>
<td>( \beta_2 )</td>
<td>-0.20*</td>
<td>-1.40</td>
<td>0.48</td>
</tr>
<tr>
<td></td>
<td>(-1.92)</td>
<td>(-1.44)</td>
<td>(1.01)</td>
</tr>
<tr>
<td>( \beta_3 )</td>
<td>0.17</td>
<td></td>
<td>-7.66***</td>
</tr>
<tr>
<td></td>
<td>(0.59)</td>
<td></td>
<td>(-16.16)</td>
</tr>
<tr>
<td>( \beta_4 )</td>
<td>0.32</td>
<td></td>
<td>1.39**</td>
</tr>
<tr>
<td></td>
<td>(1.69)</td>
<td></td>
<td>(5.07)</td>
</tr>
<tr>
<td>( \beta_5 )</td>
<td>-0.34*</td>
<td></td>
<td>-0.91</td>
</tr>
<tr>
<td></td>
<td>(-2.28)</td>
<td></td>
<td>(-2.31)</td>
</tr>
<tr>
<td>( \beta_6 )</td>
<td></td>
<td></td>
<td>1.18***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(16.94)</td>
</tr>
<tr>
<td>( \beta_7 )</td>
<td></td>
<td></td>
<td>0.57***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(10.68)</td>
</tr>
<tr>
<td>( \beta_8 )</td>
<td></td>
<td></td>
<td>0.24*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(3.09)</td>
</tr>
<tr>
<td>( \beta_9 )</td>
<td></td>
<td></td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-0.10)</td>
</tr>
<tr>
<td>No. Observation</td>
<td>12</td>
<td>12</td>
<td>12</td>
</tr>
<tr>
<td>R</td>
<td>50.8%</td>
<td>81.6%</td>
<td>99.9%</td>
</tr>
<tr>
<td>F-stat</td>
<td>–</td>
<td>3.35</td>
<td>457.50</td>
</tr>
<tr>
<td>p-value</td>
<td>–</td>
<td>0.11</td>
<td>0.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B Frequency decomposition of average daily profits (mln. euro)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ultimate (1min)</td>
</tr>
<tr>
<td>-----------------</td>
</tr>
<tr>
<td>Ultra High (1min)</td>
</tr>
<tr>
<td>High (1min-5min)</td>
</tr>
<tr>
<td>Medium (5min-1hour)</td>
</tr>
<tr>
<td>Low (1hour-1day)</td>
</tr>
<tr>
<td>Level</td>
</tr>
<tr>
<td>Gross profit</td>
</tr>
</tbody>
</table>
Frequency decomposition on different types of factor-based intermediaries leads to several observations. First, both SpaceOnlyInts and TimeSpaceInts have statistically significant profits from the ultrahigh frequency bins. It shows that both groups of intermediaries profits from the highest frequencies. Second, most of the profits of SpaceOnlyInts are from medium frequency bins. SpaceOnlyInts have an average daily profit of 5.5 million euro from medium frequency bins, which is significant at 99% confidence level. Third, most of the profits of TimeSpaceInts are from the level bin, with a daily average of 7.4 million euro. It is also significant at 99% confidence level. All these observations show that the taxonomy of factor-based intermediaries also leads to different frequency patterns of profits.

2.6.4 Comparison between stock- and factor-based intermediaries

Table 2.11 compares the factor-based intermediaries with the stock-based intermediaries. First, the factor-based intermediaries trade more actively than the stock-based intermediaries. The total trading volume of the 12 factor-based intermediaries is 183.8 billion euro, which is larger than that of the 15 stock-based intermediaries. The number of trades of the factor-based intermediaries is 10 million more than that of the stock-based intermediaries. Likewise, the market share of the factor-based intermediaries is also larger than that of the stock-based intermediaries.

Second, the factor-based intermediaries are more profitable than the stock-based intermediaries. The average daily profit of the former is 11.7 million euro, almost three times as much as that of the latter. Also, results from Table 2.5 and Table 2.10 show that TimeSpaceInts have a higher daily profit in the case of factor-based intermediaries than that of stock-based intermediaries. More importantly, the gross profit of factor-based intermediaries is statistically significant while that of stock-based intermediaries is not. The reason behind the high profitability of the factor-based intermediaries could be the relatively high risk of statistical arbitrage.
Third, factor-based intermediaries with larger position variance (on risk factors) make higher profits, while profitability of stock-based intermediaries does not vary when the nature of cross-market activity changes. It suggests that factor-based intermediaries are compensated for bearing higher risk, which is proxied by the larger position variance.

Fourth, the intersection between these two groups of intermediaries are very active but not very profitable. Their trades account for about half of the stock-based intermediaries, in terms of both total volume and number of trades. Their proportion in the factor-based intermediaries is around 40%. But the intersection group has an average daily profit of 0.4 million euro, which is only 12.5% of that of the stock-based intermediaries and 3.4% of the factor-based intermediaries. A closer look at the intersection group reveals that two of them are SpaceOnlyInts in both stock- and factor-based intermediaries. That explains why the results of SpaceOnlyInts in both cases are quite similar. It suggests that it is almost the same group of intermediaries that arbitrage across venues and across securities, with mean-reverting positions in high frequencies.

**Table 2.11: Comparison between stock- and factor-based Intermediaries**

This table compares factor-based intermediaries with stock-based intermediaries. Factor-based intermediaries are identified based on their mean-reverting positions on risk factors, while stock-based intermediaries are identified based on their mean-reverting positions on stocks.

<table>
<thead>
<tr>
<th></th>
<th>Stock-based</th>
<th>Factor-based</th>
<th>Intersection</th>
</tr>
</thead>
<tbody>
<tr>
<td>NumTraders</td>
<td>15</td>
<td>12</td>
<td>4</td>
</tr>
<tr>
<td>TotalVolume (bln. euro)</td>
<td>163.5</td>
<td>183.8</td>
<td>78.6</td>
</tr>
<tr>
<td>NumTrades (mln.)</td>
<td>17.5</td>
<td>27.8</td>
<td>11.1</td>
</tr>
<tr>
<td>MarketShare</td>
<td>14.7%</td>
<td>21.3%</td>
<td>8.5%</td>
</tr>
<tr>
<td>DailyProfit (mln. euro)</td>
<td>3.2</td>
<td>11.7</td>
<td>0.4</td>
</tr>
</tbody>
</table>

**2.7 Conclusion**

This paper studies intermediaries along both the time dimension and the space dimension. There are 15 intermediaries and 211 end-users in our sample. Intermediaries account for
14.7% of total trades. We find that on average intermediaries make a daily profit of 3.2 million euro from end-users.

Further analysis suggests that intermediaries connect end-users across both time and venues. Intermediaries in general are more active in multi-venue trading than end-users. Out of the 15 intermediaries, only one trades in single market, while 80 out of the 211 end-users trade in single market. The proliferation of intermediaries that trade in multiple venues indicates that the physically fragmented security trading is virtually integrated.

Frequency domain analysis reveals the different profitability patterns for different types of intermediaries. Intermediaries that supply immediacy within one venue make profits mostly in high frequency bins with reverting periods between one minute and five minutes. Intermediaries that arbitrage across markets has significant profits in ultrahigh frequency bins with reverting periods less than one minute. Intermediaries that connect end-users in both time and space dimensions make profits in both ultrahigh and high frequency bins.

Intermediaries have an average daily profit of 18.2 million euro during volatile periods, which is much higher than that for quiet periods. When markets are volatile, which is proxied by the high VIX of S&P 500, intermediaries make profits no matter whether or how they trade across markets. But for the quiet periods, intermediaries do not always make profits. Instead, intermediaries need to coordinate their trading in different venues to secure profits.

We also extend the analysis of cross-market arbitrage to statistical arbitrage across securities. In cross-security arbitrage, intermediaries connect end-users trading on the same risk factor across securities. In this case, intermediaries have risky arbitrage instead of deterministic arbitrage. Based on mean-reverting positions on risk factors, there are 12 intermediaries. They have an average daily profit of 11.7 million euro, much higher than that of the intermediaries who have mean-reverting positions on stocks. Moreover, the factor-based intermediaries with large position variance on risk factors have high profits. Frequency decomposition on profits shows that they profit from a longer holding period. The results indicate that factor-based intermediaries are compensated for bearing the risk of statistical arbitrage.
2.A Appendix

2.A.1 Frequency decomposition

This appendix outlines the frequency decomposition used in the paper. The techniques have been widely used to study financial markets (see e.g., Granger and Morgenstern, 1963; Hasbrouck and Sofianos, 1993; Hau, 2001; Menkveld, 2013). The discussion below is heavily based on Bloomfield (2004) and Menkveld (2013).

The mark-to-market profit $\pi_t$ in Equation 2.3 could be expressed as the product of existing position and future price change: $\pi_t = n_{t-1}(p_t - p_{t-1})$. Hence, the average mark-to-market profit $\bar{\pi}$ could be viewed as

$$\bar{\pi} = \frac{1}{T} \sum_{t=1}^{T} n_{t-1}(p_t - p_{t-1}). \quad (2.A.1)$$

Let $x_t$ denote $n_{t-1}$ and $y_t$ denote $p_t - p_{t-1}$. The average mark-to-market profit can be decomposed into different frequencies as follows. First, we find the Fourier transform of $x_t$ and $y_t$. For an equally spaced time series of length $T$, the Fourier frequencies are given by $\omega_k = 2\pi k / T$, for $k = 0, 1, ..., T - 1$. The Fourier component of $x_t$ at frequency $\omega_k$ is $J_x(\omega_k)$ and that of $y_t$ is $J_y(\omega_k)$.

$$J_x(\omega_k) = \frac{1}{T} \sum_{t=1}^{T} x_t e^{-j\omega_k t}, \quad J_y(\omega_k) = \frac{1}{T} \sum_{t=1}^{T} y_t e^{-j\omega_k t}. \quad (2.A.2)$$

Then, $x_t$ and $y_t$ could be recovered by the inverse transform as follows.

$$x_t = \sum_{k=0}^{T-1} J_x(\omega_k) e^{j\omega_k t}, \quad y_t = \sum_{k=0}^{T-1} J_y(\omega_k) e^{j\omega_k t}. \quad (2.A.3)$$
Finally, the average mark-to-market profit is \( \bar{\pi} = \frac{1}{T} \sum_{t=1}^{T} x_t y_t \), which can be expressed as

\[
\bar{\pi} = \sum_{k=0}^{T-1} J_x(\omega_k) J_y(\omega_k),
\]

(2.A.4)

where \( J_y(\omega_k) \) is the complex conjugate of \( J_x(\omega_k) \).

As to the frequency decomposition of position variance \( \text{Var}(x) \), we first demean the position series:

\[
\tilde{x}_t = x_t - \bar{x}.
\]

(2.A.5)

Similarly, \( \tilde{x}_t \) can also be written as: \( \tilde{x}_t = \sum_{k=0}^{T-1} J_x(\omega_k)e^{i\omega_k t} \). Moreover, since \( \text{Var}(x) = \text{Var}(\tilde{x}) \), the position variance can be rewritten as:

\[
\text{Var}(x) = \sum_{k=0}^{T-1} J_x(\omega_k) J_- (\omega_k),
\]

(2.A.6)

where \( J_- (\omega_k) \) is the complex conjugate of \( J_x(\omega_k) \).

The sampling frequency in our analysis is one minute. The mark-to-market profit and position variance are decomposed into frequency bins of reverting periods with boundaries at 5 minutes, 1 hour, and 1 day.

As a benchmark, the proportion of position variance for white noise process is 1% in high frequency bins (1min - 5min), 11% in medium frequency bins (5min - 1hour), and 88% in low frequency bins (1hour - 1day). Hence, a SpaceOnlyInt should have a proportion of position variance in high frequency bins higher than 1%.
2.A.2 Robust check of frequency decomposition of profits

In line with the analysis of Hasbrouck and Sofianos (1993), Table 2.12 shows the median for each group of traders. Overall, the median gross profits suggest that intermediaries make money from end-users. The median of intermediaries’ gross profits is 2020 euro while that of end-users’ is -20 euro. Furthermore, the decomposition into different frequency bins suggests that the majority of the three types of intermediaries make money from end-users across frequency bins.

Table 2.12: Frequency decomposition of profits (median)

This table shows the median profits of different groups of traders in frequency decomposition. Panel A and B report results for intermediaries and end-users, respectively. The unit is 1000 euro.

<table>
<thead>
<tr>
<th>Panel A Intermediaries</th>
<th>Total</th>
<th>TimeOnlyInt</th>
<th>SpaceOnlyInt</th>
<th>TimeSpaceInt</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ultrahigh (¡1min)</td>
<td>0.12</td>
<td>0.12</td>
<td>1.31</td>
<td>0.03</td>
</tr>
<tr>
<td>High (1min-5min)</td>
<td>0.64</td>
<td>0.64</td>
<td>66.00</td>
<td>3.24</td>
</tr>
<tr>
<td>Medium (5min-1hour)</td>
<td>0.20</td>
<td>0.38</td>
<td>0.20</td>
<td>2.00</td>
</tr>
<tr>
<td>Low (1hour-1day)</td>
<td>2.00</td>
<td>0.12</td>
<td>12.00</td>
<td>2.00</td>
</tr>
<tr>
<td>Level</td>
<td>0.07</td>
<td>-0.18</td>
<td>1.00</td>
<td>11.04</td>
</tr>
<tr>
<td>Gross profit</td>
<td>2.02</td>
<td>1.07</td>
<td>0.50</td>
<td>2.96</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B End-users</th>
<th>Total</th>
<th>SiMEndUser</th>
<th>MuMEndUser</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ultrahigh (¡1min)</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.04</td>
</tr>
<tr>
<td>High (1min-5min)</td>
<td>-0.01</td>
<td>0.00</td>
<td>-0.02</td>
</tr>
<tr>
<td>Medium (5min-1hour)</td>
<td>0.02</td>
<td>0.12</td>
<td>-0.02</td>
</tr>
<tr>
<td>Low (1hour-1day)</td>
<td>1.27</td>
<td>1.70</td>
<td>0.32</td>
</tr>
<tr>
<td>Level</td>
<td>-0.16</td>
<td>-0.79</td>
<td>-0.04</td>
</tr>
<tr>
<td>Gross profit</td>
<td>-0.02</td>
<td>-0.02</td>
<td>-0.01</td>
</tr>
</tbody>
</table>
Chapter 3

Systemic Risk in Real Time: A Risk Dashboard for Central Counterparties

3.1 Introduction

Both US and EU regulators introduced mandatory central clearing for standard derivatives after the 2008 crisis (through Dodd-Frank and EMIR, respectively). This removes bilateral counterparty exposure from both sides to a trade and concentrates it in a central clearing party (CCP). These CCPs have thus become high-pressure vaults at the heart of the financial system. It led former Fed chairman Bernanke to conclude that financial stability strongly depends on CCP resiliency (Bernanke, 2011).

State of the art risk management at CCPs becomes of first order importance. CPMI-IOSCO (2016a) recently published a report with detailed suggestions and emphasizes intraday monitoring of exposure (p. 32):

A CCP faces the risk that its exposure to its participants can change rapidly as a result of changes in prices, positions or both. Adverse price movements, as well as participants building larger positions through new trading (and settlement of maturing trades), can rapidly increase a CCP’s exposures to its
participants. This exposure can relate to intraday changes in both prices and positions. For the purposes of addressing these and other forms of risk that may arise intraday, a CCP should address and monitor on an ongoing basis how such risks affect all components of its margin system, including initial margin, variation margin and add-on charges.

Industry associations responded sympathetically but emphasized transparency of CCP policy (Associations, 2016). Their members prefer to know in what conditions a CCP might intervene intradaily with, for example, calls for additional collateral.

A series of recent incidents highlights the importance of real-time monitoring by a CCP. On October 7, 2016, the British pound dropped by almost ten percent in just eight minutes. On January 15, 2015, the Swiss franc rose by about 20% against the euro within five minutes after the Swiss central bank announced that it abandoned its peg against the euro as per immediately. On October 15, 2014, the 10-year US bond price dropped by 40 basis points, a huge plunge in a market where a single basis point change matters. These large price variations, coupled with high-speed electronic markets that lets traders build positions quickly, constitute real economic risk for CCPs.

**Real-time CCP exposure dashboard.** This paper proposes a CCP risk dashboard to measure and diagnose its exposure changes in real time. CCP exposure is based on the tail risk of losses in an oncoming period, aggregated across all clearing members (Duffie and Zhu, 2011; Menkveld, 2016a). (Note that aggregate gains are equal to aggregate losses, but are out of focus here as a CCP insures losses.) The motivation for this approach is that a CCP essentially insures the losses in its members’ portfolios and thus its exposure is commensurate to aggregate losses in the trading community.

The exposure measure has several appealing features:

- It is analytic and thus avoids simulations that would make real-time computation prohibitively costly.

---

1The positions that a CCP observes for all of its members is in the securities it clears. It does not see their net positions as there could be partially offsetting positions in securities that it does not clear or non-traded risk that is being hedged. A prudential CCP will have to assume no offsetting positions.
- It is firmly grounded in standard practice as it uses a delta-normal Value-at-Risk measure.

- It accounts for correlations across member portfolios and thus for the additional risk that crowded trades impose on a CCP.

Exposure changes are then decomposed in an economically meaningful way to identify their main causes. The decomposition implements a strict one-factor-at-a-time (OFAT) approach that allocates the exposure changes in each step to the variable that was changed. The sequencing of variables matters in the presence of interaction effects (Daniel, 1973, Exhibit A1). It has to be picked in an intelligent and reasoned way given the diagnostics one aims for.\textsuperscript{2} For example, we propose to change price variables first, and then trade variables. Changing price variables identifies the part of exposure change that is purely driven by price. It identifies it by only updating the return covariance matrix based on the price changes in the interval (keeping member portfolios fixed). Subsequent updating of member portfolios based on the new trades in the interval then identifies the part of exposure change is due to trades.

The price-change variables are then further decomposed into volatility changes, correlation changes, and price level changes. Changing volatility and correlation separately relies on a covariance matrix decomposition that is often used in the time-varying volatility literature models (Bollerslev, 1990; Engle, 2002).

The trade-change variables are further decomposed into member-by-member position changes and how these changes collectively affect cross-member portfolio correlations or, for short, the level of crowding (i.e., if all members chase the same trade(s) either long or short then the correlation in portfolio losses across members increase). These position and crowding changes are both further decomposed based on whether trades were on client or on house accounts (the latter represents trades that were done on a member’s

\textsuperscript{2}Alternatively, one could take a rather mechanical approach and compute a lower and upper bound for a variable’s contribution to overall exposure change. These bounds can be obtained by iterating over all possible sequences. This approach however is computationally costly and precludes implementation in real time. More importantly, a CCP risk manager might actually prefer a particular sequence with the implicit allocation of interaction effects that comes with it.
own book). As clearing members are mostly sell-side banks, a sudden run-up in CCP exposure due to house-house trades merits further scrutiny. Such banks are often highly leveraged institutions and operate under limited liability and therefore are likely to impose considerable (counterparty) risk on a CCP.

**Application to CCP data.** To illustrate real-time monitoring of CCP exposure, the risk dashboard is implemented on equity CCP data, more specifically on a 2009-2010 sample of Nordic equity trades. Such equity CCP essentially insures settlement of equity trades. These trades are subject to counterparty risk because the actual exchange of securities for money typically occurs three days after the trade was concluded. An equity trade is in this sense a three day forward contract. Admittedly, an application to a CCP that insures CDS contracts or interest-rate derivatives would have been more relevant in terms of systemic risk, but disaggregated CCP data is extremely hard to come by. The application to actual CCP data could therefore in and of itself be considered a contribution (as will become clear when we discuss our contribution to the literature).

The application reveals that the largest CCP exposure increases are not only extremely large, they are also different in nature than regular exposure changes. For example, the largest five-minute increase is one hundred times larger than the average exposure change. More importantly, when comparing the average decomposition of top-10 increases to the full sample of exposure changes one learns that they are different in the following ways. First, average exposure changes are completely driven by position changes in the interval: house-house trades and client-house trades both contribute 45% and the remaining 10% is due to client-client trades. When zooming into the top-10 changes, the top three contributors are house-house trades with 47%, volatility with 20%, and crowding with 17%. When further decomposing crowding one finds that half of the contribution is from house-house trades. This suggests that extreme CCP exposure increases are caused by sudden increases in volatility and heavy trading on house accounts concentrating in a single portfolio (that could consist of a single security). Such quick expansion and crowding of positions by highly leveraged firms is potentially worrisome. If there is a large price shock to this portfolio then half of these institutions face large (variation) margin calls.
3.1 Introduction

The application further shows that idiosyncratic events can have systemic impact in terms of CCP exposure. Of the top three sudden jumps in CCP exposure, two were related to the first bail-out of Greece, but one was related to a firm-specific event: an earnings announcement by Nokia. On April 22, 2010, at noon Nokia surprised analysts with earnings that were far below the consensus. Some interpreted it as Nokia surrendering in the smartphone market to its main rivals Apple and Samsung. Its share price fell in the minutes after by about 15% and did not recover in the remainder of the day. Volume jumped and stayed at an elevated levels throughout the afternoon, 400% above volume earlier in that day. Real-time exposure analysis reveals that the immediate steep exposure jump was due to volatility. This jump however was only a relatively small part of the extremely large CCP exposure increase that day. Most of it was due to rapid expansion of positions in member accounts, both house and client accounts, built up through lots of trading that afternoon. (Note that this is a non-trivial finding as the heavy volume could have been due to traders reducing their positions after observing elevated volatility.\(^3\)) Finally, the contribution of the crowding component that day is positive and about the same size as the volatility component — not surprisingly the crowding that day was in the Nokia stock. In summary, a CCP risk manager should be focused not only on macro news, but also on security-specific news as it can trigger active position taking (potentially speculation) which is potentially toxic when combined with a volatility spike and crowding in portfolios. The dashboard will alert him to such scenario in real time.

**Related literature**  
This paper contributes to a rapidly expanding empirical literature on central clearing. CCP trade data disaggregated across members are scarce. Proprietary daily data have been used to compare CCP exposure to the margins that were collected (Jones and Perignon, 2013; Menkveld, 2016a; Lopez et al., 2013). Duffie, Scheicher, and Vuilleme (2015) analyze a snapshot of bilateral exposures on uncleared credit default swaps to assess the netting efficiency potential of central clearing. Event studies on CCP introductions yield insight in how trading is affected (Loon and Zhong, 2014, 2016; Menkveld, Pagnotta, and Zoican, 2015; Benos, Payne, and Vasios, 2016). This paper con-

\(^3\)Bignon and Vuilleme (2016, Fig. 3 and A1) do forensic analysis on the Paris commodity futures CCP that failed in 1974. They, for example, find that there was elevated activity (in terms of transactions) in the half year before failure, but open positions declined (measured in 1000 tons sugur).
tributes to this literature by proposing a feasible approach to CCP exposure changes in real time and offers an economically meaningful decomposition.

