Essays on Corporate Governance and Asset Pricing

D I S S E R T A T I O N
of the University of St.Gallen,
School of Management,
Economics, Law, Social Sciences,
International Affairs and Computer Science,
to obtain the title of
Doctor of Philosophy in Finance

submitted by

Wei Lin

from

China

Approved on the application of

Prof. Dr. Roland Füss

and

Prof. Paul Söderlind, PhD

Dissertation no. 5231

Difo-Druck GmbH, Untersiemau 2022

The University of St.Gallen, School of Management, Economics, Law, Social Sciences, International Affairs and Computer Science, hereby consents to the printing of the present dissertation, without hereby expressing any opinion on the views herein expressed.

St.Gallen, May 25, 2022

The President:

Prof. Dr. Bernhard Ehrenzeller

Acknowledgements

I thank wholeheartedly Xiaoxu Zhang, the love of my life, who has lent me her unyielding support, and whose faith-like trust in me that has carried me all the way through this challenging and sinuous journey.

My utmost gratitude to my parents, Yanhong Nie and Wen Lin, who have made this all possible. To my parents-in-law, Jianhua Qin and Hualin Zhang, who along with my wife have inspired and encouraged me to take on this journey. And to my son, Yige, whose bravery and smiles have given me so much to look forward to.

Special thanks to Winfried Ruigrok, whose advice and kindness have substantially fostered my courage to finish this journey.

I thank my co-supervisor and thesis committee member, Paul Söderlind and Karl Frauendorfer, who offered so much more support than expected, and whose generous help have carried me through one of my most difficult times. Special thanks to Enrico de Girogi, who so kindly offered help and support during the trough of my low in this journey. Last but not least, my supervisor, Roland Füss, who has presented me with myriad learning opportunities.

Huge thanks to all those who have taught me lectures, discussed with me ideas, commented on my papers, and sat with me for coffee – you have no idea how important those meant to me. Special thanks to Nicole Hentschel, whose cherished friendship has alleviated much of the suffering part. And my heartfelt thankfulness to all those whose efforts have enabled me to embark on and push through this journey.

August 16, 2022 Wei Lin

St. Gallen, Switzerland

Contents

Summary . . . I
Zusammenfassung . . . II

Article 1: *Corporate Transparency and Bond Liquidity* . . . 1
1. Introduction . . . 2
2. Literature Review . . . 5
3. Hypotheses Development . . . 8
4. Data Description . . . 9
   4.1. Measures of Bond Liquidity . . . 10
   4.2. Measures of Transparency . . . 11
   4.3. Control Variables . . . 12
   4.4. Summary Statistics . . . 13
5. Empirical Results . . . 16
   5.1. Panel Data Regression . . . 16
   5.2. Relationship between Bond Liquidity and Firm-level Transparency . . . 17
   5.3. Relationship between Bond Liquidity and Firm-level Transparency in Times of Financial Distress . . . 19
   5.4. The Moderating Effects of Unexpected Rating Changes . . . 21
   5.5. Relationship between Bond Liquidity Uncertainty and Firm-level Transparency . . . 23
6. Robustness Checks . . . 24
7. Conclusion . . . 26
References . . . 28
Appendix . . . 48

Article 2: *Pricing the Location of Commercial Properties* . . . 65
1. Introduction and Motivation . . . 66
2. Methodology and Research Design . . . 69
   2.1. A net-present-value-based approach: the GPME and its extension into a pricing context . . . 69
   2.2. Our extended-GPME . . . 71
3. Pricing Framework . . . 73
   3.1. Estimating Location Value . . . 74
   3.2. Factor Construction by Estimating Portfolio Returns . . . 75
4. Data Description . . . 77
5. Empirical Results . . . 78
   5.1. Location Value Estimations . . . 78
   5.2. Real Estate Portfolio Returns from the HRM . . . 79
   5.3. Equal-size clustering outcome . . . 79
   5.4. GPME estimates: CAPM . . . 79
   5.5. GPME estimates: multi-factor . . . 80
6. Conclusion . . . 81
References . . . 82

Article 3: *Does Investor Protection Laws Benefit Investors? Evidence from a natural experiment on cross-listed firms* . . . 102
1. Introduction . . . 103
2. Related Literature and Institutional Background . . . 106
3. Research Setting and Hypotheses Development . . . 110

4. Data and Methodology 113
4.1. Summary Statistics 115
5. Empirical Results 117
5.1. Difference in differences. 117
5.2. Propensity score matching. 118
5.3. Propensity-score-matched difference in differences. 119
5.4. Supplementary analyses: board composition upon turnover 121
6. Conclusion 121
References 135

Summary

This dissertation consists of three articles striding topics from corporate governance to asset pricing. It seeks to understand the costs and benefits of better corporate governance, and how assets such as real estate are priced. My ultimate focus is on corporate governance on both sides of the equations – as causes and effects, which culminates in my third article investigating the causality of legal revisions on investors through independent directors. My apparent detour in the second piece results from that my finance background has lectured me on the importance of how asset prices are determined. Through this detour, I have recognized that I should rather combine the topics of intrigue into my topics of pursuit. Hence my blending of my learnings from the first two articles into my final piece of this dissertation.

Article 1, *Corporate Transparency and Bond Liquidity,* investigates how firm accounting transparency affects the liquidity of bonds issued by such firms. The dataset consists of firm- and bond- level data for US listed firms across multiple years. We find a positive relationship between firm transparency and bond liquidity, which becomes stronger in times of financial distress. Further, we find a negative relationship between firm transparency and liquidity risk. Economically speaking, bond liquidity is less (more) information-sensitive when the probability of default is lower (higher).

Article 2, *Pricing the Location of Commercial Properties*, proposes a pricing framework for cash flow datasets, using US commercial properties as a case. We adapt the net-present-value-approach of Korteweg and Nagel (2016) from a performance-evaluation context to a pricing context. As an example to test this proposed framework, We use the hedonic regression models of Clapp- Giaccotto (1998) to generate commercial real estate specific location risk factors. Our results show that a one-factor stock market model works rather well for commercial property pricing in comparison to multi-factor models including the factors of Fama and French (1996) and a physical-distance-based location risk factor.

Article 3, *Does Investor Protection Laws Benefit Investors? Evidence from a Natural Experiment on Cross-Listed Firms,* studies the causal effects of investor protection laws on investors from a governance and financial perspective. I exploit a natural experimental setting where firms cross-listed on both China's mainland and Hong Kong are subject to the legal revisions. First, I find that more independent directors turn over amongst the cross-listed firms. Second, my results show that the directors appointed to succeed the resigned directors tend to be younger and include more female. The above combined, I argue that my findings suggest that firms have taken the opportunity to appoint directors more befitting to the new environment, hence increased board turnover might be conducive to the firm in the long run. Third, I find no evidence of significant changes in board independence in the short run. Combined with increased director turnovers, my findings reconcile the arguments advanced by the finance and the strategy literature on the effects of strengthened institutions in that strengthened shareholder-friendly corporate governance at the firm level and symbolic adoption of certain governance practices could take place jointly.

Zusammenfassung
Diese Dissertation besteht aus drei Artikeln, die Themen von Corporate Governance bis Asset Pricing behandeln. Es versucht, die Kosten und Vorteile einer besseren Unternehmensführung zu verstehen und zu verstehen, wie Vermögenswerte wie Immobilien bewertet werden. Mein ultimativer Fokus liegt auf Corporate Governance auf beiden Seiten der Gleichungen – als Ursachen und Wirkungen, was in meinem dritten Artikel gipfelt, der die Kausalität von Gesetzesrevisionen bei Anlegern durch unabhängige Direktoren untersucht. Mein offensichtlicher Umweg im zweiten Stück resultiert daraus, dass mein Finanzhintergrund mich über die Bedeutung der Bestimmung von Vermögenspreisen unterrichtet hat.
Artikel 1, *Corporate Transparency and Bond Liquidity*, untersucht, wie sich die Transparenz der Rechnungslegung von Unternehmen auf die Liquidität von Anleihen dieser Unternehmen auswirkt. Der Datensatz besteht aus Daten auf Unternehmens- und Anleiheebene für börsennotierte US-Firmen über mehrere Jahre. Wir finden eine positive Beziehung zwischen Firmentransparenz und Anleiheliquidität, die in Zeiten finanzieller Notlagen stärker wird. Darüber hinaus finden wir einen negativen Zusammenhang zwischen der Firmentransparenz und dem Liquiditätsrisiko. Ökonomisch gesehen ist die Liquidität von Anleihen weniger (mehr) informationssensitiv, wenn die Ausfallwahrscheinlichkeit geringer (höher) ist.
Artikel 2, *Pricing the Location of Commercial Properties*, schlägt einen Preisrahmen für Cashflow-Datensätze vor, wobei als Beispiel US-amerikanische Gewerbeimmobilien verwendet werden. Wir adaptieren den Barwertansatz von Korteweg und Nagel (2016) von einem Leistungsbewertungskontext auf einen Preiskontext. Als Beispiel zum Testen dieses vorgeschlagenen Rahmens verwenden wir die hedonischen Regressionsmodelle von Clapp-Giaccotto (1998), um spezifische Standortrisikofaktoren für Gewerbeimmobilien zu generieren. Unsere Ergebnisse zeigen, dass ein Ein-Faktor-Aktienmarktmodell für die Preisgestaltung von Gewerbeimmobilien im Vergleich zu Multi-Faktor-Modellen, einschließlich der Faktoren von Fama und French (1996) und eines entfernungsbasierten Standortrisikofaktors, ziemlich gut funktioniert.
Artikel 3, *Does Investor Protection Laws Benefit Investors? Evidence from a Natural Experiment on Cross-Listed Firms*, untersucht die kausalen Auswirkungen von Anlegerschutzgesetzen auf Anleger aus Governance- und Finanzperspektive. Ich nutze ein natürliches experimentelles Umfeld, in dem Firmen, die sowohl auf dem chinesischen Festland als auch in Hongkong börsennotiert sind, rechtlichen Revisionen unterliegen. Erstens finde ich, dass mehr unabhängige Direktoren zwischen den börsennotierten Unternehmen wechseln. Zweitens zeigen meine Ergebnisse, dass die neue Direktoren tendenziell jünger sind und mehr Frauen haben. Zusammengenommen meine Erkenntnisse hindeuten, dass Unternehmen die Gelegenheit ergriffen haben, Direktoren zu ernennen, die dem neuen Umfeld angemessener sind, daher könnte eine höhere Vorstandsfluktuation für das Unternehmen langfristig förderlich sein. Drittens finde ich kurzfristig keine Hinweise auf signifikante Veränderungen in der Unabhängigkeit des Vorstands. Kombiniert mit erhöhten Vorstandsfluktuationen bringen meine Ergebnisse die Argumente der Finanz- und Strategieliteratur über die Auswirkungen gestärkter Institutionen in Einklang, indem eine verstärkte aktionärsfreundliche Unternehmensführung auf Firmenebene und die symbolische Übernahme bestimmter Führungspraktiken gemeinsam stattfinden könnten.

Corporate Transparency and Bond Liquidity

Falko Fecht* Roland Füss† Wei Lin‡ Philipp B. Rindler§

Abstract

This paper analyzes the impact that transparency of corporate accounting information has on the liquidity of a firm's traded bonds. We therefore indirectly provide an answer to the question what causes an asset to be illiquid. In particular, we focus on how this relationship depends on liquidity and the financial state of the firm. We use an extensive panel data set comprising 72,980 quarterly bond observations between 2004Q1 and 2016Q2. We find a statistically and economically significant impact of transparency on bond liquidity. This relationship becomes stronger during times of financial distress. More important, we show that the impact of transparency on liquidity is non-linear, or rather convex. Economically speaking, bond liquidity is less (more) information-sensitive when the probability of default is lower (higher). In addition, we find that the impact of transparency on liquidity is much larger than the influence of credit risk. Finally, we also find that information transparency has a strong effect on liquidity risk.

Keywords: *Corporate bonds*; *liquidity*; *transparency*; *information quality*; *financial crises.*
JEL Classification: $C23$, $G01$, $G12$, $G30$, $M41$

Acknowledgements: We thank Martin Brown, Karl Frauendorfer, Nils Friewald, Philipp Horsch, Gianluca Marcato, David Oesch, Markus Schmid, Paul Söderlind, and Xiaoxu Zhang, as well as the participants of the World Finance Conference 2014 and the research seminars of the EBS Business School, Nanyang Technological University, Singapore Management University, the Frankfurt School of Finance and Management, the NTNU Business School, and the DekaBank for useful comments and helpful suggestions.

*Frankfurt School of Finance and Management, Phone: +49 69 154008 441, E-mail:f.fecht@fs.de.

†Corresponding author: Swiss Institute of Banking and Finance (s/bf), University of St.Gallen, Unterer Graben 21, CH-9000 St. Gallen, Switzerland and Research Associate at the Centre for European Economic Research (ZEW), Phone: +41 (0)71 224 7055, Fax: +41 (0)71 224 7088, E-mail: roland.fuess@unisg.ch.

‡Swiss Institute of Banking and Finance (s/bf), University of St.Gallen, Unterer Graben 21, CH-9000 St. Gallen, Phone: +41 (0) 71 224 7027, E-mail: wei.lin@unisg.ch

§UBS AG, Bahnhofstrasse 45, CH-8001 Zürich, Switzerland, Phone: +41 (0)44 234 11 11, E-mail: philipp.rindler@gmail.com.

1 Introduction

Transparency is intuitively desirable and the right thing for a corporate to pursue. In practice the enforcement of transparency, however, requires compliance costs ranging from hundreds of thousands for the smaller public firms to millions for the larger corporates. We are thus interested in quantifying the benefits of corporate transparency as well as through which channels such benefits come forth. We argue that higher transparency is associated with higher level of bond liquidity, that in turn contributes to lower the firm's cost of capital. Several studies have examined how much of the cross-section of corporate bond spreads are attributable to credit and liquidity risk (see, e.g., Bao *et al.* (2011), Lin *et al.* (2011), and Dick-Nielsen *et al.* (2012)). Common to all these studies is the conclusion that liquidity has first-order effects on bond markets and that liquidity risk is a priced factor in bond returns (some studies suggest that liquidity risk is as important as credit risk). What these studies do not explain, however, is why a particular bond is traded more or less liquidly.

A large literature is concerned with explaining the level of liquidity of assets. At least since Bagehot (1971), it has been recognized that a primary cause of illiquidity in financial markets is the adverse selection which arises from the presence of privately informed traders. The theoretical implications of the adverse selection paradigm for financial market equilibrium have been analyzed extensively. Diamond and Verrecchia (1991) argue that to the extent that the release of accounting information can reduce information asymmetry in the market place such information can improve liquidity. A number of studies have therefore analyzed the level of liquidity around the release of accounting information (Lee *et al.* (1993); Kim and Verrecchia (1994); Affleck-Graves *et al.* (2002)) and the impact of private information (Vega (2006); Francis *et al.* (2007)). Several works also discuss the relation between disclosure policy and liquidity (Brown and Hillegeist (2007); Brown *et al.* (2004)). Because bonds are highly liquidity-sensitive, this relationship should be more pronounced for bonds than for stocks.

While private information in the stock market is predominantly inside information about a firm's cash flows, private information in the bond market mainly derives from heterogeneous interpretation of public information (Green (2004); Brandt and Kavajecz (2004)) or private observations of investors' order flows by dealers (Lyons (2001)). Though investors observe the same set of public information, they differ in their abilities to analyze the information. For example, a large investment bank may have more skilled analysts or use more sophisticated models to analyze public information than a pension fund. This heterogeneity can create information disparity among traders similar to the effect of private information in the traditional sense. Pasquariello and Vega (2007) examine the role of private and public information in the process of price formation in the U.S. Treasury market and find that daily bond price dynamics are related to fundamentals and agents' beliefs. These studies highlight the importance of asymmet-

ric information in bond markets. Because bond liquidity is very sensitive towards accounting information and reduced bond liquidity increases the firm's cost of debt, it is worthwhile to study how accounting transparency affects bond liquidity.

As for the link between liquidity and returns, bond returns are more sensitive to liquidity risk than stock returns. Brennan and Subrahmanyam (1996) report that on average, stocks with high levels of liquidity have a 9.12 percent higher annual return than stocks with low levels of liquidity. The average return in their sample is 12 percent annually.[1] For liquidity risk in the stock market, Pástor and Stambaugh (2003) study the period from 1966 to 1999 using annualized risk-adjusted average return and find that the correlation between firm-level stock returns and market-wide liquidity is a priced risk factor in stock returns. They find that stocks with high sensitivities to liquidity earn a 7.5 percent excess return compared to those with low sensitivities, while the average annual return of the value-weighted CRSP index was 22.2 percent in this period. The bond market exhibits a similar liquidity premium, though the market-wide returns are significantly different. Using the same method as Pástor and Stambaugh (2003), Lin *et al.* (2011) study the period from 1994 to 2009, reporting also the annualized risk-adjusted average return. They find that bonds with high sensitivities to aggregate liquidity earn an excess return of about 4 percent. However, the annual average return on bonds is only 1.93 percent in contrast to CRSP's 22.2. This stark contrast shows that liquidity risk might play a much larger role in bond returns than in stock returns.

The relationship between accounting transparency and bond liquidity is state-dependent, and thus, non-linear—a feature which is much more common to bonds than to stocks. It is this inherent non-linearity that makes the analysis of the transparency-liquidity relationship in the bond market highly important. Dang *et al.* (2012) show that debt minimizes the incentives to produce private information and that it is less information acquisition sensitive in phases when the bond's payoff is known. For instance, a fully collateralized triple-A-rated corporate bond, which is very unlikely to default, is generally less costly to issue and less information-sensitive. This hypothesis on information acquisition insensitivity also holds for bonds that are close to default or whose issuing firms are very likely to bankrupt. In contrast, for bonds with an increasing probability of default or for bonds whose credit ratings take a turn for the worse, precise information becomes more important. That is, if default is possible but the probability of default is still low, for instance when firms are in financial distress or in case of a common shock such as the financial crisis, bond liquidity becomes more accounting information-sensitive.

Prior research on bond liquidity has focused on the impact of bond characteristics (bond age, maturity, issue size, coupon) on its liquidity and the impact of liquidity risk on credit

[1]These estimates are based on Table 3 in Brennan and Subrahmanyam (1996) from which we calculate the return premium in their sample as the difference between the high liquidity portfolios (λ group 5) and the low liquidity portfolios (λ group 1). The average return is the average of all portfolios.

spreads. We complement these studies by investigating the cross-sectional differences in liquidity and liquidity risk. In our panel regression with firm- and time-fixed effects, we proxy bond liquidity as dependent variable by Amihud (2002) illiquidity measure, Roll (1984) bid-ask spread, and Feldhütter (2012) imputed roundtrip costs. Our main (lagged) independent variables are the proxies for company level transparency which are accruals quality, earnings precision, and the degree of consensus among analysts concerning future earnings. We also add control variables to account for bond characteristics which are closely related to liquidity and credit risk.

We document 3 important relationships in our analysis. First, we find that firms with greater transparency have bonds that trade at significantly higher levels of liquidity. Hence, to the extent that liquidity affects the cost of capital, transparent accounting information decreases the cost of debt. Second, we document that transparency has a strong impact on liquidity risk of bonds. As liquidity risk is a large component of bond spreads, accounting transparency has a direct impact on the riskiness of bonds. Third and most important, we show that the relationship between accounting transparency and bond liquidity is non-linear. This is especially true for firms which are in financial distress, either measured by credit rating or the probability of default. As long as bonds are very unlikely to default, they are an information-insensitive asset. However, as market (such as a financial crisis) or firm conditions (such as the probability of default) deteriorate, bonds become increasingly information sensitive. In particular, when we group our cross-section of U.S. corporate bonds with respect to rating categories or default risk, respectively, we find a S-shaped or at least a convex curve: for low and high rating categories bond liquidity is less accounting information-sensitive. Similarly, in situations where the likelihood of default is very low, bond liquidity becomes very information-insensitive. Our analysis confirms the theory by Dang *et al.* (2012) that the information acquisition sensitivity of debt is state-dependent.

This paper contributes to the literature about the effects of asymmetric information on financial markets, in particular, the effects of disclosure quality on market liquidity and the effects of accounting transparency on cost of capital, as surveyed in Healy and Palepu (2001) and Leuz and Wysocki (2016). Diamond and Verrecchia (1991) and Kim and Verrecchia (1994) argue that for firms with transparent accounting information, investors can be relatively more confident that stock transactions occur at fair prices, which increases the liquidity of the stocks. This argument has also been substantiated empirically (Welker (1995) and Leuz and Verrecchia (2016)). We extend the existing literature by showing that this argument extends to bond markets. Our results show a large increase of bond liquidity for more transparent firms, indicating that transparency could reduce information asymmetry in bond markets and that a policy of higher quality disclosures might improve the liquidity of a firm's bonds.

The remainder of this paper is organized as follows. Section 2 discusses the literature

that motivates this paper. Section 3 develops the testable hypotheses. Section 4 describes the data. Section 5 introduces the statistical methodology and then discusses the empirical results. Section 6 further tests our results for robustness against a variety of models and parameter specifications. Section 7 concludes.

2 Literature Review

Our primary interest is in the relationships between firm-level transparency and the level as well as the variability of bond liquidity.[2] To our knowledge, this is the first study that analyzes such relations in the bond market. Recent research in financial economics has focused strongly on the impact of both firm-level and systematic liquidity on asset prices. The literature has made it abundantly clear that liquidity has first-order effects and cannot be ignored. In light of these studies, it seems desirable to understand why particular assets are traded more or less liquidly and to quantify the effects. We review in this section a number of theories that have been proposed to explain why information transparency should affect liquidity on asset markets. We first introduce studies that investigate the sources of liquidity and then discuss the literature that links transparency and liquidity. We also present empirical results of similar studies that are focused on the stock market.

In terms of the sources, liquidity is affected by disclosure quality because information asymmetry among investors induces adverse selection (Verrecchia (2001)). Theories of disclosure quality typically focus on the effects of such quality on the following aspects: stock market liquidity, cost of capital, and firm valuation. There is a two-step pass-through mechanism we consider that information asymmetry could affect cost of capital by first affecting liquidity: it influences less informed investors to decrease liquidity and subsequently raises the cost of capital. First, less informed investors have to be concerned about trading with better informed investors who might have access to private information. Consequently, less informed investors require a price discount (premium) for buying (selling) the stock to protect themselves against losses from trading with better informed counterparties. This increases the bid-ask spreads in the stock market. At the same time, adverse selection reduces the number of shares that less informed investors are interested in trading. Therefore, both effects of asymmetric information on less informed investors decrease the liquidity of the stock market. Second, bid-ask spreads and illiquidity can raise the cost of capital as investors require higher rates of return and

[2]In this paper, we address the relationship of transparency and liquidity. We do not investigate how transparency of accounting information influences credit spreads. Consistent with the incomplete accounting information model of Duffie and Lando (2001), Yu (2005) finds that firms with higher disclosure rankings tend to have lower credit spreads. This transparency spread is especially large for short-term bonds.

hence impact firm valuation. Since bid-ask spreads and illiquidity impose additional trading costs on investors, they need to be compensated in equilibrium by higher rates of return on these securities (Constantinides (1986); Amihud and Mendelson (1986)). In addition, adverse selection can potentially distort investors' trading decisions, thereby leading to inefficient asset allocations (Gârleanu and Pedersen (2004)). This also leads to higher required rates of return in equilibrium.

An early view on illiquidity in asset markets is Bagehot (1971) who argues that its cause is the adverse selection that arises from the presence of privately informed traders. The theoretical implications of adverse selection on equilibrium in asset markets have been extensively analyzed. There seems to be consensus both in the theoretical and empirical market microstructure literature that greater information asymmetry reduces stock liquidity (Brennan and Subrahmanyam (1995); Verrecchia (2001)). Easley *et al.* (2002) find that the probability of information-based trades carries a positive premium in asset prices. This point of view is also emphasized in the review by Amihud *et al.* (2005). In summary, to the extent that corporate information transparency can reduce adverse selection, it should increase liquidity.

Another source of illiquidity, emphasized in the search frictions model of Duffie *et al.* (2005), is the difficulty of locating a counterparty who is willing to trade a particular security or a large quantity of a security. Once a counterparty is identified, agents must negotiate the price in a less than perfectly competitive environment since alternative trading partners are not immediately available. In her searching process, the trader incurs additional financing costs or opportunity costs when his trade is delayed. Moreover, he may be subject to price concessions in the negotiation with the counterparty that he eventually finds. Alternatively, he may trade quickly with a dealer and bear illiquidity cost. In general, a trader faces a tradeoff between search and quick trading at a discount. The implications for asset pricing of search frictions are discussed in Duffie *et al.* (2007). Search frictions are particularly relevant in over-the-counter (OTC) markets that have no central marketplaces.

In terms of research that link accounting information transparency and stock liquidity, we have identified 3 strands of literature. First, the literature on transparency and the level of liquidity, surveyed in Amihud *et al.* (2005) and Lang and Maffett (2011), investigates the role of transparency in mitigating information asymmetry. Second is the theoretical research investigating liquidity variability and covariability by Brunnermeier and Pedersen (2009) and Vayanos (2004). They propose mechanisms that cause liquidity to fluctuate, evaporate suddenly, and covary with market-wide returns and market-wide liquidity. Third, Acharya and Pedersen (2005) provide theoretical and empirical evidence that the covariances of firm-level liquidity with market liquidity and market returns are systematic risk factors that are components of cost of capital. Diamond and Verrecchia (1991) and Kim and Verrecchia (1994) argue that voluntary

disclosure reduces information asymmetries between less informed and better informed investors. As a result, for firms with high levels of disclosure, investors can be relatively confident that any stock transaction occurs at a fair price, thereby increasing the liquidity of the firm's stock. In addition, these studies argue that expanded disclosure and stock liquidity are associated with increased institutional ownership.

In terms of empirical research, transparency can potentially affect liquidity variability. Lang and Maffett (2011) document that this is because transparency reduces uncertainty about the intrinsic value of the firm. The mechanism of how transparency influences liquidity variability is as follows. Transparency reduces uncertainty about the intrinsic value of the firm, to the extent that transparency provides information. Such reduction in uncertainty might potentially reduce the sensitivity of liquidity to market shocks. These effects of transparency on liquidity are more pronounced during crisis periods. During market downturns, liquidity tends to be particularly fragile because capital becomes scarce and overall uncertainty is high. Consequently, opaque assets will be particularly sensitive to exogenous shocks on liquidity in such market environment. Models employed by Brunnermeier and Pedersen (2009) and Vayanos (2004) show that liquidity can dry up in case of a "flight to quality" when uncertainty about the fundamental value of assets fluctuates. In such a situation liquidity providers move away from assets whose fundamental values embed higher uncertainty. Liquidity providers are found to be more risk averse in the face of increased uncertainty about fundamental values, according to Vayanos (2004). Therefore, increased information transparency has the potential to reduce liquidity providers' tendency to withdraw liquidity, to the extent that such transparency reduces uncertainty.

More recent evidence has also been supportive of that transparency can improve liquidity and mitigate liquidity risk. Lang *et al.* (2012) document that greater firm-level transparency lowers transaction costs and increases liquidity on equity markets. Lang and Maffett (2011) show that transparency reduces firm-level liquidity uncertainty, while Ng (2011) shows that increased information quality can reduce a firm's exposure to systematic liquidity risk. Ng (2011) provides evidence that measures of accounting information transparency are related to stock liquidity risk. Lang and Maffett (2011) document that the effects of firm-level liquidity variability and covariability on firm value are separable and incremental. Healy *et al.* (1999) find that firms with expanded disclosures experience significant contemporaneous increases in stock prices that are unrelated to current earnings performance. Gelb and Zarowin (2002) find that the stock prices of firms with higher disclosure ratings are more informative about future earnings compared to those of firms with lower disclosure ratings. These findings suggest that a firm's disclosure strategy affects the speed that information is incorporated into stock prices. In an attempt to measure stock liquidity and to examine its relation to firm disclosure proxies, Welker (1995) finds a significant negative relationship between analyst ratings of firms'

disclosures and bid–ask spreads. To summarize, many studies have examined the transparency-liquidity relationship with a heavy focus on the stock market. However, to our best knowledge, none of the current literature explicitly addresses whether, when, and to what extent firm-level transparency affects the level of bond liquidity and mitigates its variability.