The paper further contributes to a nascent literature on CCP systemic risk. Capponi, Cheng, and Rajan (2014) analyze the endogenous build-up of asset concentration due to central clearing. Amini, Filipović, and Minca (2015) investigate partial netting for a subset of liabilities in a network setting that accounts for knock-on effects and asset liquidation effects. Glasserman, Moallemi, and Yuan (2015) compare margining in dealer markets and a centrally cleared market. Menkveld (2016c) endogenizes the fire sale premium that a CCP will have to pay in the catastrophic state that a critical mass of members default and liquidity supply is thus impaired. The risk dashboard with its ability to diagnose quick run-ups in exposure adds a tool that might be useful in assessing the predictions developed in these models.\(^4\)

The rest of the paper is organized as follows. Section 3.2 develops the real-time CCP exposure dashboard step by step. Section 3.3 presents the CCP equity data. Section 3.4 implements the dashboard using this data and discusses the various insights it yields. Section 3.5 concludes.

### 3.2 Approach

This section develops the risk dashboard to monitor CCP exposure in real time. CCP exposure is measured as the tail risk of aggregate losses based on the framework of Duffie and Zhu (2011) and Menkveld (2016a). Changes in CCP exposure are decomposed into two types of risk factors: price-change factors and trade-change factors. A simple example is used to illustrate the decomposition method.

---

\(^4\)A related set of papers does not focus on concentration and systemic risk but rather on incentives and economic efficiency Koeppl, Monnet, and Temzelides (2012); Fontaine, Perez-Saiz, and Slive (2014); Acharya and Bisin (2014); Biais, Heider, and Hoerova (2016).
3.2.1 Real-time CCP exposure: tail risk in aggregate losses

Consider the case of one CCP, $I$ securities, and $J$ clearing members also referred to as traders. $R$ is an $I \times 1$ vector consisting of next period’s security returns. $R$ is assumed to be normally distributed: $R \sim N(0, \Omega)$ where $\Omega$ is the $I \times I$ covariance matrix of security returns. Let $n_j$ be an $I \times 1$ vector that captures a trader’s current dollar positions. The dollar portfolio return for a trader in the next period is a scalar $X_j$ where $X_j = n_j' R$.

Collect all $n_j$ into an $I \times J$ matrix $N$ which thus becomes the dollar position matrix of all traders. Collect all $X_j$ into the $J \times 1$ vector $X$ which thus becomes the future return vector for all traders, where $X = N'R$. Since $X$ is linear in $R$, $X$ is normally distributed: $X \sim N(0, \Sigma)$ where $\Sigma$ is the $J \times J$ covariance matrix of portfolio returns:

$$\Sigma = N'\Omega N$$

As a CCP is exposed to losses, define

$$L = -\min(0, X)$$

as the loss in trader $j$’s portfolio. Define $A$ as the aggregate loss in the trader community:

$$A = \sum_j L_j,$$

Duffie and Zhu (2011) propose to base CCP exposure on the mean aggregate loss:

$$E(A)$$

and derive an analytical expression for it. This suffices for their analysis of netting efficiency. Menkveld (2016a) considers the Value-at-Risk (VaR) of aggregate loss a better measure for CCP risk management. He uses the delta-normal method and computes the
standard deviation of $A$ to arrive at the following analytical expression:

$$ExpCCP = (A) + \alpha(A)$$

$$= \sum_{j=1}^{J} (\sigma_{jj})^{\frac{1}{2}} + \alpha \left( \sum_{k=1}^{J} \sum_{l=1}^{J} \left( \pi - \frac{1}{2\pi} \right) \sigma_{k}\sigma_{l}M(\rho_{k,l}) \right)^{\frac{1}{2}}$$

\[ (3.1) \]

where $\sigma_{ij}$ is element $i, j$ of the covariance matrix of member portfolio returns $\Sigma$. The function $M(.)$ maps portfolio return correlations into portfolio loss correlations and its analytic expression is in Menkveld (2016a, eqn. 14). As our focus is also on CCP risk management we will also use $ExpCCP$ in our analysis.

### 3.2.2 Decomposition: Root cause(s) of CCP exposure change

Changes in CCP exposure are decomposed to identify their root cause(s). The decomposition is done with an OFAT approach, the variables that CCP exposure depends on are changed sequentially to compute their contribution. The sequencing matters and the following principles have guided the risk dashboard we propose.

- Price variables are changed first, followed by trade variables. The reason for this sequencing is that it identifies a “pure” price effect. In other words, the price components communicate what CCP exposure change would have been had member portfolio not changed.

- Changes in individual variances precede changes in correlations. In other words, we first consider changes in the diagonal and then changes in the off-diagonal of a covariance matrix. This approach makes interpretation of the components straightforward: Changes in variances become pure in the sense that they are evaluated keeping correlations constant. Interaction effects due to correlation changes all enter the correlations component.
3.2 Approach

**The approach in detail.** To describe the approach in more detail, it is useful to explicitly develop how CCP exposure depends on the variables that will be changed sequentially. First off, note that CCP exposure depends only on the covariance matrix of member portfolio returns:

\[ \text{ExpCCP} = f(\Sigma). \]  
(3.2)

Since we are interested in separating diagonal and off-diagonal effects it is useful to decompose \( \Sigma \) into its variance and correlation components. Following the time-varying volatility literature and using their notation, we write \( \Sigma \) as (Bollerslev, 1990; Engle, 2002)

\[ \Sigma = D\Sigma R\Sigma D\Sigma, \]  
(3.3)

where \( D\Sigma \) is a diagonal matrix with \( \sigma_{ii}^2 \) as the \( i \)th element on the diagonal\(^5\) and \( R\Sigma \) is the correlation matrix corresponding to \( \Sigma \). Finally, we write both \( D\Sigma \) and \( R\Sigma \) as functions of the variables that enter the OFAT approach:

\[ D\Sigma = D(D_{\Omega}, R_{\Omega}, P, \tilde{N}), \]
\[ R\Sigma = R(D_{\Omega}, R_{\Omega}, P, \tilde{N}), \]  
(3.4)

where the deep parameters (that enter OFAT) are: the covariance matrix of security returns \( \Omega \), the price level \( P \), and the member portfolio holdings’ matrix \( \tilde{N} \) expressed in terms of the number of securities (as opposed to \( N \) which was expressed in dollars). The reason for using \( \tilde{N} \) is that we want to pull out the price effect when considering an update from \( N_{t-1} \) to \( N_t \). This ensures that the trade components \( \text{TrPosition} \) and \( \text{TrCrowding} \) capture a clean trade effect. So putting it all together we have

\[ \text{ExpCCP} = f(\Sigma) \]
\[ = g(D\Sigma, R\Sigma) \]
\[ = g(D(D_{\Omega}, R_{\Omega}, P, \tilde{N}), R(D_{\Omega}, R_{\Omega}, P, \tilde{N})). \]  
(3.5)

\(^5\sigma_{ij} \) refers to element \((i, j)\) of \( \Sigma \).
and therefore

\[ \Delta \text{ExpCCP}_t = g \left( D \left( 1, 2, 3, 4, 5 \right), R \left( 1, 2, 3, 4, 5 \right) \right) - g \left( D \left( 1, 2, 3, 4, 5 \right), R \left( 1, 2, 3, 4, 5 \right) \right) \] (3.6)

The decomposition into the five components is done by sequentially updating the various terms from \( t - 1 \) to \( t \). The sequencing is illustrated by the (red) numbers on top of the various terms in eqn. (3.6). For example, the first component becomes:

\[ \text{RetVolat}_t = g \left( D \left( 1, 2, 3, 4, 5 \right), R \left( 1, 2, 3, 4, 5 \right) \right) - g \left( D \left( 1, 2, 3, 4, 5 \right), R \left( 1, 2, 3, 4, 5 \right) \right) \] (3.7)

This component captures the contribution of volatility change. The five components constructed this way are listed below (where the numbers correspond to the red numbers in eqn. 3.6):\(^6\)

**Price components.**

1. **RetVolat**: The impact of the change in volatilities of security returns on CCP exposure change. This effect is due to the well established empirical fact that volatility is time-varying (commonly referred to as “GARCH” or “stochastic volatility” in the financial econometrics literature).

2. **RetCorr**: The additional impact of a change in the correlations of security returns on CCP exposure change. The time-varying nature of such correlations is another well known empirical fact (e.g., identified through a dynamic conditional correlation (DCC) model, Engle, 2002). The impact of changing correlations is particularly important on a sudden steep drop in security prices. Not only does volatility increase in such crisis periods, correlations also tend to increase (Preis et al., 2012). This interaction effect is, by first considering volatilities and then correlations in the decomposition, completely assigned to **RetCorr**.

\(^6\)We include explicit formulas for all these components in Appendix 3.A.1 for completeness.
3. *PrLevel*: The additional impact of a change in the price level of securities. This effect is entirely due to covariance matrices being defined in relative terms (i.e., it is based on percentage returns as opposed to dollar returns). For example, a covariance matrix might not have changed in the interval, but if price levels dropped, then CCP exposure dropped because the latter is defined in terms of dollars. Such effect is picked up by *PrLevel*.

**Trade components.**

4. *TrPosition*: The additional impact due to new trades that arrived in the interval. These trades might expand or reduce traders’ legacy positions. CCP exposure therefore does not necessarily increase on new trades. It declines if their overriding effect was to reduce traders’ positions.

5. *TrCrowding*: The additional effect due to a change in the extent to which traders’ portfolio returns correlate. If such correlations increased as a result of the new trades, then CCP exposure increased. This effect is referred to as crowding as increased correlations imply that the new trades tilted their portfolios towards the same risk factor(s).

The trade components can be further decomposed into contributions by client-client (CC) trades, client-house (CH) trades, and house-house (HH) trades. This further decomposition is a straightforward extrapolation and is left to Appendix 3.A.1. The only important choice is the sequencing where we chose to change CC first, CH second, and HH last. This assigns any interaction effects mostly to house trades, which we believe is the most natural option. It is likely that clearing members being mostly intermediaries respond to client trades by trading on their own account rather than the other way around. House-house trades coming last in the sequence might be the final stage where clearing members risk-share by trading with one another.
3.2.3 Simple example to illustrate the exposure-change decomposition

Table 3.1 illustrates the decomposition of CCP exposure changes with a simple example. Suppose there are four agents ($A_1, A_2, A_3, A_4$) and two securities ($S_1$ and $S_2$) that trade at a price of one and whose returns are standard normal and independently distributed, at least at the beginning of time. All agents start with a zero position the securities. To illustrate real time CCP exposure monitoring, we will consider a sequence of events, where every period features some event. We compute CCP exposure change for each period and present its decomposition. This controlled “lab experiment” serves to familiarize with the approach before implementing it on real data.

The first two columns in the table illustrates the sequence of events. The first column serves as an index of time. CCP exposure is computed at each snapshot for the oncoming period. The second column illustrates the event that took place in the period just ended. Horizontal arrows correspond to positions in the first security. Arrows right denote long positions, arrows left denote short positions. Vertical arrows correspond to positions in the second security. Arrows up denote long positions, arrows down denote short positions. The remaining columns show CCP exposure, its change over the period just ended, and the decomposition.

- At $t = 0$, CCP exposure is 0 for the simple reason that none of agents has a position.

- At $t = 1$, $A_1$ enters a one unit long position on $S_1$ and $A_2$ is on the opposite side of that trade. CCP exposure becomes 3.8. The decomposition shows that 4.9 is due to expanded positions ($TrPosition$) and the crowding component is -1.1 ($TrCrowding$). The reason for this negative term is simply that in this case the traders necessarily take the opposite site of the same trade and their portfolio returns are thus perfectly negatively correlated.

- At $t = 2$, $A_3$ enters a one unit long position in $S_2$ with $A_4$ taking the short side. CCP exposure increases by 2 units to 5.8. The decomposition shows a positive $TrPosition$.


Table 3.1: Simple example to illustrate decomposition of CCP exposure changes

This example illustrates how the decomposition method identifies the different components in CCP exposure changes. There are four agents (A1, A2, A3, A4) and two securities (S1, S2). Arrows denote positions in these securities. Arrows right and left illustrate long and short positions in S1, arrows up and down long and short positions in S2. Red dashed arrows correspond to new trades in the interval. CCP exposures are based on a VaR with $\alpha = 7$. Exposure changes are decomposed into five components.

<table>
<thead>
<tr>
<th>$t$</th>
<th>Trades/changes</th>
<th>$ExpCCP_t$</th>
<th>$\Delta ExpCCP_t = \text{RetVolatility} + \text{RetCorrelation} + \text{Price Level} + \text{TrPosition} + \text{TrCrowding}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>$\sigma_1 = \sigma_2 = 1, \rho = 0, p_1 = p_2 = 1$</td>
<td>0.0</td>
<td>0.0 0.0 0.0 0.0 0.0 0.0</td>
</tr>
<tr>
<td>1</td>
<td>$\sigma_1 = \sigma_2 = 1$</td>
<td>3.8</td>
<td>3.8 0.0 0.0 0.0 4.9 -1.1</td>
</tr>
<tr>
<td>2</td>
<td>$\sigma_1 = \sigma_2 = 1$</td>
<td>5.8</td>
<td>2.0 0.0 0.0 0.0 0.0 2.9 -0.9</td>
</tr>
<tr>
<td>3</td>
<td>Volatility changes from $\sigma_1 = \sigma_2 = 1$ to $\sigma_1 = 2, \sigma_2 = 1$</td>
<td>9.1</td>
<td>3.3 3.3 0.0 0.0 0.0 0.0 0.0</td>
</tr>
<tr>
<td>4</td>
<td>Return correlation changes from $\rho = 0$ to $\rho = 0.5$</td>
<td>9.7</td>
<td>0.6 0.0 0.6 0.0 0.0 0.0 0.0</td>
</tr>
<tr>
<td>5</td>
<td>Price level changes from $p_1 = p_2 = 1$ to $p_1 = 0.5, p_2 = 1$</td>
<td>6.3</td>
<td>-3.4 0.0 0.0 -3.4 0.0 0.0 0.0</td>
</tr>
<tr>
<td>6</td>
<td>$\rho = 0.5, p_1 = 0.5, p_2 = 1$</td>
<td>3.8</td>
<td>-2.5 0.0 0.0 0.0 0.0 -2.5 0</td>
</tr>
<tr>
<td>7</td>
<td>$\rho = 0.5, p_1 = 0.5, p_2 = 1$</td>
<td>7.6</td>
<td>3.8 0.0 0.0 0.0 0.0 2.9 0.9</td>
</tr>
</tbody>
</table>
of 2.9 and a negative $TrCrowding$ of 0.9. The positive position risk is because the new trade leads to larger positions. Furthermore, the new trade between $A3$ and $A4$ is in $S2$ and therefore orthogonal to the positions between $A1$ and $A2$. In other words, the new trade between $A3$ and $A4$ lowers the interconnectedness between traders’ portfolio returns. Hence, there is less crowding now than before.

- At $t = 3$, the return volatility of $S1$ increases from 1 to 2. CCP exposure increases to 9.1, an increase of 3.3. The decomposition rightfully attributes it to the volatility component ($RetVola$).

- At $t = 4$, the correlation between $S1$ and $S2$ returns increases from 0 to 0.5. CCP exposure increases by 0.6 to 9.7. The decomposition assigns it all to the correlations component ($RetCorr$).

- At $t = 5$, the price of $S1$ drops from 1 to 0.5. CCP exposure drops by 3.4 which is completely assigned to the price level ($PrLevel$). This is simply the result of volatility being defined in relative terms. If it does not change, but the price level drops then the VaR in dollar terms drops.

- At $t = 6$, $A3$ and $A4$ effectively undo their earlier trade by entering a reverse trade. In the trade $A3$ is long one unit of $S2$ and $A4$ is on the short side. CCP exposure declines by 2.5 to 3.8. The decomposition shows that it is all due to a reduction in outstanding (net) positions (i.e., the drop is assigned to $TrPosition$). This event shows that trade does not necessarily imply more exposure, it could mean less exposure when, as a result of it, outstanding positions shrink.

- At $t = 7$, $A3$ continues to trade with $A4$ but this time he enters a one-unit long position in $S1$ where $A4$ takes the short side. CCP exposure increases by 3.8 to 7.6. Since as a result all positions now crowd in a single risk factor ($S1$), the decompositions assigns 0.9 of the increase to $TrCrowding$ and the remaining 2.9 to $TrPosition$. Note that combining $t = 6$ and $t = 7$ the size of trading positions have not changed — traders are long or short the same amount of risk — but CCP exposure has changed due to crowded positions at $t = 7$. 
In short, the decomposition of CCP exposure changes disentangles various channels. *Tr-Position* picks up whether new trades extend or reverse legacy positions. *TrCrowding* captures the interconnectedness between traders’ portfolio returns. *RetVola*, *RetCorr*, and *PrLevel* identify exposure changes due to changes in the volatility of returns, their correlations, and price levels, respectively. After this lab experiment, we now turn to implementation of the risk dashboard on real-world CCP data.

### 3.3 Data

European Multilateral Clearing Facility (EMCF) provided us with a data sample. EMCF — now merged with DTCC into EuroCCP — is an equity CCP for Nordic stock markets, including Denmark, Finland, and Sweden. The sample consists of trade reports with for each trade a time stamp, the number of securities traded, the transaction price, and for each side to the trade an anonymized counterparty ID and whether the trade was done on house account or on client account. A trade on house account is on a clearing member’s own books whereas a client account is trade done for clients.\(^7\) The data sample runs from October 19, 2009 through September 10, 2010 and includes trades on almost all exchanges: NASDAQ-OMX, Chi-X, Bats, Burgundy, and Quote MTF. The only exchange whose Nordic trades it did not clear was Turquoise. Turquoise, however, had a market share of less than 1% at the time.

A equity CCP insures counterparty risk for equity trades in the period until a trade is settled. When an exchange concludes a trade, the money and the securities are not immediately transferred, only three days later in our sample. In this system, referred to as T+3, the CCP insures this commitment to do so for these three days. It is conceptually similar to a forward contract. To fix language, we therefore refer to yet to settle trades as positions. Note that these positions change overnight absent any trade. This change is simply due to settlement of legacy trades and these trades are therefore removed from

\(^7\)The new post-crisis EMIR regulation in Europe requires a CCP to segregate trades on house accounts from those on client accounts as of 2013. Our data sample precedes this date but EMCF had already implemented such segregation.
traders’ positions. In other words, if a trader does not trade for three consecutive days, his position in all equities becomes zero as all his earlier trades settled. Finally, we refer to a trader’s set of open positions at any point in time as his portfolio. Note that this is not be confused as a trader’s portfolio in terms of the equity he is holding. It is simply refers to the yet to settle trades as these are relevant for CCP exposure since it is for these open positions that he insures counterparty risk.

**Summary statistics.** Table 3.2 presents some statistics to summarize the data. Panel A reveals that the sample captures trading in 242 stocks on 228 days. It contains 226 trading accounts, 87 are house accounts and 139 are client accounts.

Panel B characterizes trading by presenting summary statistics on volume and open positions. For all accounts, the average daily volume is 1.2 million shares, with a standard deviation of 2.3 million shares. The overall average position is zero because the CCP, by construction, always has a matched book. The overall standard deviation of position is €1.5 million. The within (account) standard deviation of both volume and position is relatively modest. In other words, most variation of volume and position is across accounts, but there is nevertheless substantial trough-time variation in accounts (at least a third of overall variation).

Separating house and client accounts, one observes that house accounts trade more actively than client accounts. The average daily volume on house accounts is 1.6 million shares, twice as large as volume on client accounts. The standard deviation of house volume is 2.7 million shares, again substantially higher than the standard deviation of client volume which is 1.5 million shares. House accounts also have larger variation in terms of position. The standard deviation of house position is €1.9 million whereas the standard deviation of client position is €1.1 million.
Table 3.2: Summary statistics

This table characterizes the CCP data sample by presenting some summary statistics. Clearing members are referred to as traders. Trades on house accounts are for a clearing member’s own book, whereas client accounts refer to trading that a clearing member does for clients.

<table>
<thead>
<tr>
<th>Panel A: General information</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of trading days</td>
</tr>
<tr>
<td>Number of stocks</td>
</tr>
<tr>
<td>Number of traders</td>
</tr>
<tr>
<td>House accounts</td>
</tr>
<tr>
<td>Client accounts</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Trade information</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean of daily volume (shares)</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Std of daily volume (shares)</td>
</tr>
<tr>
<td>Within trader std of daily volume (shares)</td>
</tr>
<tr>
<td>Mean of end-of-day position (euro)</td>
</tr>
<tr>
<td>Std of end-of-day position (euro)</td>
</tr>
<tr>
<td>Within trader std of end-of-day position (euro)</td>
</tr>
</tbody>
</table>

3.4 Application

In this section, the risk dashboard is implemented on actual CCP data. We first discuss some implementation details. We then compute intraday CCP exposure changes and decompose them. Finally, we zoom into the right tail of exposure increases and compare the profile of risk changes for in extreme increases to that of average changes.

3.4.1 Implementation details

We implement the risk dashboard on five-minute intervals. It could conceptually be implemented at arbitrarily high frequency, but we pick five minutes inspired by real-world practice. The Swiss clearinghouse, for example, considers a five-minute interval an appropriate period to collect collateral to insure counterparty risk (SIX, 2014). Hence, the covariance matrix $\Omega_t$, the price matrix $P_t$, and the position matrix $\tilde{N}_t$ are updated every five minutes. For ease of exposition we continue to refer to this implementation as real time CCP exposure measurement.
Deseasonalize returns. It is well known that intraday volatility has a U shape pattern (e.g., Lockwood and Linn, 1990; Andersen and Bollerslev, 1997). As our focus is on surprise CCP exposure changes we prewhiten the return series by removing the diurnal pattern. We first estimate this pattern based on raw returns that are winsorized at 5% and 95% to remove outliers. Let $\tilde{r}_{i,d,\tau}$ denote the winsorized return at time $t = (d, \tau)$ where $d$ denotes day and $\tau$ intraday time point (e.g., 10:00:00 AM). Following Andersen and Bollerslev (1997), the intraday seasonality is estimated as the standard deviation of returns at $\tau$ across different days (averaging across stocks):

$$\sigma_\tau = \left( \frac{1}{t} \sum_i \left( \frac{1}{D} \sum_d \tilde{r}_{i,d,\tau}^2 \right) \right)^{\frac{1}{2}}, \quad (3.8)$$

where $\tilde{r}_{i,d,\tau}$ denotes the raw return of stock $i$ on day $d$ and intraday time point $\tau$. These standard deviations are then scaled by their mean to ensure that their overall average equals one:

$$\bar{\sigma}_\tau = \frac{\sigma_\tau}{\frac{1}{T} \sum_\tau \sigma_\tau}, \quad (3.9)$$

where $T$ denotes the number of intraday time points in a day. The raw returns of each stock can now be scaled by this series without affecting its unconditional volatility (because the scaling series averages to one by construction). The prewhitened return series thus becomes:

$$r_{i,d,\tau} = \frac{\tilde{r}_{i,d,\tau}}{\bar{\sigma}_\tau}. \quad (3.10)$$

For completeness, the diurnal volatility pattern that we estimated from the data was added to the appendix. The pattern illustrates the importance of U.S. markets. The start of floor trading in U.S. index futures coincides with a substantial volatility increase Nordic equities. This Nordic volatility increases further when the U.S. equity markets open one hour later.