3 Hypotheses Development

In this section, we formulate the hypotheses to be tested based on the questions that we investigate. These all focus on the effects that transparency of accounting information has on the liquidity of corporate bonds.

Dang *et al.* (2012) note that a debt security's information intensity varies with news about the quality of the security or its issuer: As long as there is no doubt about the solvency of the issuer, ex ante information has little value or impact on trades. However, when doubts arise about the solvency of the issuer, information acquisition becomes profitable for potential investors. This leads to adverse selection that dries up liquidity. In a similar manner, models with search frictions in OTC markets (for example, Duffie *et al.* (2007)) argue that the causes of illiquidity are information asymmetry and transaction costs that are due to search frictions. To the extent that accounting information transparency can reduce information asymmetry, we expect a positive relationship between measures of transparency and measures of liquidity.

Hypothesis 1 (H1): *Higher transparency of accounting information is associated with higher levels of bond liquidity.*

Dang *et al.* (2012) argue that the impact of information on bond markets is inherently asymmetric: Good news about the issuer has little effect while bad news about fundamentals of a firm can decrease the market value of its bonds. This mechanism of bonds being information-sensitive under certain circumstances can incentivize agents to learn about tail risk. More precisely, the above hypothesis states that bonds are less information acquisition sensitive in phases when their payoffs are known, that is, when their defaults are either very likely or very unlikely. In contrast, with increasing probability of default or deteriorating credit ratings, precise information becomes more important. Hence, if default is possible but default risk is low, bond liquidity becomes more information sensitive. This phenomenon intensifies when either the bond is opaque or the entire market is in distress, reflecting the non-linear relationship between transparency and bond liquidity.

Hypothesis 2 (H2): *The effect of transparency on bond liquidity is non-linear and becomes more pronounced in periods of financial distress.*

Several studies show that the liquidity of bond markets is strongly affected by flight-to-quality. Acharya *et al.* (2013) argue that, during the recent financial crisis, the price reduction due to decreases in liquidity is lower for investment grade bonds. Chen *et al.* (2007) and Friewald *et al.* (2012) provide similar empirical evidence for flight-to-quality in the bond markets. In addition, Brunnermeier and Pedersen (2009) argue that funding for liquidity providers tends to dry up during market downturns because uncertainty is higher and funding becomes scarcer. Opaque firms are more likely to be affected because greater uncertainty about intrinsic value means that it is more difficult and expensive for investors to borrow against the securities of such firms. Furthermore, the model in Dang *et al.* (2012) implies that during times of financial distress bonds, that are generally insensitive to information acquisition, suddenly become information sensitive.

Brunnermeier and Pedersen (2009) and Vayanos (2004) suggest that liquidity can be fragile in assets with high uncertainty about fundamental value. Such fragility comes in the sense that liquidity can spiral downwards unexpectedly and thus cause trades to be prohibitively expensive. To the extent that transparency reduces uncertainty about fundamental value, liquidity would tend to become more predictable and less sensitive to factors such as economy-wide uncertainty, funding availability, and risk aversion. Hence, we expect that a negative relationship between transparency and the variability of liquidity.

Hypothesis 3 (H3): *Higher transparency of accounting information is associated with lower variability of bond liquidity.*

4 Data Description

Our sample consists of quarterly observations from Q1 2004 until Q2 2016. We obtain bond trading data from the Enhanced TRACE (ETRACE) database which has been disseminating all secondary over-the-counter corporate bond transactions of the members of the Financial Industry Regulatory Authority since July 2002. We filter the raw ETRACE data as described in Dick-Nielsen (2014) to eliminate potentially erroneous data entries. We also apply the median filter and reversal filter from Edwards *et al.* (2007). Finally, we exclude all retail-sized trades (i.e., trades below USD 100,000 in value). We obtain bond information from the FISD database. We only consider senior and super-senior bonds with a rating of at least CC.

We obtain quarterly accounting data from Compustat, daily equity data from CRSP, and monthly EPS forecasts from the IBES database. We exclude all financial firms and firms with

a rating of C or D. To ensure that sufficient observations per bond are available, we remove all bond issues with less than 8 quarters of data. After matching the data of all databases[3] and removing entries with missing values, we are left with an unbalanced panel dataset that comprises 743 companies with a total of 3,997 bond issues. Our final data set consists of 72,980 quarter-bond observations. On average, we have 1,460 observations per quarter with a standard deviation of 580.

In the remainder of this section, we present the models and describe the empirical methodologies that underlie our measures of bond liquidity and firm-level transparency. First, we describe the measures of liquidity and liquidity risk. Then we explain our methodology to measure the transparency of accounting information utilizing public sources. Finally, we present the controls that we use to take into account bond characteristics as well as credit and equity risk.

4.1 Measures of Bond Liquidity

Liquidity and transaction costs are related but separate concepts (Amihud and Mendelson (2008)). Both the direct transaction costs of trading in a firm's securities and the ability to form and liquidate a substantial position in a timely manner are potentially important determinants of the price that an investor is willing to pay for a security. As there is no consensus in the literature on how to measure the liquidity of an asset, we consider three measures of bond liquidity. For convenience of interpretation, we define each measure by multiplying the standard measure by -1 so that a higher value implies a higher level of liquidity.[4]

The first measure we use is a slightly modified version of the Amihud (2002) measure, which indicates the price impact of a trade per unit traded. Price impact is a major consideration of investors who contemplate investments in bonds because it reduces the potential return by increasing roundtrip transaction costs. In particular, corporate bond markets are characterized by less frequent trading and larger volumes per trade compared to stock markets, and hence such costs are generally sizable. Moreover, this measure is consistent with the theoretical research that defines market liquidity as price deviations from fundamental values due to buying and

[3]We use the CRSP/Compustat merged database to match gvkeys and permnos. We match the IBES data based on the 9-digit CUSIP. We match enhanced TRACE and FISD data based on the 9-digit CUSIP of the bond issues. Finally, we merge the firm- and bond-level identifiers using the 6-digit company CUSIP and the exchange ticker. We only use the data if both identifiers match.

[4]Appendix A of the Internet Appendix describes in detail our liquidity measures and their implementation. Goyenko *et al.* (2009) show that the measures used by Amihud (2002) and Roll (1984) are good proxies for price impact and effective spread, respectively. While the Roll measure shows a high and consistent correlation with other effective and realized spread measures, the Amihud measure performs consistently well over sub-sample periods. Furthermore, they show that all liquidity measures based on low frequency (monthly or annually) capture adequately high frequency measures of transactions costs.

selling pressure (Grossman and Merton (1988) and Brunnermeier and Pedersen (2009)). We note the limitation with this measure is that while stocks are generally traded daily, corporate bonds are typically not traded that often and hence we adopt quarterly averages rather than run our analyses using shorter intervals.

The other two measures that we use are both proxies for the bid–ask spread of a bond. The first is the Roll (1984) measure that is motivated by the observation that the bid–ask spread can be extracted from the covariance between consecutive returns. This measure gauges trading costs in an efficient market, which we assume implicitly that the bond markets would follow to a large extent given the intensity of information flows among traders and issuers. The second measure is the imputed roundtrip costs (IRC) of Feldhütter (2012). The IRC is based on what he denotes imputed roundtrip trades (IRT), that is, two trades close in time that are likely to be both a buy and a sell executed by the same dealer. Further, the IRC is shown to be able to identify liquidity crises in OTC trading with search frictions, which is characteristic of corporate bond markets.

We obtain a daily value for each liquidity measure. We then use the median value of each measure in a given quarter as the quarterly estimate. To measure (total) liquidity risk, we use the standard deviation of the daily values of the three liquidity measures in a given quarter. By doing so, we do not differentiate between systematic and idiosyncratic risk. However, since we are not examining the pricing of bonds, this issue should not pose a problem.

4.2 Measures of Transparency

Because information transparency is inherently difficult to measure and has many potential facets, we consider three such measures.[5] We define each measure in a way that a higher value implies that the company's accounting information is more transparent.

For our first transparency measure of accruals quality (AQ), that is, the extent to which the management of a company engages in accruals management, we rely on extensions of the classic Jones (1991) specification. As suggested by Dechow and Dichev (2002) and Francis *et al.* (2005), earnings with an accrual component that map with less variability into the cash flow component may be considered more informative. We use the regression model by Francis *et al.* (2005) to regress out fundamental determinants of accruals. Then we obtain AQ as the opposite of the standard deviation of the regression residuals.

Our second transparency measure is earnings precision (EP), measured as the volatility in

[5]Appendix B of the Internet Appendix describes in detail our transparency measures and their implementation. In a previous version of this paper, we also test discretionary earnings smoothing and fundamental earnings smoothing measures that are commonly used in international studies. The unreported results for these two transparency measures are qualitatively the same.

reported earnings. Disclosure theories generally predict that uncertainty about firm value and adverse selection among investors are higher when information precision is lower (Verrecchia (2001)). Our use of earnings as a source of information for investors follows Ng (2011). Less volatile earnings are presumably more precise and are expected to be of higher quality on average. Consistent with this argument, Dichev and Tang (2009) show that more precise earnings are associated with higher earnings predictability after controlling for a variety of economic characteristics.

Our third transparency measure is the *Precision* of agreement among analysts in terms of their forecasts similar to Zhang (2006). Several studies suggest that analysts gather and aggregate information from public and private sources to assess firm value, improving overall transparency of the firm (Brennan and Subrahmanyam (1995); Lang and Lundholm (1996); Lang *et al.* (2012)). Furthermore, investors are more likely to regard forecasts as having greater precision if there is greater consensus among analysts (Lang and Lundholm (1996); Barron *et al.* (1998); Diether *et al.* (2002); Zhang (2006)). We measure the *Precision* as the inter-analyst standard deviation of the one-quarter-ahead EPS deflated by the stock price at the time when the standard deviation is computed. We require that at least three analysts cover the firm.[6]

4.3 Control Variables

To control for bond characteristics, we rely on the many prior studies that have examined determinants of bond liquidity, among them are Garbade and Silber (1979), Sarig and Warga (1989), Chakravarty and Sarkar (1999), Stoll (2000), Schultz (2001), Brandt and Kavajecz (2004), Houweling *et al.* (2005), and Longstaff *et al.* (2005). These studies suggest that the level of bond liquidity is dependent on the age, maturity, issue size, and the coupon rate of a bond. In terms of bond age, bond markets are generally characterized by an on-the-run effect, that is, younger bonds tend to be traded more liquidly than more mature bonds. As for bond maturity, long-maturity bonds tend to be less liquid than bonds with short maturities. In addition, larger issue sizes and higher coupon rates are generally associated with higher liquidity. We control for all the above 4 characteristics as they are mostly related to clientele effects (see Amihud and Mendelson (1986)).

To control for credit risk, we follow Blume *et al.* (1998) and add the ratio of operating income to sales (IS), long-term debt to assets (DA), the book-to-market (BM) ratio, and interest

[6]Francis (2004) and Fan and Wong (2005) suggest that the informativeness of accounting data is likely to be higher if such data are audited by an affiliate of a global accounting firm. We therefore tried to include an indicator variable if a firm's auditor is affiliated with a Big-4 audit firm. However, for our matched sample, we found that more than 99% of our companies were audited by a Big-4 firm.

coverage (IC) to the regressions. We also include the ratio of net income to total assets (NIA). Additionally, we obtain bond ratings from Standard and Poor's. If this rating is missing, we use the rating from Moody's and if this is missing, the rating from Fitch. If we still do not have a rating we use the company rating. Prior studies indicate that equity risk impact credit risk and liquidity (Bao *et al.* (2011); Lin *et al.* (2011); Dick-Nielsen *et al.* (2012)). Following the logic of structural models of credit risk, and assuming that higher equity volatility implies higher asset volatility, the likelihood of default increases as equity becomes riskier. We therefore include equity risk ($Vola$), measured as the volatility of daily stock returns in a given quarter.

4.4 Summary Statistics

This section provides summary statistics for our matched sample of the US corporate bond market. Table 1 reports the cross-sectional variation of the variables used in our study. All liquidity and transparency measures are defined so that larger values represent higher levels of liquidity and transparency, respectively.[7] All continuous variables are winsorized at the 0.5% and 99.5% level. The data set spans the period from Q1-2004 to Q2-2016 for a total of 72,980 observations. Overall, the sample contains 743 companies with 3,997 bonds.

Panel A of Table 1 shows considerable variation in our liquidity measures. The mean *Amihud* liquidity measure is 0.34 bps per USD 1 million implying that a USD 1 million trade moves prices of a bond by 0.0034 percent on average. The measure shows a very large cross-sectional variation with 5th percentile at 0.01 and the 95th percentile at 1.29 and a median value of 0.14. The *Roll* measure estimates the average bid-ask spread as 1.04% of the bond price, with values of 0.19%, 0.83%, and 2.61% at the 5th, 50th and 95 percentile, respectively. The *IRC* measure estimates the average round trip cost in percentage of the price at 0.35%. At the 5th percentile this value drops to almost 0%, whereas its 95th percentile value is 1.25% with a median value of 0.18%. These numbers show that there are significant trading costs in the bond market.

Panel C of Table 1 demonstates that the corporate transparency measures exhibit a similar strong variation. AQ and EP are, by construction, relative valuations of the company's transparency. Their numerical values are therefore difficult to interpret. However, the *Precision* measure shows that analysts agree frequently on the predicted earnings of a company. The 5th percentile value is only 0.02% with a median value of 0.09%. This means that the standard deviation of the earnings per share forecasts one quarter ahead is only 0.09% of the current

[7] We choose to rescale some of the liquidity and transparency variables, relative to their standard definition in other papers, so that their magnitudes are similar. We do this to avoid having to report very small or large coefficients later on. No method that we employ is dependent on the absolute scale of a variable so this choice does not affect results.

stock price at the median. The average value of *Precision* is 0.23% with a standard deviation of 0.53% and a 95th percentile value of 0.86%. The distribution is therefore highly skewed with large disagreement for some companies.

[Table 1 about here]

Panel D of Table 1 presents the characteristics of our bonds that show reasonable variation. The average bond in our sample is 3.97 years old with a range from 0.34 (5th percentile) to 9.95 years (95th percentile). The average maturity is 10.22 years with a range from 1.09 to 28.50 years. The issue amount varies from USD 196 million to USD 1.50 billion with an average of USD 526 million. Our bond statistics are similar to other studies that have worked with the TRACE bond data (see, for example, Friewald *et al.* (2012)).

Panel E of Table 1 contains the credit risk control variables. They show wide dispersion reflecting the fact that our sample contains all ratings from AAA to CC. We excluded the ratings C and D from the data. The most frequent rating is BBB, followed by A, and then BB. In total, 56,875 (77.9%) observations are from investment grade bonds (rating BBB or better) and 16,105 (22.1%) are from speculative grade bonds.

Table 2 presents the correlations between the various measures of transparency and liquidity that we employ. For the transparency measures (Panel A) we find moderate to strong correlations with values from 0.188 to 0.556. For the liquidity and liquidity risk measures (Panels B and C), all correlations are high with values between 0.397 and 0.628. The magnitude of the correlations of the transparency measures suggests that multicollinearity might be an issue if they were used simultaneously as regressors. The high bivariate correlations suggest that the different measures share commonality, motivating us to conduct the robust principal component analysis (PCA) in Table C1.

[Table 2 about here]

We conduct the robust PCA on all three sets of variables to see if the relevant information can be condensed.[8] The first principle component (PC) for each set of variables is able to account for a large portion of the common variation. The first PC accounts for 60%, 73%, and 67% of the common variation for the measures of transparency, liquidity, and liquidity risk, respectively. For each set of variables, the loadings on the first PC are all positive. This facilitates the interpretation of each first PC as a parsimonious measure of transparency, liquidity, and liquidity

[8]Because transparency and liquidity variables are highly skewed (see Panel F of Table 1), we take the logarithms of these variables rather than levels to guarantee a more symmetric distribution. We then estimate a robust PCA proposed by Hubert *et al.* (2005).

risk, respectively. Hence, we define each first PC as an aggregate measure called *Trans*, *Liq*, and *Liq Risk*, respectively.[9]

[Table C1 about here]

Since transparency is inherently difficult to measure, there is concern that whether our *Trans* measure is related to the informativeness of the accounting statements of a company. To address this concern, we compare our measure to two other measures that are frequently used: the number of analysts following a company and the probability of informed trades (PIN).

To the extent that analysts serve as information intermediaries, their presence should increase transparency. We find that our *Trans* variable has a positive, but small, correlation with the number of analysts covering the companies in our sample. The estimated (Spearman) correlation is 0.064 with a standard error of 0.0037 for the entire sample of firm-quarter observations. Similarly, we find that the (Spearman) correlation between the average transparency of a firm and the average number of analysts covering the company is 0.088 with a standard error of 0.037. These results indicate that higher numbers of analyst coverage is, at best, weakly associated with higher transparency. Moreover, Derrien and Kecskés (2013) find that analyst coverage is endogenous. The loss of analyst average decreases total investments and leads to financing that is less sensitive to information asymmetry. That is, companies keep the use of short-term debt unchanged but replace their long-term debt by increasing cash holdings.[10]

A very common measure of information asymmetry in equity markets is the PIN, originally developed by Easley and O'Hara (1987, 1992). We use the PIN data provided by Brown and Hillegeist (2007) who extend the original empirical estimation method by Easley *et al.* (1996).[11] This data extends until Q4 of 2012. We find, as expected, a small and negative correlation between *Trans* and the PIN measure of the stock of the company. The overall estimated (Spearman) correlation is -0.062 with a standard error of 0.0050. Therefore, given the weak linkage of both the analyst coverage and the PIN measures to our *Trans* measure, we do not employ these two measures.

[9]The descriptive statistics of these aggregated (standardized) measures are shown in Panel F of Table 1.

[10]See also Table B1 in the Internet Appendix for the correlation structure among different transparency measures.

[11]The data is downloaded from: http://www.rhsmith.umd.edu/faculty/sbrown/pinsdata.html. We match the quarterly data to our data set using the permno identifier from CRSP. Overall, we are able to match 11,385 firm-quarter observations from 425 companies.

5 Empirical Results

5.1 Panel Data Regression

Our data set consists of the quarterly time series data for each bond. The dependent variables to be explained are the different measures of bond liquidity. Our main independent variables are the proxies for company level transparency. We add controls for bond characteristics which are known to affect liquidity and credit risk to the regressions.[12] One might argue that instead of increased transparency would result in increased bond liquidity, the causal relationship could be the other way around. For instance, firms with more liquid bonds could afford lower cost of debt and hence have more resources available, which they can direct to improve accounting quality. Hence to account for potential reverse causality problems and ensure that the information of the accounting information is contained in the bond trades, all independent variables are lagged by one quarter. To control for firm-level unobserved heterogeneity and time variation, we perform panel regressions with firm- and time-fixed effects as we are mainly interested in explaining cross-sectional differences in bond liquidity and liquidity risk.[13] The model we investigate is therefore given by

$$\begin{aligned} \text{Liquidity}_{i,t} = \mathbf{a} \cdot \text{Transparency}_{i,t-1} + \mathbf{b} \cdot \text{Bond Controls}_{i,t-1} \\ + \mathbf{c} \cdot \text{Credit Controls}_{i,t-1} + \alpha_i + \lambda_t + \epsilon_{i,t}. \end{aligned} \tag{1}$$

As we are using a panel of data with possible multiple bonds per firm we use two-way clustered standard errors, at the bond level and the time dimension (Petersen (2009)).

[12] Note that we cannot use age and maturity at the same time since they are linearly related over time for each bond. As it is common in the bond liquidity literature, we retain bond age in our regressions. However, we find similar (highly significant) results when we replace age by maturity, i.e. long-maturity bonds tend to be less liquid.

[13] In a previous version of the paper, we estimate coefficients based on within estimator, that is equivalent to having bond-fixed effects, in order to account for variation in bond liquidity that is unrelated to our proxies and to control for the omitted variable bias. As can be seen from Table 3, the results are qualitatively and quantitatively the same indicating that there is no severe omitted variable bias problem. In addition, since we employ firm-level transparency measure to explain bond-level liquidity, using the bond- instead of firm-fixed effects in the regression would kill off too much variation on the right-hand-side.

5.2 Relationship between Bond Liquidity and Firm-level Transparency

In this section, we examine whether firm-level transparency influences the level of a bond's liquidity. As argued in Section 3, we expect to find significantly higher levels of liquidity for bonds whose issuing firm has more transparent accounting information.

To get an initial picture of the overall relationship between the two sets of variables we perform a Canonical Correlation Analysis (CCA). The results are presented in Table D2. Details about the structure of the canonical variates are presented in Table D1 in the Internet Appendix. The first canonical correlation is 0.261 with a canonical R^2 of 0.068. Wilk's lambda strongly rejects the hypothesis that there is no correlation between the two sets of variables. In terms of absolute magnitude, the canonical correlation is of moderate size. The weights and loadings of the first canonical function are all positive, as expected. These results imply that there is a measurable and positive relationship between corporate transparency and bond-level liquidity.

The relationship between the measure of transparency ($Trans$) and liquidity (Liq) is illustrated in Figure 1. The graphs show scatterplots between the two variables with a regression line (red) and a LOESS fit (blue) superimposed. In Figures 1(a) and 1(b), we compare the average measured transparency to the average measured liquidity per bond and firm, respectively. The positive association between the two variables is clear, although there is much variation in bond liquidity that is not captured by transparency. In order to eliminate the influence of the time variation of both measures and focus on cross-sectional differences, we also report the relationship between average transparency and average liquidity after subtracting the respective quarter average from each measure before taking the averages. Figures 1(c) and 1(d) again show the relationship per bond and firm, respectively. Again, we find strong support for the hypothesis that higher levels of accounting transparency are associated with higher levels of bond liquidity.

[Figure 1 about here]

To test our first hypothesis, we run the pooled regression in Equation (1) for each of the three liquidity proxies as well as the aggregate liquidity measure.[14] The results of the regressions are presented in Table 3. Column (1) reports the results of the regression including only

[14]To conserve space, we only report the results for the PC1 liquidity and the PC1 transparency measure here. The results for each liquidity and transparency proxy are discussed in the Robustness Test Section 6 and can be found in Table 7. The disaggregated results are qualitatively the same as for the aggregate measures, although the coefficients are not always statistically significant for all transparency measures simultaneously. This could be a result of multicollinearity, especially between AQ and EP.

transparency as explanatory variable together with time and industry dummies. As expected, we find a positive and statistically highly significant relationship between accounting transparency and bond level liquidity. Economically, a one standard deviation increase of *Trans* increases *Liq* by 0.066 or 0.046 standard deviations.

As described in Section 2, many prior studies have documented a robust relationship between certain bond characteristics and the credit risk of a bond and its liquidity. Column (2) reports the regression results with controls for bond characteristics and Column (3) additionally includes controls for credit risk. As expected, a bond's age is strongly negatively related to its liquidity while the issue size has a positive effect. We find that several proxies for credit risk are insignificant but the signs of the coefficients are generally what would be expected in that higher credit risk is related with lower liquidity. As expected, interest coverage (IC), income to sales (IS), and net income to assets (NIA) are positively related to liquidity whereas debt to assets (DA) and equity volatility ($Vola$) are negatively related. Similarly, book to market value (BM) has a negative coefficient, but it is statistically not distinguishable from zero. Including the controls reduces the estimated impact of transparency on liquidity. In the specification (6) with controls both for bond characteristics and credit risk, a one standard deviation increase of transparency increases liquidity by 0.133, or 0.09 standard deviations. This effect is equivalent that 2 fewer years of bond age have on liquidity and about half the size of the impact that a change of each of the credit risk proxies in the direction of more credit risk by one standard deviation has on liquidity.

We also run two-way fixed effects model (columns (4) to (6)) to test whether our results are affected by a severe omitted variable bias. We use firm-fixed models since we are interested in how a change in companies' transparency affects a change in liquidity.[15] In addition, firm-fixed effects allow us to retain the independent variables which do not change over time (coupon and offering amount). Similar to the pooled regression, we use two-way clustered standard errors, at the bond-level and the time-dimension, because there are multiple bonds per firm. Unsurprisingly, the effect of transparency decreases by 50 percent but remains significant. The control variables show the right signs and the variables DA, NIA, as well as BM become highly significant. The adjusted R^2 rises by 11 percentage points or 35 percent, which, in relative terms, is a substantial increase and might indicate an omitted variable bias problem. We thus focus upon the fixed-effects regression specification in the subsequent analyses.

[Table 3 about here]

The results in this section clearly show that transparency has an economically significant effect on bond liquidity. As bonds trade with liquidity premia, these results imply that

[15] Hausman and LM tests strongly reject the null hypothesis of orthogonality between unobserved heterogeneity among firms and regressors.

accounting transparency has a direct impact on the cost of capital of firms.

5.3 Relationship between Bond Liquidity and Firm-level Transparency in Times of Financial Distress

In this section, we explore if and how the relationship between bond liquidity and firm transparency depends on financial distress. As argued in Section 3, we expect the impact of transparency to increase during times of distress: as the solvency of a company comes into question debt becomes information sensitive and adverse selection worsens. This effect is expected to be smaller for companies with relatively more transparent accounting information. We measure financial distress on three different levels: on an aggregate level by time period, by a bond's credit rating, and a bond's estimated default probability.

The recent financial crisis has had a profound impact on the liquidity of bond markets (see, e.g., Dick-Nielsen *et al.* (2012) and Friewald *et al.* (2012)). Hence, to test if and how the relationship between transparency and bond liquidity is affected by aggregate changes in bond market liquidity, we split our sample into two subperiods: Normal and Crisis. The Crisis period is taken to be from Q3 2007 to Q4 2009. Figure 2 presents time series plots of our liquidity proxies. The strong effect of the crisis can be clearly seen. The *Amihud*, *Roll*, and *IRC* measures all exhibit a several standard deviations large drop around the Lehman Brothers collapse. The aggregated liquidity measure confirms this pattern.

[Figure 2 about here]

The results for the panel regression in Equation (1) for the two sub-periods are presented in Panel A of Table 4. To conserve space, we only report the coefficients for the transparency variable. We find that the relationship between transparency and bond liquidity is robust over the different time periods and that the convexity of the relationship is measurable in both. Only for the normal time periods, the estimated marginal effect is positive and significant. There is also a split around the crisis period. Quantitatively, we find that the estimated marginal effect during the crisis is very close to 0 (and there is a level effect during the crisis as liquidity is much lower). These results indicate that transparency can account for some of the cross-sectional differences in liquidity mainly during calm but not turbulent financial times, in particular not during the recent liquidity crisis. To test directly for the differential explanatory power of transparency for cross-sectional differences in bond liquidity during the crisis, we add an additional interaction term between *Trans* and an indicator for the crisis period (column 5). The interaction term shows a negative and significant coefficient. That is, during the financial crisis the combined effects nets out to economically zero which we interpret as that

the *transparency level* channel stops working in times of financial distress. We reason that this is justifiable given that the crisis in question is one with liquidity dried-out. However, as we shall discuss in our analysis with *transparency risk* channel instead it becomes more pronounced during the financial crisis.

[Table 4 about here]

As a more direct measure of potential financial distress, we use the credit ratings of the bonds.[16] We expect to find that transparency has a larger impact for speculative bonds. The results for the different ratings are presented in Panel B of Table 4. To ensure that sufficient observations are available for each rating, we group the ratings AAA and AA, as well as CCC and CC together. We find that transparency has a statistically significant and positive influence on bond liquidity for speculative bonds rated BB and B. For investment-grade bonds rated A and above, no strong association was found (the coefficients are positive, however, they are close to 0 and thus economically insignificant). The BBB rating group - a line between speculative and investment-grade bonds - has an economically large sign but its statistical significance is marginal. These results are consistent with the theory of Dang *et al.* (2012) in that for information sensitive bonds, i.e. those where default is a concern, liquidity depends on the transparency of accounting information. For bonds which are around the investment grade threshold, accurate information is particularly relevant for active trade. Hence, bonds with high transparency are traded with higher market liquidity. The results show that the relationship between transparency and liquidity is contigent on ratings.[17]

The theory suggests an S-shaped relationship between transparency and liquidity. Figure 3 presents the scatterplot of the coefficients on transparency that we obtain by estimating our model in equation (1) through splitting the data by 100-quantiles of the EDF. Consistent with the information sensitivity argument of Dang *et al.* (2012), we find some support of an S-shaped relationship, though much more flattened with high EDF. For either very high (AAA-AA) or very low (CCC-CC) bond ratings the coefficient for $Trans$ is insignificant. Still the highest coefficient is reached for BBB ratings, i.e. for debt claims for which credit ratings deteriorate and precise information becomes more important. Hence, our empirical results confirm the hypothesis that in situations where default is possible but default risk is low, for instance when firms are in financial distress, bond liquidity becomes more accounting information-sensitive. In contrast, as long as bond's payoff is known, i.e. the bond is either relatively safe or bond's

[16] Results are the same when using company ratings as a measure of distress. The only difference is that the coefficient for transparency for CCC-CC rated companies is statistically not significant. This is most likely due to the fact that very few observations are available in that category.