Estimate the return covariance matrix. To account for time-varying volatility, the return covariance matrix is estimated as an exponentially weighted moving average (EWMA) of the outer product of returns. This follows standard practice (e.g., RiskMetrics) and corresponds to estimating an IGARCH(1,1). A further benefit is that the frequency is
low enough to avoid contamination of the volatility estimate by “microstructure noise” (Hansen and Lunde, 2006). What remains is to pick the decay parameter. RiskMetrics uses 0.94 for its highest frequency, daily returns. We decide to the decay parameter for five-minute returns such that the half life of a shock corresponds to the half life of a daily shock in RiskMetrics. As a full day return comprises 131 five-minute intervals (where the non-trading overnight period is expressed in five-minute trading hour intervals based on average volatility).\(^8\) The five-minute decay parameter should therefore imply a half life of 11 days to correspond to what is implied by the RiskMetrics approach. It solves:

\[
\lambda_{5\text{min}}^{11 \times 131} = \lambda_{\text{RiskMetrics,daily}}^{11} = 0.94^{11} \approx \frac{1}{2}.
\]  

(3.11)

This implies a five-minute decay parameter of 0.9995. Hence, the five-minute EWMA covariance is calculated recursively by

\[
\Omega_{t+1} = 0.0005(r_t r'_t) + 0.9995 \Omega_t.
\]

(3.12)

The sample we use for the risk dashboard runs as of October 19, 2009, but we used data as of September 1 that year to have a burn-in period for \(\Omega_t\). We start the series off at a zero matrix, but given the half-life of 11 days, the effect of this choice is negligible by the time we arrive at October 19, 2009.

**Pick \(\alpha\) to make ExpCCP a standard 99% VaR.** The Principles for Financial Market Infrastructure (CPMI-IOSCO, 2012) sets an international standard for CCP risk management. It recommends that a CCP sets the margin requirement for a trader equal to the 99% VaR on the his (unsettled) positions. To make ExpCCP adhere to this standard, the number of standard deviations used in its definition (i.e., alpha) should be picked so that it becomes a 99% VaR. A simple calibration exercise computes how often ExpCCP is exceeded by the aggregate loss in the (oncoming) period to which ExpCCP pertains. Figure 3.1 illustrates exceedance frequency for various levels of alpha and shows that setting it to five yields a 1% exceedance rate and makes ExpCCP a 99% VaR. It further illustrates

\(^8\)The trading hours contain 120 five-minute intervals, 11 were added to capture the overnight non-trading period, which is well known to exhibit lower volatility per time unit than the trading period.
that the empirical distribution of $\text{ExpCCP}$ has fat tails when compared to various standard benchmarks. It also plots the Chebyshev’s upper bound which reveals that the empirical distribution’s tail is still substantially below the most extreme case.

### 3.4.2 Real-time CCP exposure

Figure 3.2 plots real-time CCP exposure for the entire sample period. Average five-minute CCP exposure is €3 million. There are two periods with extremely large CCP exposure. The first one is April 22-23, 2010. The second one is May 5-11, 2010. We identify two sets of events that arguably led to these extreme exposures.

The first event is Nokia announcing earnings far below analyst expectations at noon on April 22, 2010. Some interpreted it as Nokia surrendering in the smartphone market to its main opponents Apple and Samsung. Its share price dropped by about 15% in the minutes after the announcement. Trading volume jumped and remained high throughout the afternoon, 400% above what volume was in the morning of that day. CCP exposure increased steeply from €2.4 million at the start of April 22 to €8.8 million at the end of April 23.

The second set of events corresponds to major developments in the Greek sovereign debt crisis. A chronological review of these developments is as follows. On May 5, mass protests erupt in Greece against the imposed austerity measures, with three deaths reported. This social turbulence leads to market concerns that it could jeopardize the rescue package proposed by the European Union and the International Monetary Fund on May 2. To fund this intervention and future ones, the European Commission creates the European Financial Stabilisation Mechanism on May 9 (EC, 2010b). On May 10, the European Central Bank announces the Securities Markets Programme to address “dysfunctional” securities markets (ECB, 2010). Figure 3.2 illustrates that CCP exposure starts to increase on May 5 and reaches its peak of €11.0 million at 9:00 am on May 10 and stays at a level of €8.5 million until the end of trading on May 11.
Figure 3.1: ExpCCP exceedance frequency

This figure plots the frequency of ExpCCP exceedance along with various standard distributions as benchmark. An exceedance occurs when the aggregate loss in a particular period exceeds its Value-at-Risk prediction ExpCCP. The frequency of exceedance is calculated for various values of alpha since ExpCCP is defined as the mean of aggregate loss plus alpha times the standard deviation of aggregate loss: \( \text{ExpCCP} \equiv \text{VaR}(A) = (A) + \alpha(A) \). The red solid line shows the exceedance frequency as a function of alpha. The exceedance probability for some standard distributions is added as benchmark, denoted by blue marked lines. All exceedance rates are one-sided (i.e., \( \text{Prob}(X \geq x) \)). The black dashed lines reveal what alpha makes ExpCCP be the 99\% VaR recommended by the Principles of Financial Market Infrastructures (CPMI-IOSCO, 2012).
Figure 3.2: CCP exposure in real time

This figure plots CCP exposure in real time, implemented by cutting the sample up into five-minute intervals. The CCP exposure measure ExpCCP is defined as the 99% Value-at-Risk on (stochastic) aggregate loss for the oncoming five-minute interval. This aggregate loss is constructed by summing the (stochastic) losses in all clearing members’ trade accounts. Each shaded interval corresponds to one week.
3.4 Application

Figure 3.3: Histogram of CCP exposure changes

This figure shows the histogram of CCP exposure changes over five-minute intervals. Darker shades of red are used to illustrate the 100 and the 10 largest increases.

3.4.3 Decomposition of CCP exposure changes

Figure 3.3 illustrates the distribution of intraday CCP exposure changes.\(^9\) The histogram uses a darker shade of red to indicate the top 100 changes, and an even darker shade for the top 10 changes. We will analyze these subsamples separately to establish whether the profile of these exposure changes is different from average exposure changes. In other words, does the system behave differently when entering the tail? The histogram itself shows that the right tail is rather fat. Large exposure increases seem disproportionately large and therefore worrisome.

Table 3.3 presents the decomposition results for intraday CCP exposure changes for the full sample, the top 100 largest increases, and the top 10 largest increases. The average

\(^9\)We discard the overnight changes as they are trivial and simply due to some trades dropping from the sample as they get settled. Overnight changes are therefore reduce CCP exposure.
Table 3.3: Decomposition of CCP exposure changes

This table presents the decomposition of CCP exposure changes for the full sample, the 100 largest increases, and the 10 largest increases. Panel A presents the value of the various components and Panel B repeats Panel A with these values expressed in relative terms.

<table>
<thead>
<tr>
<th></th>
<th>Full sample</th>
<th>Top 100</th>
<th>Top 10</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Risk components</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{RetVola}$</td>
<td>-202</td>
<td>13,110</td>
<td>94,695</td>
</tr>
<tr>
<td>$\text{RetCorr}$</td>
<td>-62</td>
<td>1,507</td>
<td>-4,848</td>
</tr>
<tr>
<td>$\text{PrLevel}$</td>
<td>-96</td>
<td>2,911</td>
<td>-29,479</td>
</tr>
<tr>
<td>$\text{TrPositionCC}$</td>
<td>846</td>
<td>12,205</td>
<td>40,309</td>
</tr>
<tr>
<td>$\text{TrPositionCH}$</td>
<td>3,492</td>
<td>49,859</td>
<td>67,335</td>
</tr>
<tr>
<td>$\text{TrPositionHH}$</td>
<td>3,590</td>
<td>97,851</td>
<td>221,840</td>
</tr>
<tr>
<td>$\text{TrPosition}$</td>
<td>7,928</td>
<td>159,916</td>
<td>329,484</td>
</tr>
<tr>
<td>$\text{TrCrowdingCC}$</td>
<td>28</td>
<td>1,675</td>
<td>7,330</td>
</tr>
<tr>
<td>$\text{TrCrowdingCH}$</td>
<td>154</td>
<td>9,420</td>
<td>29,875</td>
</tr>
<tr>
<td>$\text{TrCrowdingHH}$</td>
<td>73</td>
<td>11,359</td>
<td>43,884</td>
</tr>
<tr>
<td>$\text{TrCrowding}$</td>
<td>254</td>
<td>22,454</td>
<td>81,089</td>
</tr>
<tr>
<td>$\Delta\text{ExpCCP}$</td>
<td>7,822</td>
<td>199,898</td>
<td>470,942</td>
</tr>
<tr>
<td><strong>Panel B: Relative importance</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{RetVola}$</td>
<td>-2.6%</td>
<td>6.6%</td>
<td>20.1%</td>
</tr>
<tr>
<td>$\text{RetCorr}$</td>
<td>-0.8%</td>
<td>0.8%</td>
<td>-1.0%</td>
</tr>
<tr>
<td>$\text{PrLevel}$</td>
<td>-1.2%</td>
<td>1.5%</td>
<td>-6.3%</td>
</tr>
<tr>
<td>$\text{TrPositionCC}$</td>
<td>10.8%</td>
<td>6.1%</td>
<td>8.6%</td>
</tr>
<tr>
<td>$\text{TrPositionCH}$</td>
<td>44.6%</td>
<td>24.9%</td>
<td>14.3%</td>
</tr>
<tr>
<td>$\text{TrPositionHH}$</td>
<td>45.9%</td>
<td>49.0%</td>
<td>47.1%</td>
</tr>
<tr>
<td>$\text{TrPosition}$</td>
<td>101.3%</td>
<td>80.0%</td>
<td>70.0%</td>
</tr>
<tr>
<td>$\text{TrCrowdingCC}$</td>
<td>0.4%</td>
<td>0.8%</td>
<td>1.6%</td>
</tr>
<tr>
<td>$\text{TrCrowdingCH}$</td>
<td>2.0%</td>
<td>4.7%</td>
<td>6.3%</td>
</tr>
<tr>
<td>$\text{TrCrowdingHH}$</td>
<td>0.9%</td>
<td>5.7%</td>
<td>9.3%</td>
</tr>
<tr>
<td>$\text{TrCrowding}$</td>
<td>3.2%</td>
<td>11.2%</td>
<td>17.2%</td>
</tr>
<tr>
<td>$\Delta\text{ExpCCP}$</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

of five-minute CCP exposure change is €7,822, €199,898, and €470,942 for the full sample, the top 100, and the 10, respectively.

For the full sample, the most important components are position changes due to house-house trades, client-house trades, and client-client trades. Together they make up roughly the full 100% of CCP exposure change, accounting for 45.9%, 44.6%, and 10.8%, respectively. It is perhaps not surprising that, on average, exposure increases seem to be driven entirely by new trades.

When zooming in on large CCP exposure increases, a different picture emerges. The contribution of new trades drops from virtually all of the change for the full sample to...
80% for the top 100 increases, and 70% for the top 10 increases. The components that grow in importance are volatility, which is 6.6% for the top 100 increases and 20.1% for the top 10 increases. Crowding is the other important component making up 11.2% for the top 100 and 17.2% for the top 10. Further decomposing this crowding component reveals that house-house trades contribute most to crowding, 5.7% for the top 100 increases and 9.3% for the top 10.

The significant contribution of crowding on house accounts coupled with a volatility shock is potentially worrisome. Most clearing members are highly leveraged sell-side banks who, if trading for speculative reasons, might default on their position if they turn out to be on the wrong side of the bet. Given that they seem to crowd on the same (set of) risk factors, there might be multiple that are heavily underwater on their bets at the same time. Admittedly, it is unlikely that they default on their equity trades, but if the same pattern holds true for CCPs that clear interest rate derivatives or CDS contracts, then such dynamic does become a systemic worry.

### 3.4.4 Three largest exposure increases

We further zoom into the three largest CCP exposure increases (largest one first):

- April 22, 2010, 12:00-12:05,
- May 5, 12:30-12:35,

The first and second one corresponds to a Nokia event and the Greek sovereign debt crisis, as discussed in Section 3.4.2. The third one is after an aftershock to this crisis when on May 20 the European Commission proposes a permanent crisis resolution mechanism (EC, 2010a). In the analysis below we treat the entire period, May 5-20, as the sovereign debt crisis period.
**Diagnostic analysis Nokia announcement.** The analysis is done in two steps. We first decompose the five-minute exposure increase to perform forensic analysis on its root causes. We then zoom out to study how exposure continued to evolve and how it developed immediately prior to the jump in CCP exposure.

Figure 3.4 graphically decomposes the five-minute exposure jump immediate following Nokia’s disappointing announcement. A couple of features stand out. First, return volatility is by far the largest component: €0.9 million. Its effect is moderated some by the price-level component being negative: €0.3 million. In other words, volatility spikes due to a large and immediate negative on Nokia of about -15%, but relative volatility operates at a lower price level *because* of the negative return. It is the latter effect that is subsumed by the price-level component. Finally, the trade components all add to CCP exposure implying that on average traders are expanding their positions and their position-taking leads to more crowding, in particular for house-house trades. All these trade component however are dwarfed by the volatility component.
Figure 3.4: Decomposition of the largest CCP exposure increase: Nokia’s announcement

This figure presents the decomposition of the largest CCP exposure increases: April 22, 2010, 12:00-12:05. It followed a Nokia earnings announcement at noon that day which was far below analyst expectations. The green bars correspond to negative values of components (i.e., exposure decreases), the red bars correspond to positive values of components (i.e., exposure increases). The gray bar shows the total CCP exposure change.
Figure 3.5 zooms out and shows how CCP exposure built up throughout the day of the Nokia event. Its most salient feature is that while the volatility spike dominates exposure change in the five minutes after the event, it is only about a fifth of the daily exposure change. The reason is that volatility is a negligible component (i.e., no further strong changes in volatility) in the hours after the event, but trade components contribute lots to CCP exposure changes in the afternoon. Elevated volume in the afternoon turns out to be of the nature that traders expand position in the aftermath of the event, they do not reduce them. This might be due to diverging beliefs on how the Nokia events affect’s the company’s fundamental value. All trading components contribute substantially to daily volume, with client-house and house-house trading contributing most. There is also substantial crowding due to house-house trades. In fact, crowding is economically important since when adding all crowding components together it contributes as much to daily exposure change as volatility. Finally, there does not seem to be substantial position-taking ahead of the announcement as all components only start to contribute substantially as of noon that day.

Perhaps the most important message of the Nokia event results that a firm-specific shock can have systemic impact through heightened CCP exposure. News that strikes like lightning causes volatility to spike and, more importantly, makes traders expand their position in such a way that there more concentration in their portfolios (i.e., crowding).
Figure 3.5: Decomposition of CCP exposure changes on the day of its largest increase: Nokia’s announcement

This figure presents a decomposition of cumulative CCP exposure changes on April 22, 2010 when Nokia announced earnings far below analyst expectations. Each shaded interval is half an hour.
Diagnostic analysis sovereign debt crisis period. Figure 3.6 illustrates the nature of the two second largest five-minute CCP exposure increases by decomposing change into the various components. Both sudden increases occur in the midst of the Greek sovereign debt crisis. The decomposition shows that the increase is all but caused by position expansions due to house-house trades. In the first event, May 5, 12:30-12:35, there is some moderation from a negative crowding component on house-house trades. It seems that the expansions lead to more diversity in portfolios, which takes off about a fifth of the elevated CCP exposure due to house-house position taking. In the second event, May 20, 10:40-10:45, it seems that the expansions reduce diversity as the crowding component adds substantially to the CCP exposure increase, about a quarter of the total increase. The decomposition illustrates the importance of explicitly considering crowding. Its impact is not only economically large, it might either moderate the exposure increase or multiply it.
Figure 3.6: Decomposition of the second and third largest CCP exposure increases

This figure presents the decomposition of the second and third largest CCP exposure increases: May 5, 12:30-12:35 and May 20, 10:40-10:45. These increases happened in the midst of the Greek sovereign debt crisis. The green bars correspond to negative values of components (i.e., exposure decreases), the red bars correspond to positive values of components (i.e., exposure increases). The gray bar shows the total CCP exposure change.

<table>
<thead>
<tr>
<th>Date</th>
<th>Time</th>
<th>ΔExpCCP</th>
<th>RetVola</th>
<th>RetCorr</th>
<th>PrLevel</th>
<th>TrPositionCC</th>
<th>TrPositionCH</th>
<th>TrPositionHH</th>
<th>TrCrowdingCC</th>
<th>TrCrowdingCH</th>
<th>TrCrowdingHH</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010-05-05</td>
<td>12:30-12:35</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
</tbody>
</table>
Figure 3.6 continued.
Figure 3.6 zooms out and illustrates the nature of exposure changes for the entire Greek sovereign debt crisis period. First off, note that the graph has a sawtooth pattern to it. This is due to settlement of some trades in the overnight period (see T+3 discussion in Section 3.3). The graph further shows that the pattern of house-house trades contributing most of the two largest sudden exposure increases in the debt crisis, extends to the entire period. Contrary to these extreme increases, the entire period does not show any strong effect on any crowding component. The other striking difference is that client-house trades did not contribute much in the five minutes of extreme increases, but do contribute substantially in the entire period. To sum up, the strong contribution of house-house trades, both *per se* and through crowding, in the two sudden and extreme jumps in CCP exposure is “extraordinary.”
Figure 3.6: Decomposition of CCP exposure changes in the midst of the Greek sovereign debt crisis

This figure presents a decomposition of cumulative CCP exposure changes from May 5 through May 20, 2010. This period covers major events in the Greek sovereign debt crisis. Each shaded interval is one trading day. The series is started off at zero at the start of each day as the focus is on the intraday build-up of CCP exposure. The series show the cumulative sum of exposure changes measured in units of €1 million dollar per five minutes.
3.5 Concluding remarks

In summary, this paper proposes a risk dashboard for CCPs to gauge their exposure changes in real time. These changes are decomposed into two types of components: price-change variables and trade-change variables. Price-change variables disentangle three channels by which security price changes affect CCP exposure: changes in volatilities, changes in correlations, and changes in price levels. Trade-change variables include changes in member positions and the extent of crowding in their portfolios. The position component captures whether a new trade extends or reverses existing positions, while the crowding component identifies changes in the interdependence of member portfolio returns. Furthermore, in order to identify whose trades give rise to CCP exposure changes, both the position and the crowding component changes are decomposed according to the nature of trades (client-client trades, client-house trades, or house-house trades).

We implement the dashboard on trade data obtained from an equity CCP. Real-time CCP exposure turns out to exhibit extreme right skewness, as the sample features disproportionately large sudden jumps in CCP exposure. Decomposition results reveal that volatility and crowding contribute substantially to extreme exposure run-ups. They are negligible in average exposure changes but contribute almost a third to extreme CCP exposure increases. These extreme increases are further characterized by strong crowding due to house-house trades. These findings make a strong case for intraday exposure monitoring for CCP risk managers and those who regulate them. These types of events might call for contingency planning, but what actions are appropriate is left for future research.
3.A Appendix

3.A.1 Decomposition of CCP exposure change into components

This section defines the various components that make up CCP exposure change from $t-1$ to $t$

$$\Delta \text{ExpCCP}_t = \underbrace{\text{RetVola}_t + \text{RetCorr}_t + \text{PrLevel}_t + \text{TrPosition}_t + \text{TrCrowding}_t}_\text{Price components}$$  \hspace{1cm} (3.A.1)

where the final two components can be decomposed further based on client/house account classification for each side to a trade (i.e., buyer and seller). The sequencing is motivated by first focusing on changes in individual variances and then on changes in their correlations. In other words, we first consider changes in the diagonal and then changes in the off-diagonal of a covariance matrix.