[17] See also the cross-sectional descriptive statistics for the aggregated liquidity and transparency proxies in Table E1 of Appendix E in the Internet Appendix.

default is very likely, debt is an information-insensitive asset.[18]

[Figure 3 about here]

There is evidence that accounting transparency has an impact on credit ratings (Ashbaugh-Skaife *et al.*, 2006). At the same time, it is well known that credit ratings are only an imperfect measure of a bonds credit risk. In order to measure the likelihood of financial distress more directly, we therefore use a bond's expected default frequency (EDF) as a measure of the likelihood of default (see Bharath and Shumway (2008) and Vassalou and Xing (2004) for details). This measure is a direct measure of the likelihood of default and may be more appropriate to measure financial distress. We split the sample into bonds with low and high EDF. Low (high) expected default frequency (EDF) refers to observation with an EDF below the first (above the third) quartile and medium to observations within the interquartile range. The results for the different EDF categories are presented in Panel C of Table 4. We find that the impact of transparency increases as the EDF increases and becomes more concave. The interaction is positive as expected though not significant, indicating that at higher levels of financial distress the impact of transparency on liquidity is more pronounced. Summary statistics by EDF bucket is shown in Table E3 in the Internet Appendix. These results confirm that when the likelihood of default increases that cross-sectional differences in transparency are associated with larger changes in bond liquidity. However, when we jointly control for the different categories of expected default frequency by performing a piece-wise regression analysis (in Panel C of Table 4), the estimates suggest that for either extremely low or high levels of credit risk an increase in transparency significantly raises bond liquidity.

5.4 The Moderating Effects of Unexpected Rating Changes

The causal relationship between corporate transparency and bond liquidity is of interest since it provides key information for firm decisions on whether or not to improve transparency. Here the ideal setting would be an exogenous shock directly on transparency. Nonetheless, from the above discussion about credit ratings and EDF, we utilize unexpected changes in credit ratings as a shock on the EDF, through which we would expect an asymmetric effect on bond liquidity if transparency does have a causal effect (this is similar to an instrumental variable approach where the unexpected change in EDF would have the same impacts on liquidity if the liquidity-impacts of transparency does not vary across EDF). While changes in credit ratings might have been expected by market participants, we rely upon unexpected changes in the credit ratings. For instance, a one-step downgrade from A to A- might well be within expectation, however,

[18] See also the discussion on the disaggregated transparency measures in the Robustness Test Section 6, when we additionally include quadratic and cubic terms for individual transparency proxies.

a two-step downgrade from A to BBB+ is more likely to cast a surprise. Importantly, some firms might experience rating changes more often than others, thus we construct our measure of unexpected rating changes by taking into account the volatility of rating changes. Specifically, we standardize the number of steps in changes by the volatility of such steps of changes. [19]

$$URC_{f,t} = \frac{\#Steps\ in\ Credit\ Rating\ Changes}{Volatility\ of\ Rating\ Changes}, \tag{2}$$

where a positive URC indicates an upgrade. We thus first obtain a raw measure of all rating changes. To obtain a measure of unexpected rating changes, we look at only the non-zero values in this raw measure and excludes the inter-quartile range by setting non-zero values within this range to zero. Since we are interested in the asymmetric effects of transparency on liquidity, we partition by transparency in the second quarter firms into 3 groups from high to low transparency. That is, a firm would remain in the same group until the second quarter of next year. Firms that do not have data in this initiating quarter are classified, based upon their earliest available data, by which group their respective transparency falls into using the cutoff points from the second-quarter. We then assign a dummy of high-transparency to those in the first group, a dummy of low-transparency to those in the third group, and interact these dummies with our measure of unexpected rating changes.

Table 5 shows the estimation results by adding the URC and its interaction with the two transparency-group dummies. The coefficient on the URC is positive as expected, indicating a positive impact on bond liquidity in the presence of an upgrade. The interesting relationships are revealed in the coefficients on the interactions between the URC and the two dummies, considered together with the URC coefficient. Given our interest in the combined effects, we apply a Wald-test to jointly test the statistical significance of these variables. We obtain a p-value of 0.028 and 0.0015 for the URC variables and raw measures, respectively. We interpret our results as follows. An upgrade or downgrade for high-transparency firms have little impacts on the liquidity of their bonds. On the contrary, for low-transparency firms, upgrades constitute significant improvements on bond liquidity while downgrades severely reduce their liquidity. The literature has considered the signaling effects of ratings and our results confirm the existence of such channels. More important, the asymmetry of liquidity impacts from rating changes show that such signaling effects are most evident for firms with low-transparency. We reason that high-transparency firms are almost not subject to such effects because, due to their provision of transparent information, market participants do not need to rely on rating agencies for due diligence. Therefore, we believe that this serves to conclude the causal effects of firm transparency on bond liquidity. As a robustness check, we also run the same estimation using

[19] For firms that have never experienced a rating change during the sample period, we set the measure to 0. The point estimates do not change whether we apply this or not, however, not setting the measure to account for 0 volatility would result in exclusion of such firms.

the raw measure of rating changes, which leads to similar results.

5.5 Relationship between Bond Liquidity Uncertainty and Firm-level Transparency

To examine the relationship between the liquidity risk of corporate bonds and firm-level transparency we use a similar empirical strategy as before, i.e. we use the same regression equation but with liquidity risk as dependent variable:

$$\begin{aligned}\text{Liquidity Risk}_{i,t} = \mathbf{a} \cdot \text{Transparency}_{i,t-1} + \mathbf{b} \cdot \text{Bond Controls}_{i,t-1} \\ + \mathbf{c} \cdot \text{Credit Controls}_{i,t-1} + \alpha_i + \lambda_t + \epsilon_{i,t}.\end{aligned} \tag{3}$$

As described in Section 4, we use the variability of the liquidity proxies as measures of liquidity risk. We hypothesized that higher levels of transparency should lead to lower levels of liquidity risk. Hence, we expect the regression coefficients to be negative. We use the same set of controls for bond characteristics and credit risk. As several studies have emphasized the impact of the financial crisis on liquidity risk of bonds (see, for example, Friewald *et al.* (2012) and Dick-Nielsen *et al.* (2012)), we also report results for the different subperiods as described in the previous section. Again, we only report the results for the PC1 measures of transparency (*Trans*) and liquidity risk (*Liq Risk*). The other results are presented in Table 7.

The results, presented in Table 6, clearly confirm our hypothesis. In all regressions is the estimated coefficient of the *Trans* measure negative and significant. The first column reports the results of the regression without a measure of transparency and serves as a base case. The adjusted R^2 of this regression is 39% showing that much of the cross-sectional variation in liquidity risk is captured by the time fixed effects, bond characteristics, and credit risk. The coefficients confirm the results in the literature that credit risk and liquidity risk share commonality (see, e.g., Dick-Nielsen *et al.* (2012) and Friewald *et al.* (2012)). Also, equity volatility seems to strongly increase the volatility of bond liquidity.

The main results for the full specification are in the second column (with controls). The estimated coefficient for transparency is negative and statistically significant. This confirms our hypothesis that higher levels of transparency result in lower liquidity risk in bond markets. Also, the addition of the transparency variable has little influence on the other coefficients. This shows that the transparency variable is related to a component of bond liquidity risk that is independent of credit or equity risk. The adjusted R^2 in this regression is 39%. Quantitatively, a one standard deviation increase of *Trans* decreases *Liq Risk* by 0.05 which is a 22 percent

decrease relative to its median value.

Similar to the results for the level of liquidity, we estimate the panel regression for the samples in the Normal and Crisis period. The results are in columns 3 and 4 of Table 6. Again, we find that the impact of transparency on liquidity risk is measurable only in the normal time periods. To test explicitly whether the impact is larger during the crisis, we perform a final regression including an interaction term between *Trans* and a dummy variable for the crisis (column six). While the estimated coefficient for the crisis period is negative but insignificant, the coefficient of the interaction term is statistically and economically significant. We can conclude from this results that the marginal impact of transparency on the total variability of bond liquidity differs between normal periods and times of financial distress.

[Table 6 about here]

6 Robustness Checks

The initial results suggest that there is a strong relationship between bond liquidity and transparency of accounting information. Moreover, our results indicate that this relationship is non-linear. In this section, we provide further evidence that our measured effects are robust and economically meaningful.

Original Liquidity and Transparency Measures. The results for the different liquidity measures are very similar (compare Table 3 to Table 7). For each measure, we find a significant effect of transparency on liquidity (as in our main model with firm- and time- fixed effects, controlling for bond characteristics, credit risk, and equity risk). The coefficient in each regression is positive, as expected. Hence, the primary results for the aggregate measure also hold for the individual measures of bond liquidity. We also find that, for the *Amihud* and *Roll* measure, the coefficient for the quadratic term of $Trans$ is significant and positive. Quantitatively, the measured impact is as follows. In the linear specification without controls, a one standard deviation increase in *Trans* increases liquidity by 0.131 (*Amihud*), 0.026 (*Roll*), 0.033 (*IRC*), and 0.130 (*Liq*). This represents a decrease of 14.1, 8.1, 31.9, and 63.1 percent of the respective median values.

We find that our results are robust to the inclusion of bond and credit risk controls - all transparency coefficients remain positive. Also their numeric values are not strongly impacted by the controls. With the controls included in the linear specification with controls, a one standard deviation increase of the *Trans* measure increases the liquidity proxies by 0.088 (*Amihud*), 0.029 (*Roll*), 0.027 (*IRC*), and 0.139 (*Liq*), respectively. Relative to their median values this represents a change of 13.2, 5.1, 18.5, and 42.8 percent, respectively. For the controls, we find the expected

relationships: Higher *Age* is associated with decreased liquidity. Higher net income to assets (NIA) and profit margin (*IS*) is associated with higher liquidity. The other credit risk proxies (debt to assets (*DA*) and book-to-market value (*BM*)) are partially significant depending on the measure of liquidity. Only the coefficients for *IC* do not have the expected sign as some are negative, but mostly insignificant. Finally, equity volatility is strongly negatively related to bond liquidity, except for the *Amihud* measure.

Interaction Effects. A potential explanation of the impact of transparency on bond liquidity is that transparency is related to bond characteristics. Firms with a higher transparency proxy may simply be companies that have issued bonds with a higher coupon, a larger issue size, or lower age (shorter maturity). Each of these characteristics is generally associated with higher levels of liquidity. In addition, it is well documented that accounting transparency affects equity returns and volatility (see, for example, Stoll (2000) and Easley *et al.* (2002)). As far as equity returns and volatility have an impact on bond liquidity, this mechanism may be responsible for the large effect of transparency. To address these concerns, we re-estimate model (1) including interaction terms between the bond characteristics and the transparency proxy. In addition, we include return on equity (*RoE*), measured as the annualized average daily return of a company's stock in a quarter, to the set of controls as well as interaction terms between transparency and return and volatility of equity. We also add expected default frequency (*EDF*) and distance to default (*DD*) as further credit risk proxy to the full specification. Table 8 reports the results including the relevant interaction terms.

[Table 8 about here]

We find that RoE has little effect on bond liquidity as the coefficient is insignificant and very small in each regression. In contrast, the interaction terms of transparency with RoE and the logarithm of Vola are significant. These results indicate that the association of accounting transparency with bond liquidity is mediated by equity related influences. For the interaction effects with the bond characteristics, we find that their inclusion increases the coefficients for $Trans.$ This indicates that there are differences in the type of bonds issued by firms with different levels of transparency. Especially the offered amount seems to have a strong association with transparency. In general, the individual effect of transparency becomes insignificant (in models (3), (4), and (6)) whenever we add interaction terms between *bond* characteristics and transparency.

To shed light on the question of whether bond characteristics differ systematically by the level of accounting transparency of the issuing firm, Table 9 reports summary statistics of bond characteristics separately for firms with differing levels of transparency. Older (Age) and long-maturity bonds with larger issues ($Off.Amt.$) and lower coupon rates tend to be more

transparent. Similarly, bonds with higher operating income to sales (IS) and net income to assets (NIA), as well as lower debt to asset (DA) and equity volatility ($Vola$) are associated with higher accounting transparency. For interest coverage (IC) and book to market value (BM) the relationship to corporate transparency is less obvious.

[Table 9 about here]

Dynamic Model. Finally, one could argue that the empirical evidence for the strong relationship between corporate transparency and bond liquidity is mainly driven by a strong autoregressive process in both variables. We control for the dynamics in bond liquidity by including a lagged dependent variable on the right-hand side of Equation 1. The results are shown in Table F1 in the Internet Appendix. The $AR(1)$ term is statistically significant and ranges between 0.545 (with controls) and 0.554 (without controls) for liquidity level regressions and between 0.43 (with controls) and 0.447 (without controls) for liquidity risk regressions. Size-wise, the coefficient of $Trans$ in the liquidity-level regression reduces to about 40% of the original value in our main regression results of Table 3, while its statistical significance remains.

7 Conclusion

The purpose of this paper is to explore the relationship between corporate transparency and bond liquidity. In the theoretical literature, there is general agreement that the adverse selection created by asymmetric information is a major cause of market illiquidity. To the extent that transparent accounting information can mitigate asymmetric information and provide credible signals to investors about the prospects of a company there should be a positive relationship between measures of corporate transparency and liquidity on financial markets.