**Price components.** The three price components are identified first by, when considering the CCP exposure update from $t-1$ to $t$, updating the price variables first. The sequencing used for these components is volatility first, then correlation, and finally price level. The three components are defined in the following three equations.

$$\text{RetVola}_t = g\left(D(D_{\Omega_t},R_{\Omega_{t-1}},P_{t-1},\bar{N}_{t-1}),R(D_{\Omega_t},R_{\Omega_{t-1}},P_{t-1},\bar{N}_{t-1})\right) - g\left(D(D_{\Omega_{t-1}},R_{\Omega_{t-1}},P_{t-1},\bar{N}_{t-1}),R(D_{\Omega_{t-1}},R_{\Omega_{t-1}},P_{t-1},\bar{N}_{t-1})\right)$$  \hspace{1cm} (3.A.2)

$$\text{RetCorr}_t = g\left(D(D_{\Omega_t},R_{\Omega_t},P_{t-1},\bar{N}_{t-1}),R(D_{\Omega_t},R_{\Omega_t},P_{t-1},\bar{N}_{t-1})\right) - g\left(D(D_{\Omega_{t-1}},R_{\Omega_{t-1}},P_{t-1},\bar{N}_{t-1}),R(D_{\Omega_{t-1}},R_{\Omega_{t-1}},P_{t-1},\bar{N}_{t-1})\right)$$  \hspace{1cm} (3.A.3)

$$\text{PrLevel}_t = g\left(D(D_{\Omega_t},R_{\Omega_t},P_{t},\bar{N}_{t-1}),R(D_{\Omega_t},R_{\Omega_t},P_{t-1},\bar{N}_{t-1})\right) - g\left(D(D_{\Omega_{t-1}},R_{\Omega_{t-1}},P_{t-1},\bar{N}_{t-1}),R(D_{\Omega_{t-1}},R_{\Omega_{t-1}},P_{t-1},\bar{N}_{t-1})\right)$$  \hspace{1cm} (3.A.4)
Trade components. The sequencing used for the (aggregate) trade components is member-by-member position changes first and then their impact on correlations in portfolio returns across members. These components are defined in the following two equations.

\[
\text{TrPosition}_t = g\left(D(D_\Omega, R_\Omega, P_t, \tilde{N}_{t-1}), R\left(D(D_\Omega, R_\Omega, P_t, \tilde{N}_{t-1})\right)\right)
- g\left(D\left(D(D_\Omega, R_\Omega, P_t, \tilde{N}_{t-1}), R\left(D(D_\Omega, R_\Omega, P_t, \tilde{N}_{t-1})\right)\right)\right)
\]  
(3.A.5)

\[
\text{TrCrowding}_t = g\left(D(D_\Omega, R_\Omega, P_t, \tilde{N}_{t-1}), R\left(D(D_\Omega, R_\Omega, P_t, \tilde{N}_{t-1})\right)\right)
- g\left(D\left(D(D_\Omega, R_\Omega, P_t, \tilde{N}_{t-1}), R\left(D(D_\Omega, R_\Omega, P_t, \tilde{N}_{t-1})\right)\right)\right)
\]  
(3.A.6)

Further decomposition trade components based on client/house account distinction. A clearing member reports all trades he does to the CCP. He registers all trades he does for his own books in a so-called house account. This allows us to decompose the components TrPosition and TrCrowding further into client-client (CC) trade, client-house (CH), and house-house (HH) trade. The decomposition is done sequentially starting with CC, then CH, and finally HH.

\[
\text{TrPosition}_{CC_t} = g\left(D(D_\Omega, R_\Omega, P_t, \tilde{N}_{t-1} + \Delta \tilde{N}_{t}^{CC}), R(D(D_\Omega, R_\Omega, P_t, \tilde{N}_{t-1}))\right)
- g\left(D(D(D_\Omega, R_\Omega, P_t, \tilde{N}_{t-1} + \Delta \tilde{N}_{t}^{CC}), R(D(D_\Omega, R_\Omega, P_t, \tilde{N}_{t-1}))\right)\right)
\]  
(3.A.7)

\[
\text{TrCrowding}_{CC_t} = g\left(D(D_\Omega, R_\Omega, P_t, \tilde{N}_{t-1} + \Delta \tilde{N}_{t}^{CC}), R(D(D_\Omega, R_\Omega, P_t, \tilde{N}_{t-1} + \Delta \tilde{N}_{t}^{CC}))\right)
- g\left(D(D(D_\Omega, R_\Omega, P_t, \tilde{N}_{t-1} + \Delta \tilde{N}_{t}^{CC}), R(D(D_\Omega, R_\Omega, P_t, \tilde{N}_{t-1} + \Delta \tilde{N}_{t}^{CC}))\right)\right)
\]  
(3.A.8)

\[
\text{TrPosition}_{CH_t} = g\left(D(D_\Omega, R_\Omega, P_t, \tilde{N}_{t-1} + \Delta \tilde{N}_{t}^{CC} + \Delta \tilde{N}_{t}^{CH}), R(D(D_\Omega, R_\Omega, P_t, \tilde{N}_{t-1} + \Delta \tilde{N}_{t}^{CC} + \Delta \tilde{N}_{t}^{CH}))\right)
- g\left(D(D(D_\Omega, R_\Omega, P_t, \tilde{N}_{t-1} + \Delta \tilde{N}_{t}^{CC} + \Delta \tilde{N}_{t}^{CH}), R(D(D_\Omega, R_\Omega, P_t, \tilde{N}_{t-1} + \Delta \tilde{N}_{t}^{CC} + \Delta \tilde{N}_{t}^{CH}))\right)\right)
\]  
(3.A.9)
TCrowdingCH_t = g(D_{Ω_t}, R_{Ω_t}, P_t, N_{t-1} + \Delta N_t^{CC} + \Delta \tilde{N}_t^{CH}), R(D_{Ω_t}, R_{Ω_t}, P_t, \tilde{N}_{t-1} + \Delta \tilde{N}_t^{CC} + \Delta \tilde{N}_t^{CH})) 
- g(D_{Ω_t}, R_{Ω_t}, P_t, N_{t-1} + \Delta N_t^{CC} + \Delta \tilde{N}_t^{CH}), R(D_{Ω_t}, R_{Ω_t}, P_t, \tilde{N}_{t-1} + \Delta \tilde{N}_t^{CC}))
(3.A.10)

TrPositionHH_t = g(D_{Ω_t}, R_{Ω_t}, P_t, \tilde{N}_t), R(D_{Ω_t}, R_{Ω_t}, P_t, \tilde{N}_{t-1} + \Delta \tilde{N}_t^{CC} + \Delta \tilde{N}_t^{CH}))
- g(D_{Ω_t}, R_{Ω_t}, P_t, \tilde{N}_{t-1} + \Delta \tilde{N}_t^{CC} + \Delta \tilde{N}_t^{CH}), R(D_{Ω_t}, R_{Ω_t}, P_t, \tilde{N}_{t-1} + \Delta \tilde{N}_t^{CC} + \Delta \tilde{N}_t^{CH}))
(3.A.11)

TrCrowdingHH_t = g(D_{Ω_t}, R_{Ω_t}, P_t, \tilde{N}_t), R(D_{Ω_t}, R_{Ω_t}, P_t, \tilde{N}_t))
- g(D_{Ω_t}, R_{Ω_t}, P_t, \tilde{N}_t), R(D_{Ω_t}, R_{Ω_t}, P_t, \tilde{N}_{t-1} + \Delta \tilde{N}_t^{CC} + \Delta \tilde{N}_t^{CH}))
(3.A.12)

3.2. Intraday seasonality in volatility for Nordic equities

Figure 3.7 shows that there is strong intraday seasonality in the volatility of Nordic equity returns. The pattern was estimated from the data following Andersen and Bollerslev (1997). The estimation details are in Section 3.4.1.
Figure 3.7: Intraday seasonality in volatility for Nordic equities

This figure depicts the intraday seasonality in volatility for Nordic equities.
Chapter 4

Central Counterparty Capitalization and Misaligned Incentives

This chapter is based on Huang (2017). The research is greatly benefited from discussion with Evangelos Benos, Markus Brunnermeier, Jorge Cruz Lopez, Gerardo Ferrara, Pedro Gurrola-Perez, Bo Hu, Mark Manning, Albert Menkveld, David Murphy, Michalis Vasios, Shihao Yu, and Marius Zoican. I am grateful to the seminar participants at the Bank for International Settlements, Bank of England, City University Hong Kong, Copenhagen Business School, Goethe University, Norwegian School of Economics, Vrije Universiteit Amsterdam and Tinbergen Institute.

4.1 Introduction

After the 2007-2008 global financial crisis, central clearing is introduced for OTC derivatives to enhance financial stability. Central Counterparties (CCPs) stand between buyers and sellers, effectively providing insurance against counterparty risk (Singh, 2010). CCPs have become systemic nodes in financial markets and CCP insolvency could be a catastrophe (see, e.g., Singh, 2014; Duffie, 2015; Wendt, 2015).
CCPs have high priority on regulation agenda. The Committee on Payments and Market Infrastructure (CPMI), the International Organization of Securities Commissions (IOSCO), the Financial Stability Board (FSB), and the Basel Committee on Banking Supervision (BCBS) have agreed on a joint work plan to improve CCP resilience. As the international standard for CCPs, the Principles for Financial Market Infrastructure (PFMI) requires CCPs to “provide a viable capital plan for maintaining an appropriate level of equity” (CPMI-IOSCO, 2012). The CPMI-IOSCO and the FSB further stress the importance for CCPs to have sufficient capital to “absorb losses resulting from a participant default and the custody and investment of participant assets” (see, e.g., CPMI-IOSCO, 2014; FSB, 2014; CPMI-IOSCO, 2016b; FSB, 2016).

Although CCPs are systemically important, many CCPs operate as profit-driven public companies, such as CME in the U.S. and Eurex in Europe. Potential conflicts of interest between CCPs’ systemic role and profit-driven character spark the public debate over the capitalization problem of CCPs: Do CCPs have enough skin-in-the-game (SITG) to align proper incentives? The fact that CCPs are not infallible is highlighted by the failure of Korean exchange clearinghouse (KRX) in 2014.\(^1\) Clearing members who are exposed to CCP risk call for more CCP SITG to safeguard financial stability, arguing that CCPs are not properly incentivized to manage risk (see, e.g., Albuquerque, Perkins, and Rafi, 2016).

This paper investigates the capitalization problem and the potential misaligned incentives of CCPs. I consider a static partial equilibrium model with two dates \(t = 0, 1\), a mass-one continuum of risk-averse protection buyers, a mass-one continuum of heterogeneous risk-neutral protection sellers and a risk-neutral CCP. Buyers and sellers are randomly matched and trade a standardized protection contract.\(^2\) The CCP determines a “universal” collateral requirement for the sellers who may have strategic defaults. Furthermore, the sellers need to contribute to the default fund. A seller’s contribution to the default fund is proportional to his collateral. In case of some sellers’ defaults, the losses will be covered

---

\(^1\)There are more clearinghouse failures in recent decades: the French Caisse de Liquidation (1973), the Kuala Lumpur Commodities Clearing House (1983), the Hong Kong Futures Exchange (1987), and the New Zealand Futures and Options Exchange (1989). (see, e.g., Hills et al., 1999; Buding, Cox, and Murphy, 2016)

\(^2\)In reality, such a contract can be viewed as a Credit Default Swap (CDS).
first by the collateralized financial resources, then by the CCP’s SITG, and finally by the default fund contributed by other sellers that do not default. Without regulations on capital requirement, the CCP can choose the size of her capital, which is exposed to potential default losses. For my model, I use SITG and capital interchangeably. When the CCP exhausts all available financial resources, the CCP becomes insolvent.\textsuperscript{3}

The main frictions in the model are profit maximization and limited liability of a CCP. To maximize profit, the CCP is inclined to lower collateral requirement when there is little SITG.\textsuperscript{4} Such misaligned incentives give rise to a trade-off between high systemic risk and high trading volume.

The trading environment in the model is similar to the settings of Biais, Heider, and Horeova (2015). But there are several key features that distinguish my paper from theirs. First, I focus on CCP’s incentives and model CCP insolvency explicitly, while they stress the traders’ incentives and model the interaction between central clearing and risk-taking behaviors. Second, in order to focus on CCP’s misaligned incentives, I assume that sellers exert effort and there is no moral hazard between buyers and sellers. This is a simplification of their model. However, I do model the heterogeneity of protection sellers by introducing heterogeneous hedging capability as Perez Saiz, Fontaine, and Slive (2013) do. The benefit of doing so is to have a clean threshold between sellers who default (default sellers) and those who do not default (non-default sellers) in equilibrium. It enables me to study cases when different layers of the default waterfall are used to cover the default losses.

\textsuperscript{3}Normally, CCPs have recovery plan when their pre-funded financial resources drain out. It includes Variation Margin Gains Haircut (VMGH), cash call, and other assessment power. Strictly speaking, a CCP does not become insolvent when she exhausts all available pre-funded financial resources mentioned in the text. But since the analysis of losses allocation at the end of the default waterfall is not the focus of the current model, I simplify the real operations and assume the CCP becomes insolvent as long as the available financial resources are exhausted.

\textsuperscript{4}In the model, I assume that a CCP has full power in determining the risk management requirement. But in real operations, the change of risk models normally need to be stress tested and to be approved by regulators, which is different from the model setup. However, as long as there is asymmetric information between regulators and the CCP, there is room for the CCP to manipulate the risk management requirement. In particular, when the CCP introduces clearing service for new products, it might be tricky to assess the riskiness of the new products. Furthermore, although setting a high collateral helps safeguarding CCP resilience, high collateral requirement might impair market efficiency by making trades too expensive.
To the best of my knowledge, this paper is the first in the literature that models CCP insolvency from the perspective of CCP’s misaligned incentives. There is a large banking literature that studies capital requirement (see, e.g., Dewatripont, Tirole et al., 1994; Hellmann, Murdock, and Stiglitz, 2000). But CCPs are different from banks in several ways (see, e.g., Manning and Hughes, 2016). Figure 4.1 shows simplified balance sheets for a CCP and a Bank. One key factor is that CCPs have an additional layer for loss-absorbing: default fund contributed by clearing members. To build the connection between a bank and a CCP, one can view clearing members’ collateral as debt and a CCP’s SITG as equity. Apart from debt- and equity-type liabilities on the balance sheet, a CCP also has default fund which is a type of mutualized financial resource. Since clearing members contribute to default fund, in the case of large default losses, the default fund contributed by non-default sellers will be used to cover the losses from default sellers. When the CCP becomes insolvent, the counterparties of the default sellers will bear the remaining losses. Hence, the financial resources of a CCP create different types of incentives.

<table>
<thead>
<tr>
<th>Figure 4.1: Simplified balance sheets</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CCP</strong></td>
</tr>
<tr>
<td>Asset</td>
</tr>
<tr>
<td>Liquid asset</td>
</tr>
<tr>
<td>CCP’s SITG</td>
</tr>
<tr>
<td>Default fund</td>
</tr>
<tr>
<td>Illiquid asset</td>
</tr>
</tbody>
</table>

There are several results from the model. First, when there is no capital requirement for CCPs, a profit-driven CCP chooses the minimum capital, whereas a benevolent CCP will favor high capital when capital cost is low. A profit-driven CCP here refers to a CCP that maximizes her own value and has limited liability. On the contrary, a benevolent CCP is a CCP that maximizes total welfare surplus, including the utility improvement of traders.
and the CCP value, and will not default. These two types of CCPs reflect the reality of non-user-owned CCPs and user-owned CCPs (see, e.g., Cox and Steigerwald, 2016). My model suggests different capital regulations for different types of CCPs.

Second, without capital regulation, the low SITG chosen by a profit-driven CCP leads to insolvency problem. When the CCP only exposes little amount of her own capital to potential default losses, the CCP has strong incentive to lower risk management standards to attract higher trading volume. The traders are aware of the riskiness of CCP insolvency and will become reluctant to trade, which requires the CCP to further lower the collateral requirement to increase trading volume. Thus, the default losses in this case will be even larger than those in the case of high collateral requirement.

Third, a higher SITG gives rise to a higher collateral requirement monotonically. In other words, the higher the CCP capital is, the higher collateral cost will be paid by the traders. This is the argument used by CCPs against high SITG (see, e.g., LCH, 2014). However, the welfare effect of increasing SITG depends on the situation. On the one hand, a higher SITG makes trading more expensive because of the higher collateral cost. On the other hand, a higher SITG also makes trading less expensive by providing a safer CCP.

Fourth, the optimal capital requirement for a profit-driven CCP depends on the profitability of the volume-based fee charged by the CCP. Although the commission fee of clearing is normally not a policy instrument for regulators, it could be an indicative policy variable for regulators. When the fee level is high, the “temptation” for a profit-driven CCP to increase trading volume is high. Even with a high capital requirement, the CCP will still go for a relatively low collateral level to increase trading volume. There will be defaults in equilibrium anyway. Hence, the optimal capital requirement for a profit-driven CCP should retain market discipline. In other words, it is not optimal to use CCP’s SITG to absorb all the default losses in this case. It is better to allocate the default losses between CCP’s SITG and clearing members’ default fund contribution. To some extent, CCP’s capital is more of an incentive instrument than loss-absorbing capacity. When the fee level is low, the CCP is less incentivized to increase trading volume. In this case, the

---

5Since the focus of the paper is the misaligned incentives of profit-driven CCPs, without mentioning specifically, the CCP in the paper is a profit-driven CCP.
optimal capital requirement for a profit-driven CCP should be high enough so that there is no default in equilibrium.

Last but not least, my model also captures the impact of default fund breach and partial insurance on trading volume. Default fund breach refers to the case that the default fund contributed by non-default sellers is used to cover the losses resulted from default sellers. When traders observe low collateral and low capital, they can “foresee” potential default fund breach, which in turn will disincentivize them to trade \textit{ex ante}. Hence, the CCP needs to further decrease collateral requirement to increase trading volume. Similarly, when traders observe even lower collateral and lower capital, they can expect that they will not be fully insured when the CCP becomes insolvent. The losses from partial insurance will also lower their utility improvement from trading, which means the CCP will lower collateral requirement to maximize trading volume. It is worthwhile to point out that, in the literature, default fund breach and partial insurance will reduce trading volume (see, e.g., Murphy, 2016; Raykov et al., 2016). But in my model, since the CCP can choose the collateral level, default fund breach and partial insurance do not necessarily reduce trading volume. Instead, the CCP can still maximize trading volume at the cost of larger potential default losses.

My paper contributes to a rapidly growing literature on CCPs. Carter and Garner (2016) discuss CCP’s roles in risk management and the incentives created by CCPs’ SITG. They point out that the size of a CCP’s SITG should be substantial for the CCP but not necessarily proportional to the default fund size, since the CCP has very different risk profile from the clearing members. Their view on SITG is more of an incentive scheme than loss absorbing capability. Albuquerque, Perkins, and Rafi (2016) propose a risk-based quantitative method to calculate CCPs’ SITG, based on expected shortfall over and above the largest two clearing members’ initial margin and default fund contributions. Their calibration shows that a long-term average SITG is 8.1% for an interest rate derivative CCP and 11.4% for a credit derivative CCP. Murphy (2016) analyzes the composition of CCPs’ financial resources and finds that profit-driven CCPs will always minimize their SITG. But since clearing members may trade less in the case of large probability of default fund breach, CCPs have incentives to increase initial margin and to reduce default
fund contribution, with the assumption that the total financial resources need to satisfy the “Cover 2” principle. I take a different approach and model CCPs’ insolvency explicitly. My model suggests different capital requirements for CCPs with different ownership structures. In particular, my model takes into account the profitability of clearing industry, which alters the optimal capital requirement for profit-driven CCPs.

My model is also related to the branch of literature that studies CCPs’ total financial resources. Elliott (2013) proposes principles to guide the design of loss allocation rules for CCPs. Loss allocation rules that are intended to maintain the continuity of clearing services should incentivize traders to participate competitively and should not compromise the CCP’s risk management of open positions. Cumming and Noss (2013) use daily data on a CCP’s member exposures to assess the CCP’s total default resources and to quantify the trade-off that occurs in the balance of resources between initial margin and default fund. Singh (2014) argues that CCPs have become “too important to fail” and suggests Variation Margin Gains Haircut (VMGH) as a loss-sharing tool in case of insolvent CCPs. Murphy and Nahai-Williamson (2014) model the likelihood of CCP failure and study how the distribution of risk among clearing members affects the prudence of the “Cover 2” standard. Their findings suggest that CCPs meeting the “Cover 2” standard are not highly risky provided that tail risks are not distributed too uniformly amongst CCP members. Ghamami (2014) proposes a risk-sensitive measurement for the default waterfall of derivative CCPs based on the static copula threshold portfolio credit risk approach. Duffie (2015) has a thorough review on possible recovery and resolution plans for insolvent CCPs. Raykov et al. (2016) models a CCP as a long-term break even institute and studies two loss-sharing tools for CCPs: VMGH and cash call. The model suggests that VMGH leads to a trade-off between ex ante trading volume and ex post loss-sharing, while cash call gives rise to non-performance risk that clearing members may default on the cash calls. These are critical features of central clearing, but they all assume CCPs are benevolent organizations and overlook the misaligned incentives of profit-driven CCPs. My model shows that a profit-driven CCP with thin SITG has strong incentives to lower risk management standards. In other words, CCP failure could be an endogenous risk instead of an exogenous risk.
Another relevant stand of literature is about systemic risk in central clearing. Amini, Filipovic, and Minca (2014) study the impact of central clearing on systemic risk in financial network. Their model suggests, although CCPs mitigate aggregate bank liquidation risk, they introduce tail risk to the financial system. Menkveld (2016d) models CCP systemic risk from the perspective of crowded trades. Large default losses from speculative traders that have (same) directional positions may lead to CCP failure, which constitutes a systemic risk for financial system. Menkveld (2016a) investigates CCP exposure as a Value-at-Risk (VaR) measure of a CCP’s aggregate loss exposure to her clearing members, accounting for the crowdedness of trades by incorporating the correlations between portfolio returns. Lopez et al. (2013) propose a quantitative risk measure for CCP risk management based on CoVaR (Adrian and Brunnermeier, 2011). Their measure takes into account the bilateral interdependence between traders’ portfolio return.

The remainder of this paper is as follows. Section 4.2 introduces the model primitives and discusses the first best allocation. Section 4.3 studies the case of a benevolent CCP that maximizes the total social welfare surplus. Section 4.4 focuses on the misaligned incentives of a profit-driven CCP. Section 4.5 analyzes the optimal capital requirement of a profit-driven CCP. Section 4.6 concludes.

### 4.2 Model and first best allocation

#### 4.2.1 Model primitives

I consider a static model with two dates ($t = 0, 1$), a mass-one continuum of protection buyers, a mass-one continuum of protection sellers and a CCP. At $t = 0$, the CCP, the buyers and sellers design and participate in the trading and clearing system. The trading environment is a modified version of Biais, Heider, and Hoerova (2015). But the focus of my model is CCP’s misaligned incentives instead of protection sellers’ risk-taking incentives. At $t = 1$, payoffs of risky assets are realized and some traders may default, which could potentially wind down the CCP.
Protection buyers. There is one unit mass of homogeneous protection buyers. They are endowed with one unit risky asset at $t = 0$. The asset has random return $\tilde{\theta}$ at $t = 1$. $\tilde{\theta}$ can take on two values: $\theta$ with probability $\pi$ and 0 with probability $(1 - \pi)$.

Protection buyers are also endowed with cash $m$ at $t = 0$. Protection buyers are risk averse with mean-variance utility.\footnote{All the results are preserved with concave utility functions. However, for tractability purpose, I use mean-variance utility in the model.}

\[
U^b(m, \tilde{\theta}) = m + (\tilde{\theta}) - \frac{\gamma}{2}(\tilde{\theta})
\]

Protection sellers. There is one unit mass of heterogeneous protection sellers who are risk neutral and have limited liability. A protection seller enters into a contract with a protection buyer that the seller will have the following payment $\tilde{\tau}$ to the buyer at $t = 1$: $\tilde{\tau}$ is $(\pi - 1)\theta$ when $\tilde{\theta}$ is $\theta$ and $\pi\theta$ when $\tilde{\theta}$ is 0. The contract has zero mean and provide full insurance to the buyers. In real operations, such a contract can be implemented by a Credit Default Swap (CDS).
If protection seller $j$ trades with a buyer, he can hedge the downside risk by investing in one unit hedging asset $\tilde{R}_j$. If seller $j$ does not join the trading and clearing game, he will not invest in the hedging asset $\tilde{R}_j$. Hence, the outside option of seller $j$ is 0 instead of $(1 - \pi)r_j\pi\theta$. Different protection seller $j$ has different payoff from the hedging asset $\tilde{R}_j$ at $t = 1$: $\tilde{R}_j$ is 0 when $\tilde{\theta}$ is $\theta$ and $r_j\pi\theta$ when $\tilde{\theta}$ is 0. $r_j$ is uniformly distributed between 0 and 1, which can be viewed as seller $j$’s hedging capability. The assumption of heterogeneous hedging capability of protection sellers is not far from the reality. Dealers in OTC derivatives markets normally have their own specialty in managing their position risk (Perez Saiz, Fontaine, and Slive, 2013).