Prior research has focused exclusively on the impact of disclosure quality and accounting transparency on stock market liquidity and liquidity risk. The empirical literature is in agreement that corporate transparency has a positive effect on the level of liquidity of stocks (Welker (1995); Leuz and Verrecchia (2016); Lang *et al.* (2012)) and lowers the impact of liquidity risk (Lang and Maffett (2011); Ng (2011)). No prior study has yet analyzed the relationship for the bond market.

Recent research has highlighted that liquidity and liquidity risk has a much larger impact on bond markets than on stock markets. The improvement in data availability for bond transactions has lead to an extensive effort towards understanding the role liquidity plays on bond markets (see, e.g. Bao *et al.* (2011), Lin *et al.* (2011), Dick-Nielsen *et al.* (2012), and Friewald *et al.* (2012)). In addition, the bond market is an OTC market characterized by search-frictions

reenforce the negative effects of asymmetric information (see Duffie *et al.* (2005) and Duffie *et al.* (2007)).

We use a comprehensive sample of 3,997 bond issues with a total of 72,980 quarter-bond observations to explore the impact of accounting transparency on bond liquidity. We find a statistically strong and economically large relationship between corporate transparency and bond liquidity. Consistent with the theory of Dang *et al.* (2012), we find strong evidence of a non-linear relationship. The impact of transparency on bond liquidity is much larger than credit risk and consistent across maturities, issue size, and coupon rate.

We further find that the impact of corporate transparency on bond liquidity is larger during times of distress. This result is more consistent when distress is measured as a liquidity shock to a particular bond when liquidity for a bond issue suddenly dries up rather than as an aggregate shock to market liquidity as has occurred around the collapse of Lehman Brothers. We also find that transparency becomes more important when firms are in financial distress, consistent with the idea that debt markets become more information sensitive when investors are uncertain about a firm's prospects.

Finally, we also document that transparency has a strong impact on liquidity risk, as measured by the (total) variability of a bond's liquidity measure. This effect is particular strong during the financial crisis. Our results show that only opaque firms experience a higher sensitivity of liquidity risk on accounting transparency during the crisis.

References

Acharya, V., Amihud, Y. and Bharath, S. (2013). Liquidity risk of corporate bond returns: A conditional approach. *Journal of Financial Economics*, **110**, 358–386.

— and Pedersen, L. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics*, **77**, 375–410.

Affleck-Graves, J., Callahan, C. M. and Chipalkatti, N. (2002). Earnings predictability, information asymmetry, and market liquidity. *Journal of Accounting Research*, **40**, 561–583.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, **5**, 31–56.

— and Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics*, **2**, 223–249.

— and — (2008). Liquidity, the value of the firm, and corporate finance. *Journal of Applied Corporate Finance*, **24**, 17–32.

—, — and Pedersen, L. H. (2005). Liquidity and asset prices. *Foundations and Trends in Finance*, **1**, 269–364.

Ashbaugh-Skaife, H., Collins, D. W. and LaFond, R. (2006). The effects of corporate governance on firms' credit ratings. *Journal of Accounting & Economics*, **42**, 203–243.

Bagehot, W. (1971). The only game in town. *Financial Analysts Journal*, **27**, 12–17.

Bao, J., Pan, J. and Wang, J. (2011). The illiquidity of corporate bonds. *Journal of Finance*, **66**, 911–946.

Barron, O., Kim, O., Lim, S. and Stevens, D. (1998). Using analysts' forecasts to measure properties of analysts' information environment. *The Accounting Review*, **73**, 421–433.

Barth, M., Landsman, W. and Lang, M. (2008). International accounting standards and accounting quality. *Journal of Accounting Research*, **46**, 467–498.

Bharath, S. T. and Shumway, T. (2008). Forecasting default with the Merton distance to default model. *Review of Financial Studies*, **21**, 1339–1369.

Blume, M. E., Lim, F. and MacKinlay, A. C. (1998). The declining credit quality of U.S. corporate debt: Myth or reality? *Journal of Finance*, **63**, 1389–1401.

Brandt, M. and Kavajecz, K. A. (2004). Price discovery in the U.S. treasury market: The impact of order flow and liquidity on the yield curve. *Journal of Finance*, **59**, 2623–2654.

Brennan, M. J. and Subrahmanyam, A. (1995). Investment analysis and price formation in securities markets. *Journal of Financial Economics*, **38**, 361–381.

— and — (1996). Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. *Journal of Financial Economics*, **41**, 441–464.

Brown, S. and Hillegeist, S. A. (2007). How disclosure quality affects the level of information asymmetry. *Review of Accounting Studies*, **12**, 443–477.

—, — and Lo, K. (2004). Conference calls and information asymmetry. *Journal of Accounting and Economics*, **37**, 343–366.

Brunnermeier, M. K. and Pedersen, L. H. (2009). Market liquidity and funding liquidity. *Review of Financial Studies*, **22**, 2201–2238.

Chakravarty, S. and Sarkar, A. (1999). Liquidity in fixed income markets: A comparison of the bid-ask spread in corporate, government, and municipal bond markets, working Paper, Federal Reserve Bank of New York.

Chen, L., Lesmond, D. A. and Wei, J. (2007). Corporate yield spreads and bond liquidity. *Journal of Finance*, **62**, 119–149.

Constantinides, G. M. (1986). Capital market equilibrium with transaction costs. *Journal of Political Economy*, **94**, 842–862.

Dang, T. V., Gorton, G. and Holmström, B. (2012). Ignorance, debt and financial crises, working Paper.

Dechow, P. and Dichev, I. D. (2002). The quality of accruals and earninigs: The role of accrual estimation errors. *Journal of Accounting and Economics*, **77**, 35–59.

Derrien, F. and Kecskés, A. (2013). The real effect of financial shocks: Evidence from exogenous changes in analysts coverage. *Journal of Finance*, **68**, 1407–1440.

Diamond, D. W. and Verrecchia, R. E. (1991). Disclosure, liquidity, and the cost of capital. *Journal of Finance*, **46**, 1325–1359.

Dichev, I. D. and Tang, V. W. (2009). Earnings volatility and earnings predictability. *Journal of Accounting and Economics*, **47**, 160–181.

Dick-Nielsen, J. (2014). How to clean enhanced trace data, sSRN Working Paper.

—, Feldhütter, P. and Lando, D. (2012). Corporate bond liquidity before and after the onset of the subprime crisis. *Journal of Financial Economics*, **103**, 471–492.

Diether, K., Malloy, C. and Scherbina, A. (2002). Differences of opinion and the cross section of stock returns. *Journal of Finance*, **57**, 2113–2141.

Duffie, D., Gârleanu, N. and Pedersen, L. (2005). Over the counter markets. *Econometrica*, **73**, 1815–1847.

—, — and Pedersen, L. (2007). Valuation in over the counter markets. *Review of Financial Studies*, **20**, 1865–1900.

— and Lando, D. (2001). Term structure of credit spreads with incomplete accounting information. *Econometrica*, **69**, 633–664.

Easley, D., Hvidkjaer, S. and O'Hara, M. (2002). Is information risk a determinant of asset returns? *Journal of Finance*, **58**, 2185–2210.

—, Kiefer, N. M., O'Hara, M. and Paperman, J. B. (1996). Liquidity, information, and infrequently traded stocks. *Journal of Finance*, **51**, 1405–1436.

— and O'Hara, M. (1987). Price, trade, size, and information in securities markets. *Journal of Financial Economics*, **19**, 69–90.

— and — (1992). Time and the process of security price adjustment. *Journal of Finance*, **47**, 577–605.

Edwards, A. K., Harris, L. E. and Piwowar, M. S. (2007). Corporate bond market transaction costs and transparency. *Journal of Finance*, **56**, 1421–1451.

Fama, E. and French, K. (1997). Industry cost of equity. *Journal of Financial Economics*, **93**, 153–194.

Fan, J. and Wong, T. (2005). Do external auditors perform a corporate governance role in emerging markets? *Journal of Accounting Research*, **43**, 35–72.

Feldhütter, P. (2012). The same bond at different prices: Identifying search frictions and selling pressures. *Review of Financial Studies*, **25**, 1155–1206.

Francis, J. (2004). What do we know about audit quality. *British Accounting Review*, **36**, 345–368.

—, Lafond, R., Olsson, P. and Schipper, K. (2004). Costs of equity and earnings attributes. *The Accounting Review*, **79**, 967–1010.

—, —, — and — (2005). The market pricing of accruals quality. *Journal of Accounting and Economics*, **39**, 295–327.

—, —, — and — (2007). Information uncertainty and post-earnings-announcement-drift. *Journal of Business, Finance and Accounting*, **34**, 403–433.

Friewald, N., Jankowitsch, R. and Subrahmanyam, M. G. (2012). Illiquidity or credit deterioration: A study in the US corporate bond market during financial crises. *Journal of Financial Economics*, **105**, 18–36.

Garbade, D. and Silber, W. (1979). Structural organization of secondary markets: Clearing frequency, dealing activity, and liquidity risk. *Journal of Finance*, **34**, 577–593.

Gârleanu, N. and Pedersen, L. H. (2004). Adverse selection and the required return. *Review of Financial Studies*, **17**, 643–665.

Gelb, D. S. and Zarowin, P. (2002). Corporate disclosure policy and the informativeness of stock prices. *Review of Accounting Studies*, **7**, 33–52.

Goyenko, R. Y., Holden, C. W. and Trzcinka, C. A. (2009). Do liquidity measures measure liquidity? *Journal of Financial Economics*, **92**, 153–181.

Green, C. (2004). Economic news and the impact of trading on bond prices. *Journal of Finance*, **59**, 1201–1233.

Grossman, S. and Merton, M. (1988). Liquidity and market structure. *Review of Finance*, **43**, 617–633.

Healy, P. M., Hutton, A. P. and Palepu, K. G. (1999). Stock performance and intermediation changes surrounding sustained increases in disclosure. *Contemporary Accounting Research*, **16**, 485–520.

— and Palepu, K. G. (2001). Information assymmetry, corporate disclosure, and the capital market: A review of the empirical disclosure literature. *Journal of Accounting and Economics*, **31**, 405–440.

Houweling, P., Mentink, A. and Vorst, T. (2005). Comparing possible proxies of corporate bond liquidity. *Journal of Banking and Finance*, **29**, 1331–1358.

Hubert, M., Rousseeuw, P. J. and Branden, V. (2005). ROBPCA: A new approach to robust principle component analysis. *Technometrics*, **47**, 64–79.

Jones, J. (1991). Earnings management during import relief investigtions. *Journal of Accounting Research*, **29**, 193–228.

Kim, O. and Verrecchia, R. E. (1994). Market liquidity and volume around earnings annoucements. *Journal of Accounting and Economics*, **17**, 41–67.

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica*, **53**, 1315–1334.

Lang, M., Lins, K. V. and Maffett, M. (2012). Transparency, liquidity, and valuation: International evidence on when transparency matters most. *Journal of Accounting Research*, **50**, 729–774.

— and Lundholm, R. (1996). Corporate disclosure policy and analyst behavior. *The Accounting Review*, **71**, 467–492.

— and Maffett, M. (2011). Transparency and liquidity uncertainty in crisis periods. *Journal of Accounting and Economics*, **52**, 101–125.

—, Raedy, J. and Wilson, W. (2006). Earnings management and cross listing: Are reconciled earnings comparable to U.S. earnings? *Journal of Accounting and Economics*, **42**, 255–283.

Lee, C. M. C., Mucklow, B. and Ready, M. J. (1993). Spreads, depths, and the impact of earnings information: An intraday analysis. *Review of Financial Studies*, **6**, 345–374.

Leuz, C., Nanda, D. and Wysocki, P. (2003). Earnings management and investor protection: An international comparison. *Journal of Financial Economics*, **69**, 505–527.

— and Verrecchia, R. E. (2016). The economics of disclosure and financial reporting regulation: Evidence and suggestions for future research. *Journal of Accounting Research*, **38**, 91–124.

— and Wysocki, P. (2016). The economics of disclosure and financial reporting regulation: Evidence and suggestions for future research. *Journal of Accounting Research*, **54**, 525–622.

Lin, H., Wang, J. and Wu, C. (2011). Liquidity risk and expected corporate bond returns. *Journal of Financial Economics*, **99**, 628–650.

Longstaff, F., Mithal, S. and Neis, E. (2005). Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market. *Journal of Finance*, **60**, 2213–2253.

Lyons, R. K. (2001). *The Microstructure Approach to Exchange Rates*. Boston, MA: MIT Press.

Ng, J. (2011). The effect of information quality on liquidity risk. *Journal of Accounting and Economics*, **52**, 126–143.

Pasquariello, P. and Vega, C. (2007). Informed and strategic order flow in the bond markets. *Review of Financial Studies*, **20**, 1975–2019.

Pástor, L. and Stambaugh, R. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, **111**, 642–685.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies*, **22**, 435–480.

Roll, R. (1984). A simple implicit measure of the effective bid-ask spread in an efficient market. *Journal of Finance*, **39**, 1127–1139.

Sarig, O. and Warga, A. (1989). Bond price data and bond market liquidity. *Journal of Financial and Quantitative Analysis*, **24**, 367–378.

Schultz, P. (2001). Corporate bond trading costs: A peek behind the curtain. *Journal of Finance*, **56**, 677–698.

Stoll, H. (2000). Friction. *Journal of Finance*, **46**, 1479–1514.

Vassalou, M. and Xing, Y. (2004). Default risk in equity returns. *Journal of Finance*, **59**, 831–868.

Vayanos, D. (2004). Flight to quality, fight to liquidity, and the pricing of risk, working Paper.

Vega, C. (2006). Stock price reaction to public and private information. *Journal of Financial Economics*, **82**, 103–133.

Verrecchia, R. E. (2001). Essays on disclosure. *Journal of Accounting and Economics*, **32**, 97–180.

Welker, M. (1995). Disclosure policy: Information asymmetry and liquidity in equity markets. *Contemporary Accounting Research*, **11**, 801–827.

Yu, F. (2005). Accounting transparency and the term structure of credit spreads. *Journal of Financial Economics*, **75**, 53–84.

Zhang, F. (2006). Information uncertainty and stock returns. *Journal of Finance*, **61**, 105–137.