Each protection buyer is matched with one protection seller randomly. So the trading volume between a buyer and a seller is either zero or one. Taking into account the payoff from the hedging asset $\tilde{R}_j$, the overall payment from seller $j$ to his counterparty is denoted as $\tilde{s}_j$. $\tilde{s}_j$ is $(\pi - 1)\theta$ when $\tilde{\theta}$ is $\theta$ and $(1 - r_j)\pi\theta$ when $\tilde{\theta}$ is 0.

---

7The trading capacity of a seller is one. So, it is not the case that all the buyers will go for the seller with the best hedging capability ($r_j = 1$). Also, matching does not guarantee trading. If both trading parties do not benefit from trading, they have the outside option of no trade. I adopt the most simplified searching model here: random matching with Nash bargaining. Introducing more advanced search models will definitely have a better approximation of OTC derivatives markets. But that complicates the model unnecessarily, since the focus of my paper is the incentives of the CCP instead of the incentives of the trading parties. Interesting readers could refer to Koeppl, Monnet, and Temzelides (2012) and Biais, Heider, and Hoerova (2015) for example. In addition, since each trader only trades with one counterparty, I don’t capture the netting efficiency provided by central clearing. Although that is a very important feature of central clearing, it does not matter that much when it comes to the SITG problem of CCPs. Interesting readers could refer to Duffie and Zhu (2011) and Anderson et al. (2013).
Ex ante, the protection buyer knows the hedging capability $r_j$ of the protection seller $j$. Protection buyers and sellers have equal bargaining power in setting the price of the contract. To disincentivize protection sellers’ defaults, the CCP impose a collateral requirement $c$ and a default fund contribution $\alpha c$ for each protection seller. The unit cost of collateral and default fund contribution for each seller is $\delta$. In case of the default of seller $j$, the hedging asset $\tilde{R}_j$ will be seized by the buyer.

I assume that the collateral cost is not negligible, i.e., the collateral cost is large enough so that some seller $j$ cannot provide full collateral to cover his potential loss at $t = 1$.

$$\delta > \frac{\theta \gamma (1 - \pi)}{2} \equiv \delta$$

**CCP.** There is one CCP that clears all the trades in the market. The CCP interposes itself between protection buyers and protection sellers. Through the novation process, the trading contract between buyers and sellers splits into two contracts: one is between protection buyers and the CCP; and the other is between protection sellers and the CCP. If protection sellers default, they default on the CCP. The CCP is effectively providing insurance against counterparty risk.

---

8I assume linear cost of collateral and default fund contribution. The idea is that, in reality, the total financial resources contributed to CCP by large dealers (usually large banks) are normally a small fraction (1% or even less) of the dealers’ available liquidity. Hence, it is realistic to assume linear collateral cost (Murphy, 2016).
The CCP is a risk-neutral and profit-driven financial intermediary. The CCP has capital $K$ and the unit cost of capital is $\varphi$. According to the size of capital, the CCP chooses the optimal collateral $c$ to maximize her expected value. The collateral requirement is only for the sellers, since they are the trading party who has incentives to default. Moreover, the collateral requirement $c$ is position-specific instead of trader-specific. In other words, the CCP charges the same collateral for every seller despite their heterogeneous hedging capability. As to the default fund contributed by the sellers, I assume it is proportional to the collateral, i.e., $\alpha c$, where $\alpha$ is an exogenous variable.

The CCP charges volume-based commission fee $\frac{f}{2}$ for both buyers and sellers when they use the clearing service. The fee is exogenous and not controlled by the CCP. Instead of increasing the fee, the CCP can increase the trading volume to maximize the profit. I assume the fee is small.

$$f < \pi \theta (1 - \pi) \equiv \bar{f}$$

For the default waterfall of the CCP, I follow the order outlined in Duffie (2015). In case of seller $j$’s default, the loss will be covered as follows.

1. the collateral $c$ contributed by seller $j$
2. the default fund contribution $\alpha c$ by seller $j$

---

9In section 4.3, I analyze the case of benevolent CCP. In that case, the benevolent CCP maximizes the total social welfare.
10Again, I assume linear capital cost here.
11In reality, I normally observe both counterparties deposit collateral because they both might default when risky payoff is realized. But in my model, I have an option type contract. Only the sellers will have incentive to default. The benefit of doing so is to separate the losses born by the non-default sellers (via default fund contribution) and losses born by the counterparties of default sellers (via partial insurance losses).
12In real operations, CCPs do charge credit add-on for credit risk. But in my model, I don’t take that into account.
13In reality, the size of default fund is usually determined by stress tests and should satisfy the “Cover 2” principle (CPMI-IOSCO, 2012, 2014, 2016b).
14For notation purpose, the CCP charges $\frac{f}{2}$ for both buyers and sellers, so that the total fee paid by a pair of buyer and seller for one unit of trading volume is $f$
15The assumption of exogenous fee is to mimic the OTC derivatives clearing reality that the commission fee is determined rather by the industry consensus.
3. CCP’s capital \( K \)

4. the default fund contributed by the non-default sellers

If the CCP has not enough financial resources to cover the default losses, the CCP becomes insolvent. In that case, I assume that the protection buyers will bear the remaining losses. Hence, the protection buyers are not fully insured in that situation.

### 4.2.2 First best allocation

I first study the first best allocation. Although sellers are heterogeneous, there is no asymmetric information between buyers and sellers. A buyer knows exactly the hedging capability of the seller he trades with. In other words, \( r_j \) is common knowledge for both buyers and sellers.\(^{16}\) In the first best allocation, sellers will not default. Thus, the buyers are fully insured and receive utility gain from smoothing payoffs across states. For the sellers, they benefit from the expected payoff of the hedging asset \( \tilde{R}_j \). The utility and outside options for the buyers and the sellers are as follows.

\[
\begin{align*}
U^b & = m + \pi \theta - p_j, \\
D^b & = m + \pi \theta - \frac{\gamma}{2}(1 - \pi) \pi \theta^2, \\
U^{s_j} & = p_j + (1 - \pi)r_j \pi \theta, \\
D^{s_j} & = 0.
\end{align*}
\]

The utility improvement for a pair of seller \( j \) and his buyer is\(^ {17}\)

\[
\Delta U = U^b + U^{s_j} - D^b - D^{s_j} = \frac{\gamma}{2}(1 - \pi)\pi \theta^2 + (1 - \pi)r_j \pi \theta.
\]

\(^{16}\)It is a rather tricky question whether \( r_j \) is known by the CCP or not. On the one hand, CCPs often have strict membership requirement that identify the credit-worthiness of clearing members. On the other hand, however, the collateral requirement is not member-specific. In the current setup, I assume that the collateral requirement set by the CCP is not contingent on the hedging capability \( r_j \).

\(^{17}\)In the following analysis, I always consider the utility improvement for a pair of buyer and seller, unless I study the Nash bargaining price and need to separate the utility improvement of the buyer from that of the seller.
Thus, the total welfare surplus in trading consist of two parts: (i) the utility gain due to buyers’ risk aversion, and (ii) the expected return from the hedging asset $\tilde{R}_j$. Equation 4.2 shows the total surplus in the first best equilibrium.

$$W^{FB} = \int_0^1 \Delta U r_j$$  
$$= \frac{1}{2} (1 - \pi) \pi \theta (\gamma \theta + 1)$$  

(4.2)

### 4.3 Benevolent CCP

In this section, I analyze the case of a benevolent CCP. In other words, the benevolent CCP will maximize the total welfare surplus, including the utility improvement of buyers and sellers and the CCP’s value, by setting the optimal collateral and capital. In reality, there are CCPs that are owned by clearing members. For example, Japanese Security Clearing Corporations (JSCC) and Swiss SIX X-clear Ltd are user-owned CCPs. These user-owned CCPs normally don’t chase profits. Instead, their main purpose is to facilitate clearing and settlement among members.

The CCP maximizes the total welfare surplus.

$$\max_{k,c} W^b + W^s + V_{CCP}$$

### 4.3.1 Collateral

Since protection seller $j$ will lose both his collateral $c$ and default fund contribution $\alpha c$ when he has (large) default loss, I take both collateral and default fund contributed by seller $j$ together as seller $j$'s collateralized financial resources.\(^{18}\) In other words, the collateralized financial resources of seller $j$ is $(1 + \alpha)c$. Seller $j$ defaults when the payment

\(^{18}\)One could argue that when the default loss of seller $j$ is between $c$ and $(1 + \alpha)c$, he only lose part of the default fund contribution. In my model, I simplify that situation as seller $j$ does not default.
he need to make exceeds the collateralized financial resources. Protection seller \( j \) with hedging capability \( r_j \) will not default at \( t = 1 \) if and only if

\[(1 + \alpha)c \geq (1 - r_j)\pi\theta.\]

In other words, with given \( c \), seller \( j \) with hedging capability higher than \( \pi\theta/(1 + \alpha) \equiv \bar{r} \) will not default at \( t = 1 \). For the case that seller \( j \) does not default, i.e., \( r_j \geq \bar{r} \), the overall utility improvement for this pair of traders is as follows.

\[
\Delta U_{ND} = \frac{\gamma}{2} \pi^2 (1 - \pi)\theta^2 + \frac{(1 - \pi)\pi\theta}{\text{expected return from } R_j} - (1 + \alpha)\delta c - \frac{f}{\text{fee}}.
\]

(4.3)

When seller \( j \) has a hedging capability lower than the threshold, i.e., \( r_j < \bar{r} \), seller \( j \) defaults with probability \( (1 - \pi) \) at \( t = 1 \). If seller \( j \) defaults, both the payoff of the hedging asset \( r_j\pi\theta \) and the collateralized financial resources \( (1 + \alpha)c \) are seized by the buyer. Furthermore, since the CCP is benevolent and will not default, the rest of the default loss \( ((1 - r_j)\pi\theta - (1 + \alpha)c) \) will be covered by CCP’s capital. Hence, the buyer is still fully insured. In fact, the benevolent CCP is subsidizing seller \( j \), as seller \( j \)’s collateralized financial resources establishes a “floor” for his downside risk.
In the case of seller \( j \) defaults, equation 4.4 shows the utility improvement for this pair of traders. Note that the utility improvement for a pair of buyer and default seller is invariant in the seller’s hedging capability \( r_j \).

\[
\Delta U_D = \frac{\gamma}{2} \pi (1 - \pi) \theta^2 + (1 - \pi)(\pi \theta - (1 + \alpha)c) - (1 + \alpha)\delta c - f
\]

(4.4)

As shown in equation 4.3 and 4.4, the utility improvement is a monotonically decreasing function in collateral \( c \). Because collateralized financial resources are costly. If the CCP sets a high collateral requirement, protection sellers who join the trading game need to bear a high collateral cost. Moreover, for the sellers who have low hedging capability, the high collateral cost will drive the trading benefit to zero (or negative). Hence, with a high enough collateral requirement, the CCP could separate the sellers with high hedging capability from those with low hedging capability. In that case, the trading volume is a decreasing function of collateral.

However, the trading volume is not always decreasing in collateral due to the fact that default sellers have a “floor” for their downside risk. Figure 4.2 shows the relationship between utility improvement and hedging capability. As mentioned before, there is a kink at \( r_j = \bar{r} \). Let’s call seller \( j \) with hedging capability \( \bar{r} \) the “marginal seller”, since sellers with hedging capability smaller than \( \bar{r} \) may default at \( t = 1 \). Let \( \bar{c} \) denotes the threshold of collateral that the utility improvement of the marginal seller is 0. Because all default sellers have the same utility improvement from trading; trading volume will jump to 1 when collateral is slightly below \( \bar{c} \). The kink also means that default sellers all join the trading game when collateral is slightly lower than \( \bar{c} \), but they all do not join when \( c \geq \bar{c} \).

Proposition 1 formalizes the idea.

---

\(^{19}\)I use default sellers to stand for sellers who will default with probability \((1 - \pi)\) at \( t = 1 \).

\(^{20}\)For simplicity, I use collateral cost to stand for cost of collateralized financial resources.
4.3 Benevolent CCP

**Figure 4.2: Utility improvement with different collateral**

![Diagram showing utility improvement with different collateral levels.](image)

**Proposition 1. Trading volume (benevolent CCP)**

The trading volume in the case of benevolent CCP is as follows

\[
v(c) = \begin{cases} 
1 - \bar{r}, & c \geq \bar{c} \\
1, & 0 \leq c < \bar{c}
\end{cases}
\]  

(4.5)

where \(\bar{r}\) is the hedging capability of the marginal seller and \(\bar{c}\) is the threshold of collateral that the utility improvement of the marginal seller is 0.

\[
\bar{r} = \frac{\gamma \pi (1 - \pi) \theta^2 - 2(1 + \alpha) \delta c - 2f}{2(1 - \pi) \pi \theta}
\]

\[
\bar{c} = \frac{\pi \theta (1 - \pi)(\gamma \theta + 2) - 2f}{2(1 + \alpha)(1 - \pi + \delta)}
\]  

(4.6)

**Proof.** See appendix.

### 4.3.2 Optimal capital and collateral for a benevolent CCP

Given the two fold effects of collateral, I analyze two different cases: in the first case, the benevolent CCP charges high collateral whereas no seller defaults at \(t = 1\); in the second case, the benevolent CCP charges low collateral and some sellers may default at \(t = 1\).
Case 1: no seller defaults at \( t = 1 \). When sellers who join the trading game don’t have incentive to default at \( t = 1 \), there is no potential systemic risk. But in this case, the trading volume is not one. Hence, there is a trade-off between the decrease of systemic risk and the decrease of realized gain from trade (RGFT). The expected value of the benevolent CCP is

\[
V_{\text{CCP}}^{\text{ND}} = f(v(c)) - \varphi K.
\]

The total welfare surplus is

\[
W_{\text{ND}} = \int_{r}^{1} \Delta U_{\text{ND}r}^{j} + V_{\text{CCP}}^{\text{ND}}
\]

Note that since no sellers will default at \( t = 1 \), there is no need for the benevolent CCP to hold capital in order to absorb losses. Also, in the case of benevolent CCP, the CCP maximizes total welfare improvement. There is no need for the benevolent CCP to hold capital in order to align incentives. Thus, the optimal capital in this case is 0. As to collateral \( c \), from Figure 4.2, it is obvious that increasing collateral to more than \( \bar{c} \) will only decrease trading volume, without the benefit of “screening out” default sellers. It means that the optimal collateral in this case should be as low as possible, while keeping default sellers out of the trading game. In other words, the optimal collateral should be \( \bar{c} \). Lemma 1 summarizes the optimal capital and collateral in this case. The total welfare surplus with optimal capital and collateral in this case is less than the first best welfare surplus owing to two things: (i) the collateral is costly and (ii) the RGFT is not maximal.

**Lemma 1. No default case (benevolent CCP)**

(i) For the benevolent CCP, the optimal capital and collateral in the no default case are

\[
k_{\text{ND}}^* = 0, \quad c_{\text{ND}}^* = \bar{c}.
\]
(ii) The total welfare surplus \( W^{ND}(c_{ND}^*, K_{ND}^*) \) is

\[
W^{ND}(c_{ND}^*, K_{ND}^*) = W^{FB} - \frac{(1 + \alpha)\bar{c}}{\pi\theta} (1 + \alpha)\delta \bar{c} - \frac{\pi\theta - (1 + \alpha)\bar{c}}{\pi\theta} W^{FB}
\]

(4.9)

**Proof.** See appendix.

**Case 2: some sellers default at** \( t = 1 \). When the benevolent CCP impose a collateral requirement lower than \( \bar{c} \), all sellers join the trading game because they all have positive utility improvement from trading. But the maximal RGFT goes hand in hand with increasing systemic risk. The benevolent CCP needs to hold capital to cope with potential default losses at \( t = 1 \). In this case, the expected value of the benevolent CCP is

\[
V^{D}_{CCP} = f - (1 - \pi)K - \varphi K.
\]

The total welfare surplus is

\[
W^{D} = \int_{0}^{f} \Delta U_{D} r_{j} + \int_{f}^{1} \Delta U_{ND} r_{j} + V^{D}_{CCP}
\]

As mentioned before, the benevolent CCP is actually subsidizing default sellers because the amount of collateralized financial resources limits the downside risk of default sellers. It means that all the default losses will be covered by the benevolent CCP. Let \( L \) denote the total default losses.

\[
L = \int_{0}^{f} \left[(1 - r_{j})\pi\theta - (1 + \alpha)c\right] r_{j} = \frac{(\pi\theta - (1 + \alpha)c)^2}{2\pi\theta}
\]

(4.10)

Lemma 2 summarizes the optimal capital and collateral in this case. It turns out that the optimal collateral is zero when capital cost is smaller than collateral cost. In order to cover
the default losses, the benevolent CCP needs to hold a capital of $\frac{\pi \theta}{2}$. When capital cost is larger than collateral cost, it is better to charge some collateral so that the capital needed to cover the default losses is smaller.

In fact, in both cases, the value of the benevolent CCP with such capital and collateral is negative, i.e., the benevolent CCP is making loss instead of making profit with this arrangement. The total welfare surplus with optimal capital and collateral in this case is less than the first best welfare surplus because of the capital cost and the potential collateral cost.

**Lemma 2. Default case (benevolent CCP)**

(i) For the benevolent CCP, the optimal capital and collateral in the default case are

$$K^*_D = \begin{cases} \frac{\pi \theta \delta^2}{2}, & \varphi > \delta \\ \frac{\pi \theta}{2}, & \varphi \leq \delta \end{cases}$$

$$c^*_D = \begin{cases} \frac{\pi \theta \varphi - \delta}{1+\alpha \varphi}, & \varphi > \delta \\ 0, & \varphi \leq \delta \end{cases}$$

(ii) The total welfare surplus $W^D(c^*_D, K^*_D)$ is

$$W^D(c^*_D, K^*_D) = \begin{cases} W^{FB} - \frac{\pi \theta \delta^2}{2 \varphi} - \frac{\delta \pi \theta (\varphi - \delta)}{\varphi}, & \varphi > \delta \\ W^{FB} - \frac{\pi \theta}{2 \varphi}, & \varphi \leq \delta \end{cases}$$

*Proof.* See appendix.

**No default case v.s. default case.** Which case will lead to a higher total welfare surplus? The answer depends on how large the capital cost is. To the extreme, if capital cost is zero, the welfare surplus in the default case would be the first best welfare surplus. Hence, the CCP should charge low collateral, in fact zero collateral, and let sellers default at $t = 1$ if the low state is realized. However, if the capital of the benevolent CCP is very expensive, the benefit of subsidizing the sellers will be outweighed by the cost of capital.
4.4 Profit-driven CCP

In that scenario, the benevolent CCP should be conservative and charge high collateral. Proposition 2 formalizes this idea.

**Proposition 2. Optimal capital and collateral for a benevolent CCP**

Let $\bar{\phi}$ denote the threshold of capital cost.

$$\bar{\phi} = \frac{2}{\pi \theta} \left( W^{FB} - W^{NP}(\bar{c}, 0) \right)$$

(i) When capital cost is higher than $\bar{\phi}$, the default case will have a higher welfare surplus. The optimal capital and collateral of a benevolent CCP are

$$K^* = 0, \quad c^* = \bar{c}. \quad (4.14)$$

(ii) When capital cost is lower than $\bar{\phi}$, the no default case will have a higher welfare surplus. The optimal capital and collateral of a benevolent CCP are

$$K^* = \frac{\pi \theta}{2}, \quad c^* = 0. \quad (4.15)$$

**Proof.** See appendix.

4.4 Profit-driven CCP

In this section, I study the case of profit-driven CCP. Different from the benevolent CCP who maximizes the total welfare surplus, the profit-driven CCP only cares about maximizing her own value. Moreover, the CCP has limited liability. In other words, the capital of the CCP is the maximum that she can lose. On the one hand, to chase profit, the CCP has incentive to lower risk management standards to maximize trading volume. On the other hand, because of the limited liability, the CCP does not (fully) internalize her externality on systemic risk. Hence, the profit-driven CCP will contribute low capital and set a low collateral, leading to insolvency problem of the CCP.

At the end of the default waterfall, when the CCP becomes insolvent, I assume that the protection buyers who trade with those default sellers will bear the rest of the losses. It
is not far from the reality. In the recovery plan outlined by CPMI-IOSCO (2014), one way to recover an insolvent CCP is partially tear-up, which essentially ask the winning sides (protection buyers) to bear the losses caused by the losing side’s (protection sellers’) defaults.

It is worthwhile to point out that, for this section, I don’t have a predetermined capital requirement for the CCP set by a regulator. Hence, the CCP raise capital and set collateral requirement spontaneously.\(^{21}\) In section 4.5, I analyze the optimal capital requirement for the profit-driven CCP.

Let \( V_{\text{CCP}}^P \) denote the expected value of the profit-driven CCP. \( P \) in the superscript stands for profit-driven. The CCP’s objective function is to maximize her own expected value instead of to maximize the total welfare surplus.

\[
\max_{K,c} f(v(c)) + (1 - \pi)\max(-L, -K) - \phi K \tag{4.16}
\]

where \( L \) is the total default losses as a function of collateral \( c \) (see in equation 4.10).

### 4.4.1 Collateralized and mutualized financial resources

When the CCP is profit-driven and has limited liability, the CCP has no incentive to hold enough capital for potential default losses at \( t = 1 \), which means that the default fund contributed by non-default sellers might be used to cover the losses caused by default sellers. In this case, it is important to distinguish mutualized financial resources from collateralized financial resources. Collateralized financial resources include collateral and default fund contributed by default sellers. Section 4.3 has discussed collateralized financial resources. Mutualized financial resources refer to the default fund contributed by non-default sellers. As I will show later, the possibility that the default fund contributed by non-default sellers could be used to cover the losses caused by the default sellers will dis-

\(^{21}\)Currently, there are very few regulations on CCP’s capital. EMIR sets a capital requirement of 25% of the CCP’s operational risk, which is negligible compared to the size of default fund.
incentivize some non-default sellers to join the trading game, hence reducing the trading volume. In this subsection, I study two scenarios when the profit-driven CCP is solvent: (i) total financial resources are only covered by the CCP’s capital, and (ii) mutualized financial resources are also used to cover default losses.

**Mutualized financial resources remain untouched.** According to the default waterfall, when the collateralized financial resources and the CCP’s capital is large enough, the default fund contributed by non-default sellers will not be used. In other words, the CCP’s capital $K$ is larger than the total default losses $L$. From equation 4.10, mutualized financial resources are untouched when the following relationship holds.

$$K \geq \frac{[\pi \theta - (1 + \alpha)c]^2}{2\pi \theta} \equiv \tilde{K}$$

In this scenario, the utility improvement for traders is the same as equation 4.3 and 4.4. Hence, Proposition 1 holds when equation 4.17 holds.