Tables and Figures

Table 1: Summary Statistics

The table reports the cross-sectional descriptive statistics (5th, 25th, 50th, 75th, 95th percentiles, mean, standard deviation, and skewness) for the liquidity and transparency proxies as well as our control variables. *Amihud* is the negative Amihud (2002) measure of illiquidity, *Roll* the negative bid–ask spread proxy by Roll (1984), and *IRC* the negative imputed roundtrip costs of Feldhütter (2012). *AQ* measures the negative of the standard deviation of the residuals of the regression to explain accruals following Francis *et al.* (2005). *EP* measures earnings precision according to Ng (2011). *Precision* is the negative of the standard deviation of these forecasts scaled by the stock price. *Age* is the time in years since a bond was issued, *Maturity* its time in years until it is redeemed, *Offering Amount* is the issue volume of the bond in million USD, and *Coupon* its coupon rate. *IC* is the pre-tax interest coverage ratio, *IS* the ratio of operating income to sales, *DA* is the ratio of long-term debt to total assets, *NIA* is the ratio of net income to total assets, and *BM* is the ratio of the book value of equity to its market value. *Vola* is the standard deviation of daily equity returns. The variables are described in detail in Section 4. Every continuous variable is winsorized at the 0.5% and 99.5% level.

	$Q_{0.05}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.95}$	Mean	Std. dev.	Skewness
Panel A: Liquidity Proxies								
Amihud (bp per mln)	0.008	0.044	0.139	0.370	1.294	0.341	0.611	4.362
Roll (%)	0.190	0.480	0.830	1.350	2.613	1.037	0.805	1.855
IRC (%)	0.000	0.069	0.177	0.481	1.251	0.353	0.433	2.085
Panel B: Liquidity Risk Proxies								
Amihud Risk	0.03	0.17	0.36	0.80	3.03	0.81	1.43	4.64
Roll Risk	0.06	0.15	0.28	0.52	1.25	0.42	0.44	2.82
IRC Risk	0.06	0.21	0.39	0.62	1.15	0.47	0.38	1.93
Panel C: Transparency Proxies								
AQ (*100)	0.32	0.58	0.89	1.37	2.65	1.10	0.77	1.95
EP (*100)	0.16	0.33	0.62	1.15	3.95	1.11	1.50	3.44
Precision (%)	0.02	0.05	0.09	0.20	0.86	0.23	0.53	6.01
Panel D: Bond Characteristics								
Age (yr)	0.34	1.55	3.14	5.47	9.95	3.97	3.34	1.62
Maturity (yr)	1.09	3.79	6.75	11.46	28.50	10.22	10.36	2.84
Coupon (%)	2.00	4.25	5.70	6.75	8.35	5.49	1.90	-0.20
Offer. Amt. (in mln)	196	300	500	750	1500	597	526	7
Panel E: Credit Risk Controls								
IC	0.85	4.26	7.36	12.82	28.24	10.41	11.22	3.65
IS	0.04	0.12	0.20	0.32	0.52	0.23	0.15	0.97
DA	0.11	0.19	0.27	0.36	0.54	0.29	0.14	1.12
NIA	-0.01	0.01	0.01	0.02	0.04	0.01	0.02	-2.68
BM	0.05	0.24	0.38	0.58	1.06	0.46	0.41	3.82
Vola	0.01	0.03	0.06	0.11	0.25	0.09	0.09	3.01
Rating	AAA	AA	A	BBB	BB	B	CCC	CC
N	613	3496	21670	31096	8673	6055	1310	67
Panel F: Aggregated Liquidity and Transparency Proxies								
Trans	-2.30	-0.31	0.51	1.09	1.65	0.22	1.23	-1.42
Liq	-3.10	-0.84	0.35	1.04	1.61	-0.07	1.51	-1.30
Liq Risk	-1.65	-0.96	-0.23	0.75	2.89	0.07	1.44	1.31

Table 2: Correlation Matrix of Transparency and Liquidity Proxies

The table shows the correlations between the measures of firm level transparency (Panel A), bond liquidity (Panel B), and bond liquidity risk (Panel C). The variables are described in Section 4. The values above the diagonal are Bravais-Pearson correlations, the values below are Spearman rank correlations. Values in bold are significant at the 5% level.

Panel A: Correlation of Transparency Proxies			
	AQ	EP	Precision
AQ		**0.524**	**0.188**
EP	**0.556**		**0.335**
Precision	**0.229**	**0.389**	

Panel B: Correlation of Liquidity Proxies			
	Amihud	Roll	IRC
Amihud		**0.551**	**0.517**
Roll	**0.628**		**0.566**
IRC	**0.619**	**0.581**	

Panel C: Correlation of Liquidity Risk Proxies			
	Amihud Risk	Roll Risk	IRC Risk
Amihud Risk		**0.397**	**0.457**
Roll Risk	**0.460**		**0.439**
IRC Risk	**0.586**	**0.497**	

Table 3: Liquidity Transparency Regressions

The table reports the results of the regressions to explain the *level* of a bond's liquidity:

$$\begin{aligned}\text{Liquidity}_{i,t} = \mathbf{a} \cdot \text{Transparency}_{i,t-1} + \mathbf{b} \cdot \text{Bond Controls}_{i,t-1} \\ + \mathbf{c} \cdot \text{Credit Risk Controls}_{i,t-1} + \alpha_i + \lambda_t + \epsilon_{i,t}.\end{aligned}$$

For each variable, its estimated coefficient with t-statistics in parenthesis below are reported. The final row reports the adjusted R^2 for the estimated model. Column (1) reports the results of the regression without any controls for bond characteristics or credit risk. Column (2) reports the results when bond characteristics are included as controls. In Column (3), the credit risk controls are included as well. The variables are described in Section 4 and the data set in Section 4.4. Each model is estimated using time fixed effects. Estimations in columns (4) to (6) use two-way fixed-effects (i.e., additionally include firm-fixed effects) to account for omitted variable bias. We follow Petersen (2009) and calculate robust standard errors clustered at the *bond level* and *time dimension*.

	Pooled Regression			Fixed-Effects Regression		
	(1)	(2)	(3)	(4)	(5)	(6)
Trans	0.129***	0.128***	0.108***	0.084***	0.084***	0.054***
	(0.013)	(0.013)	(0.013)	(0.017)	(0.016)	(0.016)
age		-0.064***	-0.066***		-0.034***	-0.034***
		(0.007)	(0.007)		(0.007)	(0.007)
coupon		-0.022	-0.011		-0.061***	-0.062***
		(0.016)	(0.016)		(0.016)	(0.016)
log(offeringAmount)		0.045	0.031		0.066	0.079*
		(0.032)	(0.032)		(0.041)	(0.041)
IC			0.002			0.000
			(0.001)			(0.001)
IS			0.324***			0.075
			(0.103)			(0.127)
DA			-0.050			-0.819***
			(0.110)			(0.181)
NIA			1.380***			1.753***
			(0.511)			(0.383)
BM			-0.156***			-0.337***
			(0.033)			(0.043)
log(vola)			-0.017**			-0.009*
			(0.007)			(0.005)
Time-Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Fixed Effects	No	No	No	Yes	Yes	Yes
$Adj.R^2$	0.284	0.309	0.314	0.410	0.421	0.424

$*p < 0.1, **p < 0.05, ***p < 0.01$

Table 4: Liquidity Transparency Regressions in Financial Distress

The table reports the results of the fixed effects panel regression to explain the *level* of a bond's liquidity:

$$\text{Liquidity}_{i,t} = \mathbf{a} \cdot \text{Transparency}_{i,t-1} + \mathbf{b} \cdot \text{Bond Controls}_{i,t-1} + \mathbf{c} \cdot \text{Credit Risk Controls}_{i,t-1} + \alpha_i + \lambda_t + \epsilon_{i,t}.$$

For each variable, its estimated coefficient with t-statistics in parenthesis below are reported. The final row reports the overall R^2 for the estimated model. Panel A contains the results for the Pre-Crisis, Crisis (2007Q3 - 2009Q4), Post-Crisis, and Normal period. For each period, the models in columns 1 to 4 contain only a linear transparency term. The model in column 5 captures financial distress by an additional interaction term of *Trans* with an indicator for the crisis period and is based on the full sample. Panel B contains the results separated by bond rating. Panel C contains the results separated by expected default frequency (EDF), where low (high) refers to observations with an EDF below the first (above the third) quartile and medium refers to observations within the interquartile range. Columns 4 and 5 model financial distress again with interaction terms. The variables are described in Section 4 and the data set in Section 4.4. Each model is estimated using time fixed effects. For the regressions in Panel B and Panel C, the Credit Risk Controls are excluded from the set of control variables. We follow Petersen (2009) and calculate robust standard errors clustered at the *bond level* and *time dimension*. To conserve space, only the coefficients for the transparency variables are reported.

Panel A: Time Periods						
	Pre-Crisis	Crisis	Post-Crisis	Normal	Interaction (IA)	
Trans	0.127***	-0.005	0.03	0.072***	0.071***	
	(0.044)	(0.035)	(0.02)	(0.021)	(0.02)	
Trans * crisis					-0.073***	
					(0.023)	
$Adj.R^2$	0.406	0.581	0.414	0.372	0.425	
Panel B: Credit Rating of Bond						
	AAA-AA	A	BBB	BB	B	CCC-CC
Trans	0.005	0.004	0.044**	0.107***	0.084***	0.043
	(0.056)	(0.026)	(0.022)	(0.033)	(0.03)	(0.049)
$Adj.R^2$	0.614	0.472	0.415	0.469	0.481	0.579
Panel C: Expected Default Frequency (EDF) of Bond						
	Low EDF	Medium EDF	High EDF	Interaction		
Trans	0.024	0.042**	0.069***	0.042***		
	(0.023)	(0.021)	(0.017)	(0.016)		
edf				-0.125***		
				(0.023)		
Trans * edf				0.022		
				(0.016)		
$Adj.R^2$	0.424	0.394	0.390	0.481		

$*p < 0.1, **p < 0.05, ***p < 0.01$

Table 6: Liquidity Risk Transparency Regressions

The table reports the results of the pooled regression to explain the *variation* of a bond's liquidity risk:

$$\text{Liquidity Risk}_{i,t} = \mathbf{a} \cdot \text{Transparency}_{i,t-1} + \mathbf{b} \cdot \text{Bond Controls}_{i,t-1} + \mathbf{c} \cdot \text{Credit Risk Controls}_{i,t-1} + \alpha_i + \lambda_t + \epsilon_{i,t}.$$

For each variable, its estimated coefficient with t-statistics in parenthesis below are reported. The final row reports the overall R^2 for the estimated model.The first two columns contain the results for the full sample. Column 1 contains the results including bond controls and credit risk only. Columns 2 and 3 are the results for the full specification. Columns 4 and 5 are based on the sub-samples for normal times and the financial crisis (2007Q3-2009Q4). The final column 6 contains an additional interaction term of *Trans* with an indicator for the crisis period and is based on the full sample. The variables are described in Section 4 and the data set in Section 4.4. Each model is estimated using time fixed effects. We follow Petersen (2009) and calculate robust standard errors clustered at the *bond level* and *time dimension*.

	Credit Risk	Full Sample	Normal	Crisis	Interaction
Trans		-0.041***	-0.036***	-0.023	-0.026**
		(0.013)	(0.014)	(0.034)	(0.013)
age	0.039***	0.039***	0.032***	0.068***	0.039***
	(0.007)	(0.007)	(0.007)	(0.011)	(0.007)
coupon	0.079***	0.079***	0.099***	0.007	0.080***
	(0.017)	(0.017)	(0.017)	(0.034)	(0.017)
log(offeringAmount)	-0.159***	-0.160***	-0.210***	0.152	-0.159***
	(0.042)	(0.042)	(0.038)	(0.097)	(0.042)
IC	0.003**	0.002**	0.003**	-0.001	0.002**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
IS	0.035	0.079	0.010	0.026	0.055
	(0.150)	(0.146)	(0.156)	(0.279)	(0.145)
DA	0.799***	0.708***	0.725***	0.211	0.723***
	(0.145)	(0.145)	(0.147)	(0.598)	(0.146)
NIA	-1.754***	-1.540***	-1.166***	-1.744*	-1.439***
	(0.534)	(0.508)	(0.412)	(1.028)	(0.451)
BM	0.306***	0.296***	0.243***	0.264***	0.292***
	(0.047)	(0.045)	(0.045)	(0.052)	(0.043)
log(vola)	0.011**	0.010**	0.003	0.038**	0.011**
	(0.005)	(0.005)	(0.004)	(0.015)	(0.005)
Trans:dumCr					-0.061**
					(0.025)
$Adj.R^2$	0.392	0.392	0.343	0.546	0.393

$*p < 0.1, **p < 0.05, ***p < 0.01$

Table 5: Liquidity Transparency Regressions with Rating Changes

The table shows the moderating effects of unexpected rating changes in a panel regression to explain the *level* of a bond's liquidity:

$$\begin{aligned} \text{Liquidity}_{i,t} = \mathbf{a} \cdot \text{Transparency}_{i,t-1} & \quad (4) \\ + mathbfb \cdot \text{URC} + mathbfb \cdot \text{URC} * \text{Transparency} & \quad (5) \\ + \mathbf{b} \cdot \text{Bond Controls}_{i,t-1} & \\ + \mathbf{c} \cdot \text{Credit Risk Controls}_{i,t-1} + \alpha_i + \lambda_t + \epsilon_{i,t}. & \end{aligned}$$

For each variable, its estimated coefficient with t-statistics in parenthesis below are reported. The final row reports the adjusted R^2 for the estimated model. Each model is estimated using time- and firm-fixed effects, and both the bond characteristics and the credit risk controls are included. The variables are described in Section 4 and the data set in Section 4.4. URC is the measure of unexpected rating changes, while in column (2) it is replaced by the raw measure of rating changes. We also include dummy variables that categorize the transparency level of which a group falls in, i.e. HighTrans means high transparency group. ratingChanges is the raw measure of rating changes without taking into account the unexpected part. We follow Petersen (2009) and calculate robust standard errors clustered at the *bond level* and *time dimension*.