**Mutualized financial resources are used.** When the CCP’s capital $K$ is not large enough to cover the total default losses, mutualized financial resources are used to cover the rest of the losses. Note that in this scenario, the CCP is still solvent. In other words, the buyers are fully insured. In terms of the relationship between $c$ and $K$, it means that

$$\tilde{K} \leq K < \bar{K}$$

where $\tilde{K}$ satisfies the following relationship.$^{22}$

$$\tilde{K} = \frac{[\pi \theta - (1 + \alpha)c]^2}{2\pi \theta} - ac(1 - \tilde{r})$$

$^{22}$In this equation, $\tilde{r}$ is also a function of $K$ as shown in equation 4.20. I will solve this equation in Section 4.4.3.
In this scenario, the utility improvement for a pair of default seller and his counterparty is the same as equation 4.4. But the utility improvement of a pair of non-default seller and his buyer will decrease because of the expected loss from default fund contribution. Figure 4.3 visualizes this idea. Same as in Figure 4.2, seller $j$ with hedging capability lower than $\bar{r}$ are the default sellers. But different from Figure 4.2, not every seller with hedging capability higher than $\bar{r}$ will join the trading game because of the expected loss from default fund contribution. Sellers with hedging capability between $\bar{r}$ and $\tilde{r}$ will not trade, where $\tilde{r}$ represents a second type of “marginal seller”. Thus, $1 - \tilde{r}$ is the volume of non-default sellers.

**Figure 4.3: Utility improvement when mutualized financial resources are used**

![Utility improvement diagram](image)

I assume that non-default sellers share the losses evenly. Let $d$ denote the default fund loss for each non-default seller.

$$d = \frac{L - K}{1 - \tilde{r}} \quad (4.20)$$

The utility improvement of a pair of non-default seller and his buyer is

$$\Delta U_{ND,M} = \frac{\gamma}{2} \pi (1 - \pi) \theta^2 + (1 - \pi) r c - (1 + \alpha) \delta c - f - (1 - \pi) d$$

**Expected loss from default fund**
Similar with the scenario when mutualized financial resources are not used, when the CCP decreases collateral requirement, utility improvement of traders will increase. Hence, trading volume will increase as well. Lemma 3 summarizes the relationship between trading volume and collateral when mutualized financial resources are used to cover default losses.

**Lemma 3.** **Trading volume (mutualized financial resources used)**

When $K$ and $c$ satisfy the following relationship, the CCP remains solvent but has not enough capital to cover the total default losses. Mutualized financial resources are used to cover part of the losses.

$$0 < \frac{[\pi \theta - (1 + \alpha)c]^2}{2\pi \theta} - K \leq \alpha c(1 - \bar{r}) \quad (4.22)$$

The trading volume is as follows

$$v(c) = \begin{cases} 1 - \bar{r} + \tilde{r}, & \tilde{c} < c < \bar{c} \\ 1, & 0 \leq c \leq \tilde{c} \end{cases} \quad (4.23)$$

where $\bar{r}$ and $\tilde{c}$ are as follows.

$$\bar{r} = \frac{\pi \theta(1 - \pi)(\gamma \theta - 2) + 2f}{4(1 - \pi)(\pi \theta)^2}$$

$$+ \frac{\sqrt{[\pi \theta(1 - \pi)(\gamma \theta - 2) + 2f]^2 - 8(1 - \pi)(2(1 + \alpha)c\pi \theta(\delta - (1 - \pi)^2 - 2K))}}{4(1 - \pi)(\pi \theta)^2}$$

$$\tilde{c} = \frac{[\pi \theta(1 - \pi)(\gamma \theta + 4) - 2f]}{2(1 + \alpha)(3(1 - \pi) + 2\delta)} + \sqrt{[\pi \theta(1 - \pi)(4 + \gamma \theta - 2f)^2 + 4\pi \theta(1 - \pi)(3(1 - \pi) + 2\delta)(2K - \pi \theta)]}$$

$$2(1 + \alpha)(3(1 - \pi) + 2\delta) \quad (4.24)$$

**Proof.** See appendix.

### 4.4.2 End of default waterfall

When all the available financial resources of the CCP drain out, the CCP becomes insolvent. It is not an impossible situation. There are several clearinghouse failures in
recent decades: the French Caisse de Liquidation in 1973, the Kuala Lumpur Commodities Clearing House in 1983, the Hong Kong Futures Exchange in 1987, the New Zealand Futures and Options Exchange in 1989, and the Korean exchange clearinghouse in 2014.

$$K + \alpha c(1 - \bar{r}) - \frac{[\pi \theta - (1 + \alpha)c]^2}{2\pi \theta} < 0$$  \hspace{1cm} (4.25)

At the end of default waterfall, i.e., when the above inequality holds, I assume that the protection buyers who trade with those default sellers will bear the rest of the losses.\textsuperscript{23} These protection buyers are not fully insured now. The utility improvement of a pair of default seller and his buyer is as follows.

$$\Delta U_{D,E} = \frac{\gamma}{2}\pi(1 - \pi)(\theta^2 - w^2) + (1 - \pi)(\pi \theta - (1 + \alpha)c - w) - (1 + \alpha)\delta c - f$$  
$$= \Delta U_D - E(w)$$  \hspace{1cm} (4.26)

where $w$ denotes the wedge between the required payment and the (insufficient) financial resources and $E(w)$ is the utility loss from partial insurance.

$$w = \frac{L - K - \alpha c(1 - \bar{r})}{\bar{r}}$$

$$E(w) = \frac{\gamma}{2}\pi(1 - \pi)w^2 + (1 - \pi)w$$  \hspace{1cm} (4.27)

Equation 4.26 and 4.27 show that when both collateral and capital are very small, $\Delta U_{D,E}$ could be negative, which means the default sellers and their counterparties will not join the trading and clearing game. In this case, there is no default from sellers at $t = 1$. But different from the previous situation when $c \geq \bar{c}$, now default sellers do not have incentive to trade because of the utility loss from partial insurance. Hence, $\Delta U_{D,E} \geq 0$ will pin down a threshold $K$, which is a function of $c$. I will elaborate $K$ in section 4.4.3.

\textsuperscript{23}For simplification, it is implicitly assumed that the protection buyers share the losses evenly.
As to the non-default sellers, they lose all the default fund that they contribute. Hence, the utility improvement of a pair of non-default seller and his counterparty is as follows.

\[
\Delta U_{ND,E} = \frac{\gamma}{2}\pi(1 - \pi)\theta^2 + (1 - \pi)r_j\pi\theta - (1 + \alpha)\delta c - f - (1 - \pi)\alpha c
\]

Comparing equation 4.26 and 4.28, I distinguish two cases: one in which the partial insurance loss \(E(w)\) is smaller than the default fund loss \((1 - \pi)\alpha c\), and the other in which \(E(w) > (1 - \pi)\alpha c\). The intuition is that when \(K\) and \(c\) satisfy the relationship in equation 4.25, if \(c\) remains unchanged and \(K\) decreases, the partial insurance loss \(E(w)\) increase from 0 to some amount that is larger than the default fund loss \((1 - \pi)\alpha c\).

**Small utility loss from partial insurance.** Figure 4.4 shows the utility improvement when \(E(w) \leq (1 - \pi)\alpha c\). When collateral is relatively high (but smaller than \(\bar{c}\)), the trading volume is \(1 - \tilde{r} + \bar{r}\).\(^{24}\) When the collateral decreases, the trading volume will increase continuously till 1 when collateral reaches \(\underline{c}\).

**Figure 4.4: Utility improvement when utility loss from partial insurance is small**

**Large utility loss from partial insurance** When the utility loss from partial insurance is larger than that from default fund loss, Figure 4.5 shows the utility improvement of traders.

\(^{24}\)I will show later that this is not an equilibrium since the CCP in this situation will lose their capital and has no incentive to charge a high collateral.
Under this situation, when collateral is high, trading volume is $1 - \bar{r} + \bar{r}$. As collateral decreases, trading volume increases continuously until collateral reaches $c$. When $0 \leq c \leq \bar{c}$, the trading volume is $1$.\(^{25}\) Lemma 4 summarizes the results.

**Figure 4.5: Utility improvement when utility loss from partial insurance is large**

![Graph showing utility improvement]

**Lemma 4. Trading volume (insolvent CCP)**

When $K$ and $c$ satisfy the following relationship, the CCP becomes insolvent and some buyers may be partial insured.

$$K + \alpha c (1 - \bar{r}) - \frac{[\pi \theta - (1 + \alpha)c]^2}{2\pi \theta} < 0$$  \hspace{1cm} (4.29)

The trading volume for small and large utility losses from partial insurance are as follows. The trading volume is as follows

$$v(c) = \begin{cases} 
1 - \bar{r} + \bar{r}, & c < c \leq \bar{c} \\
1, & 0 \leq c \leq \bar{c}
\end{cases}$$  \hspace{1cm} (4.30)

where $\bar{c}$ is as follows.

$$\bar{c} = \frac{\pi \theta (1 - \pi)(\gamma \theta + 2) - 2f}{2(1 + \alpha)(1 - \pi + \delta) + 2\alpha(1 - \pi)}$$  \hspace{1cm} (4.31)

**Proof.** See appendix.

\(^{25}\)Note that default sellers and their counterparties will only trade when they could have positive utility improvement, i.e., when $K > K$. Since $K$ is a function of $c$, it is an implicit constraint for $c$ when $K$ is given.
4.4.3 Traders’ decision

I solve the equilibrium problem by backward deduction. I first analyze whether traders would join the trading and clearing game. Depending on the size of potential trading losses of sellers and the size of available financial resources of the CCP, there are six different cases where relationship between collateral c and capital K is different. Figure 4.6 shows the six different combinations of c and K. In other words, when traders observe a pair of (c, K), they “foresee” what would happen at $t = 1$ if the bad state is realized.

**Figure 4.6: Six different cases**

---

**Case 1: No seller defaults at $t = 1$.** When the trading losses of sellers are covered by the collateralized financial resources, no seller has incentive to default at $t = 1$. As discussed in section 4.3, collateral is costly and can disincentivize sellers from default. When $c \geq \bar{c}$, only the non-default sellers have positive utility surplus and will join the trading and clearing game. Hence, under such condition, there is no default losses for the CCP. I call such a case **“No Default” case**.

However, since not every trader joins the game and the trading volume is less than one, the RGFT is not fully realized. As collateral increases, the trading volume decreases further.
Case 2: Some sellers default at $t = 1$ and the CCP covers the losses. When the potential trading loss of a seller exceeds his collateralized financial resources, this seller may default at $t = 1$. If the potential trading losses of default sellers can be covered by the collateralized financial resources and the CCP’s capital, the mutualized financial resources contributed by the non-default sellers remain untouched. In other words, $K \geq \bar{K}$ as shown in equation 4.17. There is no default fund losses for the non-default sellers. I call this case “Default Covered” case.

In this case, trading volume is always one. The RGFT is fully realized. But the potential trading losses from default sellers raise systemic risk. As collateral $c$ decreases, the total default losses will increase. The threshold $\bar{K}$ also need to increase to cover the losses. Hence, $\bar{K}$ is a decreasing function in $c$.

Case 3: Default fund is consumed and the CCP is solvent. When the CCP has not enough capital, the mutualized financial resources are also used to cover the potential trading losses of default sellers. As long as the default fund is large enough to cover the losses, the CCP remains solvent. I call this case “Default Solvent” case.

When default fund contributed by the non-default sellers is used to cover the losses of default sellers, the utility improvement of a pair of non-default seller and his buyer $\Delta U_{ND,M}$ also depends on the CCP’s capital $K$, as shown in equation 4.21. Solve $\Delta U_{ND,M}(\bar{r}) = 0$, I have $\bar{r}$ as a function of both $c$ and $K$. Plug $\bar{r}$ back to equation 4.34. I have the explicit form of $\bar{K}$ as follows.

$$\bar{K} = \frac{(\pi \theta - (1 + \alpha)\bar{c})^2}{2\pi \theta} - \frac{\alpha \bar{c} [(1 + \alpha)\delta c + f + \pi(1 - \pi)(\gamma - \theta)]}{2(1 - \pi)\theta} \quad (4.32)$$

Since $c < \bar{c}$, the default sellers will join the game. But their default losses will consume the default fund contributed by the non-default sellers. As lemma 3 shows, the trading volume in this case could be either one or smaller than one. When $\bar{c} < c < \bar{c}$, trading volume will be smaller than one. Some of the non-default sellers will not like to join the game.
because the expected default fund losses make it unprofitable for them to trade.\(^{26}\) When \(0 \leq c \leq \tilde{c}\), although the non-default sellers (and their counterparties) still “subsidize” the default sellers (and their counterparties), the amount of subsidy is small enough that all non-default sellers could have non-negative utility improvement from trading. Hence, the trading volume is one when \(0 \leq c \leq \tilde{c}\).

**Case 4: CCP is insolvent and the utility loss from partial insurance is small.** When all the available financial resources of the CCP drains out, the CCP becomes insolvent. At the end of default waterfall, the remaining losses will be born by the buyers who trade with those default sellers. In other words, these buyers are partially insured. When the utility loss from partial insurance \(E(w)\) is smaller than the expected default fund losses \((1 - \pi)ac\), I call it “Insolvent Small” case.

As discussed in section 4.4.2, there is a threshold \(K\) that satisfies \(E(w) \leq (1 - \pi)ac\). I first solve the \(\tilde{r}\) from \(\Delta U_{ND,E}(\tilde{r}) = 0\), and then solve the inequality \(E(w) \leq (1 - \pi)ac\). Hence, the condition for this case is \(K \leq K < \tilde{K}\) where

\[
K = \left(\frac{\pi\theta - (1 + \alpha)c}{2\pi}\right) - \alpha c - \frac{(1 + \alpha)c}{\theta \gamma (1 - \pi) \pi^2} \left[ \sqrt{(1 - \pi)\theta [(1 - \pi)\theta + 2\theta \gamma (1 + \alpha)]} - (1 - \pi)(1 + \pi \gamma \alpha c) \right]
\]

\[\tag{4.33}\]

\(^{26}\)Murphy (2016) studies the incentives created by CCP’s financial resources. One important element is default fund. The risk of losing default fund will increase the cost for the traders, hence decreasing the trading volume. In my model, the potential default fund breach also increase the cost for the traders. But since the CCP can choose the collateral requirement, the CCP will compensate the traders by lowering collateral requirement. On one hand, lowering collateral requirement will increase the possibility of default fund breach. But on the other hand, lowering collateral requirement can directly reduce the collateral cost. Hence, the CCP still can maximize trading volume by lowering collateral requirement, at the cost of larger potential default losses.
Case 5: CCP is insolvent and the utility loss from partial insurance is large. When the CCP is insolvent and the utility loss from partial insurance is larger than the default fund loss, I call it “Insolvent Large” case.

\[
K = \frac{(\pi \theta - (1 + \alpha)c)^2}{2\pi \theta} - \alpha c \\
- \frac{(1 + \alpha)c}{\theta \gamma \pi^2} \left[ \sqrt{1 - \pi + 2\pi \gamma[(1 + \alpha)(1 - \pi + \delta)c + f]} - (1 - \pi)(\gamma \theta - 2\theta \gamma \pi^2) - (1 + \pi \alpha c) \right]
\]

(4.34)

Case 6: Extremely small capital and collateral. When capital \( K \) is smaller than \( \underline{K} \), i.e., when both capital and collateral are extremely small, the losses from partial insurance are so large that the default sellers and their counterparties will not trade with each other. In this case, there is no default at \( t = 1 \) when the bad state is realized. However, given the collateral is so small, the trading volume of non-default sellers is also very small. Hence, compared to the ND case, the trading volume is also negligible.

Figure 4.7 combines the results from lemma 3, 4 and figure 4.6. The blue shaded area is the parameter space that trading volume will be one. Note that the dashed blue line means that the boundary is not included. For instance, when \( c = \bar{c} \), the trading volume is smaller than one.
4.4 Profit-driven CCP

Figure 4.7: Trading volume

4.4.4 Optimal collateral and capital for a profit-driven CCP

As stated in equation 4.16, the optimization problem of a profit-driven CCP is

$$\text{Max}_{K, c} \quad f(v(c)) + (1 - \pi)\max(-L, -K) - \psi K.$$ 

As shown in figure 4.6, when \( c \geq \bar{c} \), only non-default sellers and their counterparties join the trading game. There is no default loss for the CCP at \( t = 1 \). Hence, the expected value of the CCP only consists of the volume-based fee income and the cost of capital.

When \( 0 \leq c < \bar{c} \), \( V_{CCP} \) takes three different formula, depending on how large the CCP capital is. When \( K \geq \bar{K} \), default sellers and their counterparts join the trading game. The CCP will cover all default losses, i.e., \( \frac{1}{2\sigma^2} \frac{(\pi\theta - (1 + \alpha)c)^2}{2\pi^2} \), at \( t = 1 \) when the bad state is realized. When \( \bar{K} < K < \bar{K} \), the CCP only contributes his capital but does not cover all default losses when the bad state is realized. When \( 0 \leq K < K \), the default sellers and their counterparts will not join the trading game because of large losses from partial insurance. In this case, there is no default losses for the CCP. Equation 4.35 summarizes the idea.
Optimal collateral as a function of capital. Although the CCP choose optimal collateral and capital simultaneously, I separate the decision procedure into two steps in order to facilitate the comparison between the CCP’s choice and the optimal level of collateral and capital in terms of maximizing social welfare, which will be discussed in section 4.5.

There are several important observations from equation 4.35. First, it shows that when $0 < K < \bar{K}$, setting collateral higher than $\bar{c}$ gets a higher CCP value than setting collateral lower than $\bar{c}$. Because trading volume in this case is increasing in $c$. Second, when $K \geq \bar{K}$, the CCP trades off between large trading volume and large default losses. On the one hand, the CCP could set collateral higher than $\bar{c}$ to minimize default losses. But the trading volume will be low. On the other hand, the CCP could set collateral lower than $\bar{c}$ to maximize trading volume, hence maximizing fee income. But the default losses will be high. The optimal collateral depends on which leads to a higher expected value of CCP. Fee would be a crucial element in determining optimal collateral. Intuitively, when fee is low, the “temptation” for the CCP to increase trading volume is small. So the CCP cares more about the expected default losses and will set a high collateral. However, when the fee is high, increasing one unit of trading volume will bring large profit. The CCP has strong incentive to maximize trading volume and will go for a low collateral. Third, when $K \leq \bar{K} < \bar{K}$, the limited CCP capital break the trade-off between high trading volume and large default losses, as the CCP does not cover all the default losses. As $K$ reduces, the CCP tends to chase high trading volume since she has very little to lose. Thus, when $K$ is smaller than some threshold $\hat{K}$, the CCP will set collateral $c$ within the blue shared area in figure 4.7 so that the trading volume is one. All RGFT will be realized. But the CCP does not cover all the default losses. If $\hat{K} \geq K$, the default losses will be covered by the default
4.4 Profit-driven CCP

...fund contributed by other non-default sellers. If $\hat{K} < K$, the default losses will also be covered by the buyers that traded with the default sellers. Proposition 3 summarizes the optimal collateral requirement with given $K$.\(^{27}\)

**Proposition 3. (Optimal collateral given specific capital)**

The optimal collateral when fee is lower than \(f\) and higher than \(f\) are

\[
c^*(K) = \begin{cases} 
\bar{c}, & K \geq \hat{K}(\bar{c}) \\
\bar{c}, & \hat{K}(\bar{c}) \leq K < \hat{K}(\bar{c}) \\
c, & 0 \leq K < \hat{K}(c) 
\end{cases}
\]

\[
c^*(K) = \begin{cases} 
[\bar{c}], & K \geq \hat{K}(\bar{c}) \\
\bar{c}, & \hat{K}(\bar{c}) \leq K < \hat{K}(\bar{c}) \\
c, & 0 \leq K < \hat{K}(c) 
\end{cases}
\]

where the threshold \(f\) and \(\hat{K}\) are

\[
f = \frac{(1 - \pi)\pi \theta [2(1 - \pi + \delta) + \gamma \theta + 2]}{6 - 4\pi + 4\delta}
\]

\[
\hat{K} = f(1 - \frac{(1 + \alpha)c}{\pi \theta})
\]

**Proof.** See appendix.

Figure 4.8 visualizes the expected value of the CCP as a function of $K$. Without loss of generality, I set $\varphi = 0$ since the capital cost applies to all different cases. The red solid line represents CCP value when default sellers join the game, while the blue dashed line is CCP value when only non-default sellers join the game. When only non-default sellers join the game, the expected value of the CCP is invariant in CCP’s capital, as there is no default losses need to be covered. But when default sellers also join the game, the expected value decreased in $K$ until $\hat{K}$. The reason is, when $K < \hat{K}$, the CCP contributes all her capital to cover the default losses. But when $K \geq \hat{K}$, the CCP’s capital is larger than the total default losses. Thus, the expected value is also invariant in $K$. The two subplots show the two cases when fee is higher or lower than \(f\). As discussed before, fee is an important factor in altering CCP’s incentives. When $f > \bar{f}$, the CCP will always maximize trading volume no matter how large her capital is. Because the fee income from the default sellers

\(^{27}\)I use the notation $[X]^{-}$ to denote the amount that is slightly smaller than $X$ and $[X]^{+}$ to denote the amount that is slightly larger than $X$. 
(and their counterparties) is larger than the expected default losses. In this case, the lower is the capital, the higher is the CCP value. When \( f \geq \hat{f} \), the fee income from the default sellers (and their counterparties) is smaller than the expected default losses. Depending on how low the fee level is, the CCP will trade-off the fee income and the expected loss of her capital. In this case, the CCP with large capital, i.e., \( K \geq \hat{K} \), will be conservative and set high collateral to disincentivize sellers’ default at \( t = 1 \). As fee decreases, the threshold \( \hat{K} \) decreases. But as long as fee is positive, \( \hat{K} > 0 \), which means when capital is very small, the CCP still will go for large trading volume since she has very little to lose.

**Figure 4.8: CCP’s value**

![Figure 4.8: CCP’s value](image)

**Optimal capital for a profit-driven CCP.** As outlined in figure 4.8, the largest expected value of the CCP is achieved at \( K = 0 \). It means that the CCP will choose zero capital to minimize her exposure to potential defaults at \( t = 1 \) when the bad state is realized. Since the CCP capital is zero, she will not have incentives to do set a high collateral to avoid default sellers. Instead, the CCP will set a low collateral to attract default sellers, hence to maximize trading volume. The collateral cannot be too low neither, since low collateral leads to too many defaults when the bad state is realized, which in return will jeopardize the counterparties of default sellers. Proposition 4 presents the optimal capital and collateral for a profit-driven CCP.
4.5 Optimal capital requirement for a profit-driven CCP

Proposition 4. (Profit-driven CCP’s optimal capital and collateral) The optimal capital and collateral for a profit-driven CCP are

\[ K^* = 0, \quad c^* = c \] (4.38)

Proof. See appendix.

Note that in section 4.3, the benevolent CCP also set \( K = 0 \) when the capital cost is high. But the benevolent CCP sets a high collateral to avoid defaults at \( t = 1 \) when the bad state is realized. Because a benevolent CCP cares about the total welfare surplus. On contrary, the profit-driven CCP in this section has no incentive to set a high collateral. The low collateral \( c \) set by the profit-driven CCP maximizes the CCP’s value; but it does not maximize the total social welfare surplus.

4.5 Optimal capital requirement for a profit-driven CCP

In the previous section, there is no capital requirement for a profit-driven CCP. The CCP choose the capital and collateral simultaneously to maximize her profit. Now I introduce a regulator that maximizes the total welfare surplus \( W \).

\[
\max_k W^b + W^s + V_{CCP}
\]

From proposition 3, I have the optimal collateral that a profit-driven CCP will choose when the capital is given. Equation 4.39 shows the total welfare surplus.

\[
W(c^*) = \int_0^{(1+y)c^*} \Delta U^{ND}(r_j)r_j + \int_{(1+y)c^*}^\infty \Delta U^{BD}r_j + V_{CCP}(c^*)
\] (4.39)

With the optimal collateral, I calculate the total welfare surplus in different cases. First of all, from proposition 3, the profit-driven CCP set high collateral and hence there is no
default when $K \geq \hat{K}(\bar{c})$ and $f \leq \underline{f}$. In this case, the welfare surplus is lower than the first best welfare surplus because of collateral cost, not-fully-realized gains from trade, and capital cost. Second, if $0 \leq K < \hat{K}(\bar{c})$, the profit-driven CCP will become insolvent. Hence, the welfare surplus is lower than the first best welfare surplus because of collateral cost, partial insurance loss and capital cost. Third, if $K$ is in between $\hat{K}(\bar{c})$ and $\tilde{K}(\bar{c})$ (or $\bar{K}(\bar{c})$) when fee is lower (or higher) than $\underline{f}$, all gains from trade are realized and the CCP remains solvent. Hence, the total welfare surplus is lower than the first best one only because of collateral cost and capital cost. Lemma 5 presents the welfare surplus when $K$ and $f$ are different.

**Lemma 5. (Total welfare surplus given specific capital)**

When $f \leq \underline{f}$, the total welfare surplus is as follows.

$$W = \begin{cases} W_{FB} - (1 + \alpha)\delta\bar{c} - \frac{(1 + \alpha)\bar{c}}{\pi\theta} & - (1 - \pi)\frac{(\pi\theta - (1 + \alpha)\bar{c})^2}{2\pi\theta} - \frac{\varphi K}{\text{collateral cost}}, & K \geq \hat{K}(\bar{c}) \\ W_{FB} - (1 + \alpha)\delta\bar{c} - \frac{\varphi K}{\text{capital cost}}, & \hat{K}(\bar{c}) \leq K < \hat{K}(\bar{c}) \\ W_{FB} - (1 + \alpha)\delta\bar{c} - \frac{(1 - (1 + \alpha)\bar{c})}{\pi\theta} & \frac{\gamma}{2}\pi(1 - \pi)w^2 - \frac{\varphi K}{\text{capital cost}}, & 0 \leq K < \hat{K}(\bar{c}) \end{cases}$$

When $f > \underline{f}$, the total welfare surplus is as follows.

$$W = \begin{cases} W_{FB} - (1 + \alpha)\delta\bar{c} - \frac{\varphi K}{\text{collateral cost}} - \frac{\varphi K}{\text{capital cost}}, & K \geq \tilde{K}(\bar{c}) \\ W_{FB} - (1 + \alpha)\delta\bar{c} - \frac{\varphi K}{\text{capital cost}}, & \tilde{K}(\bar{c}) \leq K < \hat{K}(\bar{c}) \\ W_{FB} - (1 + \alpha)\delta\bar{c} - \frac{(1 - (1 + \alpha)\bar{c})}{\pi\theta} & \frac{\gamma}{2}\pi(1 - \pi)w^2 - \frac{\varphi K}{\text{capital cost}}, & 0 \leq K < \hat{K}(\bar{c}) \end{cases}$$

Figure 4.9 shows the total welfare surplus when $\varphi = 0$. The red solid line is the total welfare surplus when there is no default and the blue dashed line is that when there are defaults at $t = 1$ when the bad state is realized. Since the total welfare surplus is decreasing in collateral and the optimal collateral set by the CCP is increasing in $K$, the welfare surplus with default (the red solid line) is decreasing in $K$ when $K \geq \hat{K}(\bar{c})$. But when
4.5 Optimal capital requirement for a profit-driven CCP

0 ≤ \( K \leq \tilde{K}(\bar{c}) \), the welfare surplus with default is increasing in \( K \) due to the partial insurance loss. For the welfare surplus without default (the blue dashed line), it is constant in \( K \) because \( \varphi = 0 \).

**Figure 4.9: Total welfare surplus**

I compare the total welfare surplus with different capital in lemma 5. The optimal capital requirement depends on the fee level \( f \) and the capital cost \( \varphi \). When capital cost is very high, i.e., \( \varphi > \bar{\varphi} \), the high cost of imposing capital outweighs the benefit of a safe CCP. Hence, the optimal capital requirement in this case will be zero. When \( \varphi \leq \bar{\varphi} \), it is socially optimal to have a safe CCP. A safe CCP in this context means a solvent CCP. In other words, the financial resources of the CCP can cover the potential default losses. But it does not mean that the CCP’s own capital will cover all default losses. Whether that should happen or not depends on the fee level. When \( f > \bar{f} \), the clearing business is so profitable that the profit-driven CCP will always chase high trading volume to maximize her profits. In this case, high capital does not help to increase total welfare surplus. Instead, high capital requirement leads to high collateral and makes transaction expensive for traders. The optimal capital in this case is to maintain a safe CCP with lowest collateral possible. Hence, \( K^* = \tilde{K}(\bar{c}) \). When \( f \leq \bar{f} \), high capital makes the profit-driven CCP conservative. In this case, \( K^* = \tilde{K}(\bar{c}) \) leads to a high collateral \( \bar{c} \) and disincentivize sellers’ defaults. Proposition 5 summarizes the optimal capital requirement for a profit-driven CCP.

**Proposition 5. (Optimal capital requirement for a profit-driven CCP)**
The optimal capital requirement for a profit-driven CCP depends on the fee level $f$ and the capital cost $\varphi$.

(i) When $\varphi > \bar{\varphi}$, the optimal capital requirement is $K^* = 0$.

(ii) When $\varphi \leq \bar{\varphi}$ and $f > f_0$, the optimal capital requirement is $K^* = \hat{K}(\bar{c})$.

(iii) When $\varphi \leq \bar{\varphi}$ and $f \leq f_0$, the optimal capital requirement is $K^* = \hat{K}(\bar{c})$.

The thresholds are as follows.

\[
\bar{\varphi} = \gamma \pi (1 - \pi) w \\
\bar{f} = \frac{\pi \gamma \theta^2 (1 - \pi) (\gamma \theta + 2)(\gamma \theta + 2 + \alpha (\gamma \theta + 6))}{4(\gamma \theta + 1)(\gamma \theta + 2 + \alpha (\gamma \theta + 4))}
\]

Proof. See appendix.

4.6 Conclusion

To the best of my knowledge, this paper is the first in the literature that models CCP’s insolvency. CCPs are not benevolent organizations. Instead, many CCPs operate as profit-driven public companies. The profit-driven character, coupled with limited liability constraint, gives rise to potentially misaligned incentives for a CCP to lower collateral requirement in exchange for higher trading volume. I show that a profit-driven CCP will choose zero capital and set a low collateral requirement to maximize her expected value, when there is no capital requirement. A benevolent CCP will choose a minimum capital when capital cost is high; but the benevolent CCP will set a high collateral requirement, since she cares about not only her own expected value but also the utility improvement of traders.

As pointed out before, CCPs are different from banks because of the mutualized financial resources. Hence, the optimal capital requirement should be designed to tailored to such features. My model suggests that the optimal capital requirement for profit-driven CCPs
should depend on both capital cost and volume-based fee. For the capital cost, it is a similar story as the capitalization problem for banking. When capital cost is very high, the optimal capital requirement should be zero because the high capital cost outweighs the benefit of a safe CCP. For the low capital cost, the optimal capitalization depends on how profitable is clearing business. Since the main profits of CCPs come from commission fee which is greatly dependent on trading volume, high volume-based fee represents a great “temptation” for the CCP. Hence, when volume-based fee is high enough, the CCP will always go for large trading volume. The optimal capital requirement in this case is to have a safe CCP with lowest collateral possible, as collateral is also costly in my model. When volume-based fee is low, imposing a high capital requirement makes a profit-driven CCP more conservative and will charge a high collateral to disincentivize traders’ default.

There are several possible extensions for the current model. First, it is possible to introduce fire sale cost and bail out cost in the case of CCP insolvency. I currently assume that the counterparties that trades with default sellers bear the remaining losses, similar to a partial tear-up. There is no fire sale cost for the collateral when there is a large amount of sellers’ defaults in the market. Such assumption could be relaxed by incorporating a “cash-in-the-market” mechanism (Acharya and Yorulmazer, 2008). To bail out or to resolve a CCP depends on how many sellers default and how large the fire sale cost will be. Second, it is possible to endogenize volume-base fee and introduce competition among CCPs, following the circular road model (Salop, 1979). Since fee and collateral both decrease traders’ utility, a profit-driven CCP will try to lower these two to maximize their own trading volume. I expect that the competition between CCPs will first drive down the fee level. But as competition gets fierce, profit-driven CCPs will also try to lower collateral requirement to increase trading volume.
4.A  Appendix

4.A.1  Variable summary

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>the ratio between default fund contribution and initial margin</td>
</tr>
<tr>
<td>$\delta$</td>
<td>convex collateral cost coefficient for protection sellers</td>
</tr>
<tr>
<td>$\pi$</td>
<td>probability of the high state</td>
</tr>
<tr>
<td>$\tilde{r}$</td>
<td>protection seller $j$’s payment to protection buyer</td>
</tr>
<tr>
<td>$\theta$</td>
<td>the high realized value of the risky asset</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>per unit capital cost of the CCP</td>
</tr>
<tr>
<td>$c$</td>
<td>collateral from the sellers to disincentivize the sellers’ defaults</td>
</tr>
<tr>
<td>$d$</td>
<td>the share of default fund contribution that survival sellers need to pay</td>
</tr>
<tr>
<td>$f$</td>
<td>volume-based fee charged by the CCP</td>
</tr>
<tr>
<td>$K$</td>
<td>capital of the CCP</td>
</tr>
<tr>
<td>$L$</td>
<td>total default losses</td>
</tr>
<tr>
<td>$m$</td>
<td>cash endowment of protection buyers</td>
</tr>
<tr>
<td>$r_j$</td>
<td>protection seller $j$’s capability to lower the downside risk</td>
</tr>
<tr>
<td>$\tilde{s}_j$</td>
<td>protection seller $j$’s real payment to protection buyer</td>
</tr>
<tr>
<td>$v$</td>
<td>trading volume</td>
</tr>
<tr>
<td>$w$</td>
<td>wedge between the required payment and the available financial resources</td>
</tr>
<tr>
<td>$W$</td>
<td>total welfare</td>
</tr>
</tbody>
</table>

4.A.2  Proof

**Proposition 1**

*Proof.* As figure 4.2 shows, as collateral decreases, traders’ utility improvement increases. I first get the hedging capability $\tilde{r}$ of the marginal non-default sellers by setting $\Delta U_{ND}(\tilde{r}) = 0$. From equation 4.3, I have

$$\tilde{r} = \frac{\gamma \pi (1 - \pi) \theta^2 - 2(1 + \alpha) \delta c - 2f}{2(1 - \pi) \pi \theta}$$  \hspace{1cm} (4.A.1)
Also, I need to take into account the fact that \( \tilde{r} \) cannot be smaller than \( \bar{r} \). Because when \( r_j \) is smaller than \( \tilde{r} \), the seller \( j \) will defaults. Thus, equation 4.A.1 and \( \tilde{r} = \frac{\pi \theta - (1 + \alpha) \bar{c}}{\pi \theta} \) pin down a threshold \( \tilde{c} \) that when \( c \geq \tilde{c} \), \( \tilde{r} \leq \bar{r} \).

\[
\tilde{c} = \frac{\pi \theta (1 - \pi) (\gamma \theta + 2) - 2f}{2(1 + \alpha)(1 - \pi + \delta)}
\]

(4.A.2)

Hence, when \( c \geq \tilde{c} \), only non-default sellers have positive utility improvement from trading. Hence, the trading volume is \( 1 - \tilde{r} \). When \( 0 \leq c < \tilde{c} \), both default and non-default sellers will join the game since they both have positive utility improvement. Trading volume is 1.

\[\square\]

Lemma 1

Proof. In the case of no default at \( t = 1 \), holding capital is only adding cost for the benevolent CCP. Hence, the optimal capital in this case is 0. As to collateral, to have no default at \( t = 1 \), collateral needs to satisfy \( c \geq \bar{c} \). Take the first order derivative of \( W_{ND} \) with respect to \( c \) leads to

\[
\frac{\partial W_{ND}}{\partial c} < 0, \quad \text{if} \quad c \geq \tilde{c}.
\]

(4.A.3)

Thus, the optimal \( c \) is \( \tilde{c} \). Plug in \( c_{ND}^* \) and \( K_{ND}^* \) into equation 4.7, I directly have

\[
W_{ND}(c_{ND}^*, K_{ND}^*) = W_{FB} - \frac{(1 + \alpha)\tilde{c} - (1 + \alpha)\delta c - \pi \theta - (1 + \alpha)\tilde{c}}{\pi \theta} W_{FB}
\]

(4.A.4)

\[\square\]

Lemma 2
Proof. Given equation 4.3 and 4.4, the objective function of the benevolent CCP is rewritten as

\[
\begin{align*}
\text{Max}_{K,c} & \quad \frac{1}{2} \pi (1 - \pi) \theta^2 + \frac{1}{2} (1 - \pi) \pi \theta - (1 + \alpha) \delta c - \varphi K \\
\text{s.t.} & \quad K \geq \frac{(\pi \theta - (1 + \alpha) c)^2}{2 \pi \theta} \\
& \quad 0 \leq c < \bar{c}
\end{align*}
\]

Since the objective function is decreasing in \( K \), the optimal \( K \) is achieved when \( K \geq \frac{(\pi \theta - (1 + \alpha) c)^2}{2 \pi \theta} \) is binding. Hence I could plug in \( K = \frac{(\pi \theta - (1 + \alpha) c)^2}{2 \pi \theta} \) into the objective function.

Take the first order derivative of the objective function with respect to \( c \) and I could see that the optimal \( c \) depends on how large is \( \varphi \). When \( \varphi \leq \delta \), the objective function is decreasing in \( c \). Thus, the optimal collateral is zero. When \( \varphi > \delta \), the optimal collateral is achieved at \( \frac{\pi \theta \varphi - \delta}{1 + \alpha} \).

With the optimal \( c_D^* \), I could have the optimal \( K_D^* \) by plugging \( c_D^* \) in \( K = \frac{(\pi \theta - (1 + \alpha) c)^2}{2 \pi \theta} \).

Hence, \( K_D^* \) is \( \frac{\pi \theta}{2} \) when \( \varphi \leq \delta \) and is \( \frac{\pi \theta \varphi^2}{2} \) when \( \varphi > \delta \).

With the \( c_D^* \) and \( K_D^* \), I have the total welfare surplus as

\[
W^D(c_D^*, K_D^*) = \begin{cases} 
W^{FB} - \frac{\pi \theta \varphi^2}{2} - \frac{\delta \pi \theta (\varphi - \delta)}{\varphi}, & \varphi > \delta \\
W^{FB} - \frac{\pi \theta \varphi}{2}, & \varphi \leq \delta
\end{cases}
\]

Proposition 2

Proof. From lemma 1 and 2, I have the optimal capital and collateral for a benevolent CCP in no default case and default case, respectively. Which case leads to a higher total welfare surplus depends on how large is the capital cost \( \varphi \). Because the total welfare surplus in
default case \( W^D(c^*_D, K^*_D) \) is decreasing in \( \varphi \), while that in no default case \( W^{ND}(c^*_ND, K^*_ND) \) is invariant in \( \varphi \). I first discuss the situation that \( \varphi \leq \delta \).

When \( \varphi \leq \delta \), the total welfare surplus in default case \( W^D(c^*_D, K^*_D) \) is

\[
W^D(c^*_D, K^*_D) = W^{FB} - \frac{\pi \theta}{2} \varphi
\]

\[
\geq W^{FB} - \frac{\pi \theta}{2} \delta
\]  

(4.A.6)

Let \( f(\delta) \) denote the function of the difference between \( W^{ND}(c^*_ND, K^*_ND) \) and \( W^{FB} - \frac{\pi \theta}{2} \delta \).

\[
f(\delta) = W^{ND}(c^*_ND, K^*_ND) - (W^{FB} - \frac{\pi \theta}{2} \delta)
\]

\[
= \frac{\pi \theta}{2} \delta - \frac{(1 + \alpha) \bar{c}}{\pi \theta} (1 + \alpha) \delta \bar{c} - \frac{\pi \theta - (1 + \alpha) \bar{c}}{\pi \theta} W^{FB}
\]

(4.A.7)

Since \( \bar{c} = \frac{\pi \theta (1 - \pi) (1 + \alpha) (1 - 2 \varphi)}{2(1 + \alpha)(1 - \pi + \alpha)} \), I have the first order derivative of \( f(\delta) \) w.r.t. \( \delta \) as

\[
\frac{\partial f(\delta)}{\partial \delta} < 0.
\]

(4.A.8)

As I assume the collateral cost is large enough that \( \delta > \delta_0 \); and \( f(\delta) < 0 \), I have \( f(\delta) < 0 \) for \( \delta > \delta_0 \). In other words, \( W^{ND}(c^*_ND, K^*_ND) < W^{FB} - \frac{\pi \theta}{2} \delta \leq W^D(c^*_D, K^*_D) \), when \( \varphi \leq \delta \). The default case leads to a higher total welfare surplus for the benevolent CCP.

When \( \varphi > \delta \), the total welfare surplus in default case \( W^D(c^*_D, K^*_D) \) is

\[
W^D(c^*_D, K^*_D) = W^{FB} - \frac{\pi \theta}{2} \delta^2 - \frac{\delta \pi \theta (\varphi - \delta)}{\varphi}.
\]

(4.A.9)

Let \( g(\varphi) \) denote the function of the difference between \( W^{ND}(c^*_ND, K^*_ND) \) and \( W^D(c^*_D, K^*_D) \).

\[
g(\varphi) = W^{ND}(c^*_ND, K^*_ND) - W^D(c^*_D, K^*_D)
\]

\[
= \frac{\pi \theta}{2} \delta^2 + \frac{\delta \pi \theta (\varphi - \delta)}{\varphi} - \frac{(1 + \alpha) \bar{c}}{\pi \theta} (1 + \alpha) \delta \bar{c} - \frac{\pi \theta - (1 + \alpha) \bar{c}}{\pi \theta} W^{FB}
\]

(4.A.10)
Take the first order derivative of $g(\varphi)$ w.r.t. $\varphi$, I have
\[
\frac{\partial g(\varphi)}{\partial \varphi} > 0. \tag{4.A.11}
\]

Let $\bar{\varphi}$ satisfy $g(\bar{\varphi}) = 0$, I have $g(\varphi) > 0$ when $\varphi > \bar{\varphi}$, i.e., $W^{ND}(c^*_ND, K^*_ND) > W^D(c^*_D, K^*_D)$. Solve $g(\bar{\varphi}) = 0$, I have
\[
\bar{\varphi} = \frac{2}{\pi \theta} \left( W^{FB} - W^{ND}(\bar{c}, 0) \right). \tag{4.A.12}
\]

\[\blacksquare\]

**Lemma 3**

**Proof.** When $0 < \frac{[\pi \theta - (1 + \alpha) c]^2}{2 \pi \theta} - K \leq \alpha c (1 - \bar{r})$, the CCP remains solvent but has not enough capital to cover the total default losses. Mutualized financial resources are used to cover part of the losses. The utility improvement of a pair of default seller and his buyer is as the same as equation 4.4. As long as $c < \bar{c}$, the default sellers and their counterparties will join the trading game.

But since the mutualized financial resources contributed by non-default sellers are used to cover the losses of default sellers, the utility improvement of a pair of non-default seller and his buyer is lower, as written in equation 4.21.

\[
\Delta U_{ND,M} = \frac{\gamma}{2} \pi (1 - \pi) \theta^2 + (1 - \pi)r_\pi \theta - (1 + \alpha)\delta c - f - (1 - \pi) d \tag{4.A.13}
\]

Expected loss from default fund
The marginal non-default seller $\tilde{r}$ should satisfy $\Delta U_{ND,M}(\tilde{r}) = 0$. Solve the equation, I have

$$\tilde{r} = \frac{\pi \theta (1 - \pi) (\gamma \theta - 2) + 2f}{4(1 - \pi)(\pi\theta)^2} + \frac{\sqrt{[\pi \theta (1 - \pi) (\gamma \theta - 2) + 2f]^2 - 8(1 - \pi)(2(1 + \alpha)c\pi\theta(\delta - (1 - \pi)^2 - 2K))}}{4(1 - \pi)(\pi\theta)^2}$$

(4.4.14)

When $\tilde{r} > \bar{r}$, the trading volume is $1 - \tilde{r} + \bar{r}$. Solve $\tilde{r} > \bar{r}$, I have $c > \tilde{c}$, where $\tilde{c}$ is as follows. Note that $\tilde{c}$ is a function of $K$ where $\tilde{c}(\bar{K}) = \bar{c}$ and $\tilde{c}(K) = c$.

$$\tilde{c} = \frac{[\pi \theta (1 - \pi) (\gamma \theta + 4) - 2f] + \sqrt{[\pi \theta (1 - \pi) (4 + \gamma \theta) - 2f]^2 + 4\pi \theta (1 - \pi)(3(1 - \pi) + 2\delta)(2K - \pi\theta)}}{2(1 + \alpha)(3(1 - \pi) + 2\delta)}$$

(4.4.15)

Hence, when $0 \leq c \leq \tilde{c}$, the trading volume is one.

\[ \square \]

**Lemma 4**

**Proof.** When $K + \alpha c(1 - \bar{r}) - \frac{[\pi \theta - (1 + \alpha)c\theta]^2}{2\theta^2} < 0$, the CCP becomes insolvent. All the default fund contribution is used to cover the losses. Equation 4.28 gives the utility improvement of a pair of default seller and his buyer.

$$\Delta U_{ND,E} = \frac{\gamma}{2} \pi (1 - \pi) \theta^2 + (1 - \pi)r,\pi \theta - (1 + \alpha)\delta c - f - (1 - \pi)\alpha c$$

(4.4.16)

Note that $K > \bar{K}$ also holds here. I leave the discussion of $K$ in section 4.4.3.
When seller $j$ with $\bar{r}$ and his counterparty have positive utility improvement, the trading volume is one. Solve $\Delta U_{ND,\varepsilon}(\bar{r}) = 0$, I have

$$c = \frac{\pi \theta (1 - \pi)(\gamma \theta + 2) - 2f}{2(1 + \alpha)(1 - \pi + \delta) + 2\alpha(1 - \pi)} \equiv \bar{c}. \quad (4.A.17)$$

Hence, when $c < c < \bar{c}$, the trading volume is $1 - \bar{r} + \bar{r}$, while the trading volume is one when $0 \leq c$.

**Proposition 3**

*Proof.* From equation 4.A.18, one can see that the CCP will set a collateral to maximize $\nu(c)$ when $c \geq \bar{c}$. From proposition 2, I know that $\bar{c}$ is the optimal collateral in this case. As to $c < \bar{c}$, figure 4.7 shows the collateral level that achieves maximum trading volume. But which collateral level maximizes the CCP value still depends on the fee level $f$. I first plug in the collateral that maximizes trading volume into equation 4.35.

$$V_{CCP} = \begin{cases} 
  f \frac{\pi \theta (1 - \pi)(\gamma \theta + 2) - 2f}{2\pi \theta (1 - \pi + \delta)} - \varphi K, & c \geq \bar{c} \\
  f - \frac{(1 - \pi)(\pi \theta (1 - \pi)(\gamma \theta + 2\delta) + 2f)^2}{8\pi \theta (1 - \pi + \delta)^2} - \varphi K, & 0 \leq c < \bar{c}, K \geq \bar{K} \\
  f - (1 - \pi)K - \varphi K, & 0 \leq c < \bar{c}, K \leq K < \bar{K} 
\end{cases} \quad (4.A.18)$$

Since when $\bar{K} \leq K < \bar{K}$, $f - (1 - \pi)K - \varphi K > f - \frac{(1 - \pi)(\pi \theta (1 - \pi)(\gamma \theta + 2\delta) + 2f)^2}{8\pi \theta (1 - \pi + \delta)^2} - \varphi K$. The comparison is mainly between $f \frac{\pi \theta (1 - \pi)(\gamma \theta + 2) - 2f}{2\pi \theta (1 - \pi + \delta)} - \varphi K$ and $f - (1 - \pi)K - \varphi K$. Let $h(f, K)$ denote the difference between $f \frac{\pi \theta (1 - \pi)(\gamma \theta + 2) - 2f}{2\pi \theta (1 - \pi + \delta)} - \varphi K$ and $f - (1 - \pi)K - \varphi K$.

$$h(f, K) = f \frac{\pi \theta (1 - \pi)(\gamma \theta + 2) - 2f}{2\pi \theta (1 - \pi + \delta)} - \varphi K - (f - (1 - \pi)K - \varphi K)$$

$$= f \frac{\pi \theta ((1 - \pi)\gamma \theta - 2\delta) - 2f}{2\pi \theta (1 - \pi + \delta)} + (1 - \pi)K \quad (4.A.19)$$
Since \( K \leq K < \bar{K} \), I could solve the inequality \( h(f, K) \geq 0 \) as \( f \leq \underline{f} \) and \( K \geq \hat{K}(\bar{c}) \) where

\[
\begin{align*}
f &= \frac{(1 - \pi)\pi\theta[2(1 - \pi + \delta) + \gamma\theta + 2]}{6 - 4\pi + 4\delta} \\
\hat{K} &= f(1 - \frac{(1 + \alpha)c}{\pi\theta})
\end{align*}
\] (4.A.20)

\[\Box\]

**Proposition 4**

**Proof.** From proposition 3, I have optimal collateral with given capital \( K \). Since \( \hat{K} > 0 \), the combination of \((\bar{c}, 0)\) will always give the highest CCP value. Hence, the optimal capital and collateral for a profit-driven CCP are

\[
K^* = 0, \quad c^* = \bar{c}
\] (4.A.21)

\[\Box\]

**Lemma 5**

**Proof.** From proposition 3, I have optimal collateral with given capital \( K \). I plug in the optimal collateral into equation 4.39.

When \( f \leq \underline{f} \) and \( K \geq \hat{K}(\bar{c}) \), the optimal collateral is \( \bar{c} \). No sellers default at \( t = 1 \) when the bad state is realized. The welfare surplus consists of two parts: the utility improvement from the non-default sellers and the CCP value. Since fee is a pure transfer from the traders to the CCP, it has no impact on the total welfare surplus directly. Hence, \( f \) disappears in the final expression. However, note that fee does matter for the thresholds on collateral and capital. Thus, the level of fee has indirect impact on the welfare surplus.

\[
W = \int_0^{\frac{t_{max}}{\theta}} \Delta U_{ND}dr_j + f\nu(\bar{c}) - \varphi K \\
=W^{FB} - (1 + \alpha)\delta\bar{c}\frac{(1 + \alpha)\bar{c}}{\pi\theta} - \frac{(1 - \pi)(\pi\theta - (1 + \alpha)\bar{c})^2}{2\pi\theta} - \varphi K
\] (4.A.22)
When \( f > f_0 \) and \( K \geq \bar{K}(\bar{c}) \), the optimal collateral is \([\bar{c}]^-\). The trading volume is one and some sellers default at \( t = 1 \). The welfare surplus is the sum of the utility improvement from the default and non-default sellers and the CCP value.

\[
W = \int_0^{(1 + \alpha)\bar{c}} \Delta U_{ND} dr_j + \int_0^{(1 + \alpha)\bar{c}} \Delta U_D dr_j + f - (1 - \pi)\left(\frac{\pi}{2\pi \theta} - (1 + \alpha)c\right)^2 - \varphi K
\]

\[
= W^{FB} - (1 + \alpha)\delta \bar{c} - \varphi K
\]

(4.A.23)

When \( f > f_0 \) and \( \bar{K}(\bar{c}) \leq K < \bar{K}(\bar{c}) \), the optimal collateral is \( \bar{c} \). The same optimal collateral also applies to the case when \( f \leq f_0 \) and \( \bar{K}(\bar{c}) \leq K < \bar{K}(\bar{c}) \). In this case, the trading volume is one and some sellers default at \( t = 1 \). The utility improvement for the default sellers and their counterparties are the same as before; but that for the non-default sellers and their counterparties is different from the previous case because of the losses from default fund contribution.

\[
W = \int_0^{(1 + \alpha)\bar{c}} \Delta U_{ND,M} dr_j + \int_0^{(1 + \alpha)\bar{c}} \Delta U_D dr_j + f - (1 - \pi)K - \varphi K
\]

\[
= W^{FB} - (1 + \alpha)\delta \bar{c} - \varphi K
\]

(4.A.24)

When \( \leq K < \bar{K}(\bar{c}) \), the optimal collateral is \( c \). In this case, the CCP becomes insolvent. The utility improvement for the default sellers and their counterparties is different because of the losses from partial insurance. For the non-default sellers and their counterparties, they loss all the default fund contribution and have a lower utility improvement as well.
But the CCP in this case has a higher expected value. That is also why they will choose zero capital if there is no capital requirement.

\[
W = \int_0^{\frac{1+\alpha K}{\pi \theta}} \Delta U_{N,D,E} dr_j + \int_0^{\frac{1+\alpha K}{\pi \theta}} \Delta U_{D,E} dr_j + f - (1 - \pi) K - \varphi K
\]

\[
= W^{FB} - (1 + \alpha) \delta C - \left(1 - \frac{(1 + \alpha)\gamma}{\pi \theta}\right) \frac{\gamma}{2} \pi(1 - \pi) w^2 - \varphi K
\]

(4.A.25)

\[\square\]

### Proposition 5

**Proof.** When \(0 \leq K < \tilde{K} (\varphi)\), whether \(W\) is increasing or decreasing in \(K\) depends on how large the capital cost \(\varphi\) is. From equation 4.41, I have the total welfare surplus when \(0 \leq K < \tilde{K} (\varphi)\) as follows.

\[
W = W^{FB} - (1 + \alpha) \delta C - \left(1 - \frac{(1 + \alpha)\gamma}{\pi \theta}\right) \frac{\gamma}{2} \pi(1 - \pi) w^2 - \varphi K
\]

(4.A.26)

Note that \(w\) is also a function of \(K\) as shown in equation 4.27. Plug in \(w\) and take the first order derivative of \(W\) w.r.t. \(K\), I have the following.

\[
\frac{\partial W}{\partial K} = \gamma \pi (1 - \pi) w - \varphi
\]

(4.A.27)

Let \(\bar{\varphi} = \gamma \pi (1 - \pi) w\). When \(\varphi > \bar{\varphi}\), \(W\) is decreasing in \(K\). Hence, the optimal capital requirement is zero.

When \(\varphi \leq \bar{\varphi}\), \(W\) is increasing in \(K\). Hence, for the total welfare surplus with default, the highest welfare surplus is achieved at \(\tilde{K} (\varphi)\). I know from proposition 3 that when \(f > f^-\), the CCP will have low collateral to maximize trading volume. Hence, for \(\varphi \leq \bar{\varphi}\) and \(f > f^-\), I have the optimal capital requirement \(K^* = \tilde{K} (\varphi)\). For the case when \(f \leq f^-\) I need to compare the welfare surplus when \(K = \tilde{K} (\varphi)\) and that when \(K = \hat{K} (\tilde{\varphi})\). Let \(l(f)\)
denote the difference between these two welfare surplus. From equation 4.40, I have the following.

\[ l(f) = W^{FB} - (1 + \alpha)\delta \hat{c} \frac{(1 + \alpha)\hat{c}}{\pi \theta} - (1 - \pi) \frac{(\pi \theta - (1 + \alpha)\hat{c})^2}{2\pi \theta} - \varphi \tilde{K}(\hat{c}) - (W^{FB} - (1 + \alpha)\delta \hat{c} - \varphi \tilde{K}(\hat{c})) \]

\[ = (1 + \alpha)\delta \hat{c} - (1 + \alpha)\delta \hat{c} \frac{(1 + \alpha)\hat{c}}{\pi \theta} - (1 - \pi) \frac{(\pi \theta - (1 + \alpha)\hat{c})^2}{2\pi \theta} + \varphi (\tilde{K}(\hat{c}) - \tilde{K}(\hat{c})) \]  

(4.A.28)

Solve \( l(f) = 0 \), I have

\[ f = \frac{\pi \gamma \theta^2 (1 - \pi)(\gamma \theta + 2)(\gamma \theta + 2 + \alpha(\gamma \theta + 6))}{4(\gamma \theta + 1)(\gamma \theta + 2 + \alpha(\gamma \theta + 4))} \]

\[ - \frac{\sqrt{(\pi \gamma \theta^2 (1 - \pi)(\gamma \theta + 2)(\gamma \theta + 2 + \alpha(\gamma \theta + 6))^2 - 8\alpha \pi \gamma \theta^2 (\gamma \theta + 1)(\gamma \theta + 2)(\gamma \theta + 2 + \alpha(\gamma \theta + 4))}}}{4(\gamma \theta + 1)(\gamma \theta + 2 + \alpha(\gamma \theta + 4))} \]  

(4.A.29)

Hence, when \( f \leq f \), \( l(f) \geq 0 \), which means the total welfare surplus without default is higher. The optimal capital requirement is \( \hat{K}(\hat{c}) \). When \( f > f \), \( l(f) < 0 \). The optimal capital requirement is \( \tilde{K}(\hat{c}) \).
Summary

During the past decade, both trading and clearing have experienced a large number of changes. On the trading side, the proliferation of trading venues, coupled with the rise of algorithmic trading, has greatly reshaped financial markets. On the clearing side, since the 2007-2008 financial crisis, global regulatory reforms (for instance, Dodd-Frank Act in the US and EMIR in Europe) introduce mandatory central clearing to a large number of financial asset classes, which puts a spotlight on Central Counterparties (CCPs). This dissertation contributes to the literature by studying these new features of trading and clearing.

Intermediaries and Venues: Connecting End-Users through Time and Space. The first chapter studies how modern financial intermediaries supply immediacy along both the time dimension and the space dimension. We develop a taxonomy of intermediaries depending on the dimension(s) they connect end-users: time (TimeOnlyInt), space (SpaceOnlyInt), or both (TimeSpaceInt). Frequency domain analysis reveals that different types of intermediaries profit in different frequency patterns. Further analysis on volatile periods and quiet periods shows that intermediaries profit tremendously from volatile periods. The taxonomy of intermediaries proposed in this chapter provides a new perspective on intermediaries’ roles in modern financial markets featured with substantial security fragmentation and algorithmic trading.

Systemic Risk in Real Time: A Risk Dashboard for Central Counterparties. The second chapter develops a risk dashboard to monitor CCP exposure in real time. Changes
in CCP exposure are decomposed into two types of components: price-related and trade-related components. Price-related components disentangle three risk channels through price variations: volatility changes, correlation changes, and price level changes. Trade-related components include position and crowding risk from house and client accounts. Using data from Nordic stock markets, the tool finds extreme right skewness of CCP exposure changes. Compared to normal times, the CCP faces different risk in turbulent periods, featured by substantial volatility and crowding risk. Moreover, half of crowding risk originates from house-house trades. The tool suggests that the CCP should keep track on volatility changes and crowding risk during market stress periods.

Central Counterparty Capitalization and Misaligned Incentives. The third chapter studies incentives and optimal regulation of a profit-driven CCP with limited liability. I construct a partial equilibrium model based on Biais, Heider, and Hoerova (2015). Conditional on available capital, the CCP fine-tunes collateral requirements to balance fee incomes against counterparty risk. High collateral reduces potential default losses, but leads to foregone profitable trades. Limited liability creates a wedge between the CCP’s collateral policy and the socially optimal solution to this trade-off. However, regulators can use capital requirements to close the wedge, unless clearing fees exceed a threshold. To the best of the author’s knowledge, this paper is the first in the literature that models CCP insolvency from the perspective of CCP’s misaligned incentives.
Nederlandse samenvatting
(Summary in Dutch)

Gedurende het afgelopen decennium hebben zowel handel als clearing een groot aantal veranderingen ondergaan. Aan de handelszijde heeft de proliferatie van handelsplaatsen, in combinatie met de opkomst van algoritmische handel, de financiële markten sterk veranderd. Aan de clearing-side, sinds de financiële crisis 2007-2008, hebben wereldwijde regelgevingshervormingen (bijvoorbeeld de Dodd-Frank-wet in de VS en EMIR in Europa) verplichte centrale clearing voor een groot aantal financiële activa ingevoerd, waarbij de nadruk wordt gelegd op Centrale Counterparties (CCP’s). Dit proefschrift draagt bij aan de literatuur door deze nieuwe kenmerken van handel en clearing te bestuderen.

Intermediaries and Venues: Connecting End-Users through Time and Space. In het eerste hoofdstuk wordt onderzocht hoe moderne financiële intermediairs liquiditeit leveren op zowel de tijdsdimensie als de ruimtedimensie. Wij ontwikkelen een taxonomie van tussenpersonen, afhankelijk van de dimensie(s) waarop zij eindgebruikers verbinden: tijd (TimeOnlyInt), ruimte (SpaceOnlyInt) of beide (TimeSpaceInt). Frequentiedomein analyse laat zien dat verschillende soorten tussenpersonen profiteren in verschillende frequentie patronen. Uitgebreide analyse over vluchtige periodes en rustige perioden laat zien dat tussenpersonen enorm profiteren in vluchtige periodes. De taxonomie van intermediairs die in dit hoofdstuk wordt voorgesteld, biedt een nieuw perspectief op de rol van intermediairs in de moderne financiële markten, waar veel versnippering van de aandelenmarkt en algoritmische handel optreedt.

Central Counterparty Capitalization and Misaligned Incentives. Het derde hoofdstuk bestudeert prikkels en optimale regulering van een door winst gedreven CCP met beperkte aansprakelijkheid. Ik constructeer een partieel evenwichtsmodel op basis van citet biaisheiderhoerova15. Afhankelijk van het beschikbare kapitaal, stelt de CCP onderpand vast als balans tussen inkomsten en het tegenpartij risico. Hoge zekerheden verminderen potentiele standaardverliezen, maar leiden tot minder winstgevende transacties. Beperkte aansprakelijkheid creert een wig tussen het onderpandbeleid van de CCP en de sociaal optimale oplossing voor deze afhandeling. Regelgevers kunnen echter kapitaalvereisten gebruiken om de wig te sluiten, tenzij de clearingkosten een drempel overschrijden. Naar de beste kennis van de auteur is dit artikel de eerste in de literatuur die CCP-insolventie modelleert vanuit het perspectief van de winst prikkels van de CCP.
Bibliography


(FIA), the Global Financial Markets Association (GFMA), the Institute of International Finance (IIF), the International Swaps and Derivatives Association, Inc. (ISDA), and the Clearing House (TCH).


Boehmer, Ekkehart, Dan Li, and Gideon Saar. 2016. “Correlated high-frequency trading.”


Coughenour, Jay F and Lawrence Harris. 2004. “Specialist profits and the minimum price increment.”


Duffie, Darrell. 2014. “Resolution of failing central counterparties.” *Available at SSRN 2558226*. 


FSB. 2014. “Key Attributes of Effective Resolution Regimes for Financial Institutions.” Manuscript, FSB.


Korajczyk, Robert A and Dermot Murphy. 2015. “High frequency market making to large institutional trades.” Available at SSRN 2567016.


Murphy, David and Paul Nahai-Williamson. 2014. “Dear Prudence, wont you come out to play? Approaches to the analysis of central counterparty default fund adequacy.”


——. 2014. “Limiting Taxpayer Puts An Example from Central Counterparties.”

SIX. 2014. “Clearing terms of SIX x-clear Ltd for SIX Swiss Exchange Ltd.” Rules and regulations six x-clear ltd, SIX Swiss Exchange Ltd.

Wendt, Froukelien. 2015. “Central counterparties: addressing their too important to fail nature.”
The Tinbergen Institute is the Institute for Economic Research, which was founded in 1987 by the Faculties of Economics and Econometrics of the Erasmus University Rotterdam, University of Amsterdam and VU University Amsterdam. The Institute is named after the late Professor Jan Tinbergen, Dutch Nobel Prize laureate in economics in 1969. The Tinbergen Institute is located in Amsterdam and Rotterdam. The following books recently appeared in the Tinbergen Institute Research Series:

651. K.A. RYSZKA, Resource Extraction and the Green Paradox: Accounting for Political Economy Issues and Climate Policies in a Heterogeneous World
652. J.R. ZWEERINK, Retirement Decisions, Job Loss and Mortality
655. D.A.R. BONAM, The Curse of Sovereign Debt and Implications for Fiscal Policy
656. Z. SHARIF, Essays on Strategic Communication
657. M. KOUDSTAAL, Common Wisdom versus Facts; How Entrepreneurs Differ in Their Behavioral Traits from Others
658. N. PETER, Essays in Empirical Microeconomics
659. Z. WANG, People on the Move: Barriers of Culture, Networks, and Language
660. Z. HUANG, Decision Making under Uncertainty-An Investigation from Economic and Psychological Perspective
661. J. CIZEL, Essays in Credit Risk, Banking, and Financial Regulation
662. I. MIKOLAJUN, Empirical Essays in International Economics
663. J. BAKENS, Economic Impacts of Immigrants and Ethnic Diversity on Cities
664. I. BARRA, Bayesian Analysis of Latent Variable Models in Finance
665. S. OZTURK, Price Discovery and Liquidity in the High Frequency World
666. J. JI, Three Essays in Empirical Finance
667. H. SCHMITTDEEL, Paid to Quit, Cheat, and Confess
668. A. DIMITROPOULOS, *Low Emission Vehicles: Consumer Demand and Fiscal Policy*
669. G.H. VAN HEUVELEN, *Export Prices, Trade Dynamics and Economic Development*
670. A. RUSECKAITE, *New Flexible Models and Design Construction Algorithms for Mixtures and Binary Dependent Variables*
671. Y. LIU, *Time-varying Correlation and Common Structures in Volatility*
672. S. HE, *Cooperation, Coordination and Competition: Theory and Experiment*
673. C.G.F. VAN DER KWAAK, *The Macroeconomics of Banking*
675. F.J.T. SNIEKERS, *On the Functioning of Markets with Frictions*
676. F. GOMEZ MARTINEZ, *Essays in Experimental Industrial Organization: How Information and Communication affect Market Outcomes*
677. J.A. ATTEY, *Causes and Macroeconomic Consequences of Time Variations in Wage Indexation*
678. T. BOOT, *Macroeconomic Forecasting under Regime Switching, Structural Breaks and High-dimensional Data*
681. Y. GAO, *Stability and Adaptivity: Preferences over Time and under Risk*
682. M.J. ZAMOJSKI, *Panta Rhei, Measurement and Discovery of Change in Financial Markets*
683. P.R. DENDERSKI, *Essays on Information and Heterogeneity in Macroeconomics*
684. U. TURMUNKH, *Ambiguity in Social Dilemmas*
686. M. LAMMERS, *Financial Incentives and Job Choice*
687. Z. ZHANG, *Topics in Forecasting Macroeconomic Time Series*
688. X. XIAO, *Options and Higher Order Risk Premiums*
689. D.C. SMERDON, *Everybodys doing it: Essays on Trust, Norms and Integration*
691. E. SILDE, *The Econometrics of Financial Comovement*

692. G. DE OLIVEIRA, *Coercion and Integration*

693. S. CHAN, *Wake Me up before you CoCo: Implications of Contingent Convertible Capital for Financial Regulation*

694. P. GAL, *Essays on the role of frictions for firms, sectors and the macroeconomy*

695. Z. FAN, *Essays on International Portfolio Choice and Asset Pricing under Financial Contagion*

696. H. ZHANG, *Dealing with Health and Health Care System Challenges in China: Assessing Health Determinants and Health Care Reforms*

697. M. VAN LENT, *Essays on Intrinsic Motivation of Students and Workers*

698. R.W. POLDERMANS, *Accuracy of Method of Moments Based Inference*

699. J.E. LUSTENHOUWER, *Monetary and Fiscal Policy under Bounded Rationality and Heterogeneous Expectations*