	Liq		Liq Risk	
	(1)	(2)	(3)	(4)
Trans	0.046**	0.047**	−0.046**	−0.047**
	(0.019)	(0.019)	(0.019)	(0.019)
HighTrans	−0.039	−0.040	0.016	0.016
	(0.025)	(0.025)	(0.024)	(0.024)
LowTrans	−0.038	−0.038	−0.019	−0.019
	(0.028)	(0.028)	(0.028)	(0.028)
ratingChanges	0.035***		−0.035**	
	(0.012)		(0.015)	
HighTrans * ratingChanges	−0.036**		0.034	
	(0.018)		(0.022)	
LowTrans * ratingChanges	0.016		−0.012	
	(0.016)		(0.017)	
URC		0.030**		−0.035**
		(0.014)		(0.017)
HighTrans * URC		−0.035*		0.038
		(0.020)		(0.025)
LowTrans * URC		0.013		−0.019
		(0.017)		(0.018)
Adjusted R^2	0.427	0.427	0.396	0.396

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7: Regressions with Original Variables

The table reports the results of the fixed effects panel regression to explain the *level* of a bond's liquidity:

$$\text{Liquidity (Risk)}_{i,t} = \mathbf{a} \cdot \text{Transparency}_{i,t-1} + \mathbf{b} \cdot \text{Bond Controls}_{i,t-1} + \mathbf{c} \cdot \text{Credit Risk Controls}_{i,t-1} + \alpha_i + \lambda_t + \epsilon_{i,t}.$$

For each model, we report, for parsimony, only the estimated coefficient on the main variable of interest with standard errors in parenthesis below. Each model is estimated using time- and firm- fixed effects, and both the bond characteristics and the credit risk controls are included. The variables are described in Section 4 and the data set in Section 4.4. We follow Petersen (2009) and calculate robust standard errors clustered at the *bond level* and *time dimension*.

Panel A: Liquidity Transparency

	PCA-liquidity				Amihud				Roll				IRC			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Trans	0.054***				0.011*				0.021**				0.016***			
	(0.018)				(0.006)				(0.009)				(0.005)			
AQ		0.049**				0.013*				0.020*				0.013**		
		(0.021)				(0.008)				(0.011)				(0.006)		
EP			0.020**				0.002				0.009*				0.005*	
			(0.010)				(0.004)				(0.005)				(0.003)	
Precision				0.170***				0.055***				0.049**				0.060***
				(0.047)				(0.013)				(0.019)				(0.013)
Adjusted R^2	0.424	0.424	0.424	0.425	0.434	0.434	0.434	0.435	0.756	0.756	0.756	0.756	0.574	0.573	0.573	0.574

Panel B: Liquidity Risk Transparency

	PCA-liquidity-Risk				Amihud-Risk				Roll-Risk				IRC-Risk			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Trans	−0.040**				−0.043**				−0.007				−0.012***			
	(0.017)				(0.017)				(0.005)				(0.004)			
AQ		−0.013				−0.001				−0.004				−0.004		
		(0.020)				(0.020)				(0.005)				(0.005)		
EP			−0.021*				−0.028**				−0.003				−0.005*	
			(0.011)				(0.013)				(0.003)				(0.003)	
Precision				−0.185***				−0.239***				−0.019				−0.062***
				(0.039)				(0.039)				(0.014)				(0.011)
Adjusted R^2	0.396	0.395	0.396	0.397	0.412	0.412	0.412	0.414	0.633	0.633	0.633	0.633	0.704	0.704	0.704	0.705

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8: Liquidity Transparency Regressions with Interaction Effects [20]

	Liq					
	1	2	3	4	5	6
	(1)	(2)	(3)	(4)	(5)	(6)
Trans	0.046***	0.062***	0.038	0.056	0.046***	0.0004
	(0.018)	(0.019)	(0.130)	(0.130)	(0.018)	(0.132)
age	−0.033***	−0.033***	−0.032***	−0.032***	−0.033***	−0.032***
	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)
coupon	−0.063***	−0.063***	−0.062***	−0.062***	−0.063***	−0.061***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
log(offeringAmount)	0.080*	0.080*	0.080*	0.080*	0.080*	0.080*
	(0.042)	(0.042)	(0.043)	(0.043)	(0.042)	(0.043)
IC	−0.0004	−0.0004	−0.001	−0.0005	−0.0004	0.0003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
IS	0.073	0.068	0.059	0.053	0.073	−0.009
	(0.134)	(0.133)	(0.133)	(0.133)	(0.134)	(0.141)
DA	−0.813***	−0.806***	−0.811***	−0.804***	−0.813***	−0.718***
	(0.197)	(0.197)	(0.196)	(0.195)	(0.197)	(0.191)
NIA	1.548***	1.512***	1.558***	1.520***	1.548***	1.007**
	(0.379)	(0.386)	(0.375)	(0.382)	(0.379)	(0.474)
BM	−0.297***	−0.293***	−0.297***	−0.293***	−0.297***	−0.285***
	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.052)
log(vola)	−0.007	−0.008	−0.007	−0.008	−0.007	−0.007
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
edf	−0.136***	−0.137***	−0.136***	−0.136***	−0.136***	−0.138***
	(0.027)	(0.027)	(0.027)	(0.026)	(0.027)	(0.027)
roe	−0.237***	−0.236***	−0.239***	−0.236***	−0.237***	−0.232***
	(0.074)	(0.074)	(0.073)	(0.074)	(0.074)	(0.075)
Trans:log(vola)		0.006		0.007		0.004
		(0.005)		(0.005)		(0.004)
Trans:edf						0.007
						(0.018)

[20] The table reports the results of the fixed effects panel regression to explain the *level* of a bond's liquidity:

$$\text{Liquidity}_{i,t} = \mathbf{a} \cdot \text{Transparency}_{i,t-1} + \mathbf{b} \cdot \text{Bond Controls}_{i,t-1} + \mathbf{c} \cdot \text{Credit Risk Controls}_{i,t-1} + \mathbf{d} \cdot \text{Trans}_{i,t} \times \text{Interaction Variables}_{i,t} + \alpha_i + \lambda_i + \epsilon_{i,t}.$$

For each variable, its estimated coefficient with standard error in parenthesis below are reported. The final row reports the adjusted R^2 for the estimated model. Column (1) adds return on equity (RoE) to the regression specification. Column (2) and (3) report the results when interaction terms of transparency with equity and bond characteristics are included, respectively. Column (4) are the results for the complete model. The variables are described in Section 4 and the data set in Section 4.4. Each model is estimated using firm- and time fixed effects. We follow Petersen (2009) and calculate robust standard errors clustered at the *bond level* and *time dimension*.

Trans:roe		−0.006		−0.003		0.001
		(0.044)		(0.043)		(0.040)
Trans:age			0.0003	0.0003		0.001
			(0.004)	(0.004)		(0.004)
Trans:coupon			−0.009	−0.009		−0.013
			(0.009)	(0.009)		(0.009)
Trans:log(offeringAmount)			0.010	0.010		0.011
			(0.020)	(0.020)		(0.020)
Trans:IC						−0.0002
						(0.001)
Trans:IS						−0.065
						(0.063)
Trans:DA						0.206***
						(0.064)
Trans:NIA						−0.105
						(0.251)
Trans:BM						0.014
						(0.019)
Observations	69,506	69,506	69,506	69,506	69,506	69,506
Adjusted R^2	0.427	0.427	0.427	0.427	0.427	0.427
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 9: Summary Statistics by Transparency

The table reports the cross-sectional descriptive statistics (5th, 25th, 50th, 75th, 95th percentiles, mean, and standard deviation) for the liquidity proxies and our control variables. The full sample of firms is separated into transparency quintiles. The variables are described in detail in Section 4.

Quintile	Amihud	Roll	IRC	Liq	Age	Maturity	Off. Amt.	Coupon	IC	IS	DA	NIA	BM	Vola
							$Q_{0.05}$							
1	0.007	0.251	0.000	-3.481	0.339	1.291	150.000	2.150	0.000	0.000	0.104	-0.074	0.000	0.009
2	0.007	0.229	0.000	-3.056	0.339	1.252	150.000	2.250	0.000	0.019	0.110	-0.036	0.039	0.007
3	0.007	0.191	0.000	-3.144	0.342	1.005	175.000	2.050	1.741	0.028	0.097	-0.007	0.033	0.005
4	0.008	0.181	0.000	-3.143	0.320	1.114	200.000	1.718	2.473	0.047	0.100	-0.001	0.063	0.005
5	0.007	0.166	0.000	-2.831	0.361	0.956	200.000	2.000	3.219	0.083	0.126	0.003	0.163	0.004
							$Q_{0.25}$							
1	0.061	0.606	0.101	-1.360	1.443	4.003	282.000	5.125	1.688	0.066	0.197	-0.007	0.218	0.042
2	0.045	0.526	0.087	-0.934	1.525	4.164	250.000	4.750	2.980	0.107	0.191	0.002	0.235	0.038
3	0.045	0.473	0.072	-0.850	1.548	3.625	300.000	4.300	4.493	0.109	0.178	0.008	0.225	0.028
4	0.046	0.469	0.069	-0.797	1.446	3.874	300.000	3.900	5.461	0.109	0.186	0.010	0.183	0.025
5	0.038	0.429	0.054	-0.530	1.640	3.622	300.000	4.125	5.195	0.155	0.200	0.009	0.280	0.021
							$Q_{0.50}$							
1	0.213	1.017	0.265	-0.130	2.968	6.431	450.000	6.500	3.688	0.149	0.285	0.005	0.459	0.091
2	0.152	0.877	0.207	0.234	3.044	6.752	400.000	6.000	5.978	0.208	0.267	0.011	0.410	0.080
3	0.140	0.812	0.182	0.347	3.124	6.505	500.000	5.750	8.615	0.171	0.261	0.014	0.413	0.064
4	0.135	0.809	0.171	0.387	3.034	7.127	500.000	5.375	8.531	0.198	0.264	0.016	0.307	0.053
5	0.113	0.755	0.129	0.551	3.392	6.795	500.000	5.400	7.890	0.222	0.268	0.015	0.377	0.047
							$Q_{0.75}$							
1	0.493	1.549	0.647	0.767	5.139	9.585	627.182	7.625	8.120	0.323	0.423	0.018	0.775	0.171
2	0.378	1.380	0.502	0.954	5.120	9.708	600.000	7.125	12.017	0.355	0.375	0.023	0.673	0.149
3	0.381	1.327	0.492	1.059	5.457	9.708	700.000	6.750	14.609	0.287	0.363	0.026	0.633	0.112
4	0.364	1.341	0.469	1.056	5.451	16.920	750.000	6.500	14.376	0.308	0.375	0.024	0.484	0.090
5	0.314	1.252	0.385	1.143	5.862	15.039	750.000	6.375	12.145	0.331	0.333	0.020	0.531	0.084
							$Q_{0.95}$							
1	1.445	2.860	1.460	1.462	9.584	27.625	1250.000	9.375	26.466	0.625	0.720	0.051	1.498	0.385
2	1.281	2.609	1.232	1.525	9.311	28.460	1100.000	8.750	26.205	0.669	0.588	0.042	1.142	0.311
3	1.366	2.615	1.237	1.606	9.637	28.331	1500.000	8.500	44.591	0.542	0.539	0.045	1.092	0.230
4	1.298	2.623	1.266	1.641	10.919	28.750	1850.000	7.750	30.952	0.441	0.519	0.040	0.840	0.200
5	1.182	2.460	1.153	1.675	10.316	28.671	1500.000	7.700	22.447	0.453	0.445	0.028	0.884	0.178
							Mean							
1	0.415	1.206	0.452	-0.452	3.796	9.337	546.193	6.251	7.179	0.214	0.331	0.001	0.587	0.129
2	0.345	1.075	0.370	-0.148	3.755	10.012	502.277	5.852	8.852	0.254	0.298	0.009	0.503	0.110
3	0.351	1.028	0.355	-0.077	3.933	9.414	589.633	5.511	13.122	0.214	0.282	0.016	0.484	0.085
4	0.339	1.026	0.348	-0.051	3.974	10.877	676.776	5.161	11.522	0.213	0.288	0.017	0.390	0.070
5	0.302	0.957	0.301	0.124	4.185	10.699	609.995	5.197	10.106	0.244	0.272	0.015	0.437	0.066
							Standard Deviation							
1	0.657	0.855	0.478	1.560	3.290	9.319	438.838	2.123	10.954	0.192	0.188	0.036	0.600	0.127
2	0.605	0.796	0.429	1.475	3.087	10.641	325.584	1.902	9.508	0.192	0.147	0.029	0.420	0.109
3	0.634	0.812	0.428	1.525	3.313	8.722	506.417	1.891	15.728	0.155	0.142	0.019	0.422	0.088
4	0.604	0.803	0.435	1.518	3.465	10.460	742.511	1.839	10.295	0.124	0.136	0.014	0.416	0.072
5	0.580	0.772	0.406	1.439	3.379	11.380	429.869	1.704	8.782	0.114	0.099	0.009	0.264	0.077
							Skewness							
1	4.001	1.667	1.628	-0.967	1.845	3.317	3.316	-0.306	3.895	1.033	1.103	-1.529	2.766	1.995
2	4.336	1.869	2.020	-1.250	1.649	3.483	1.863	-0.271	2.990	0.918	1.035	-2.230	2.882	2.356
3	4.298	1.933	2.066	-1.335	1.826	1.665	3.177	-0.119	2.995	1.221	1.067	-1.679	3.180	2.959
4	4.284	1.810	2.137	-1.334	1.565	2.317	8.199	-0.413	3.220	0.613	0.784	-0.488	5.031	3.294
5	4.712	1.964	2.394	-1.480	1.425	2.975	2.038	-0.331	4.646	0.516	0.333	-1.322	3.734	4.332

Figure 1: Scatterplots of Transparency and Liquidity

The figure shows scatterplots between the measure of transparency ($Trans$) and liquidity (Liq). In each plot, the red line indicates the linear regression fit, whereas the blue line indicates a local LOESS (Local Polynomial Regression) fit between the two variables. Figure (a) compares the average value of transparency with the average value of liquidity per bond. Figure (b) compares the average value of transparency with the average value of liquidity per firm. In Figures (c) and (d), the quarter average is subtracted from Transparency and Liquidity before the averages of the variables per bond/firm are calculated. Figure (c) shows the average values per bond, Figure (d) the average values per firm.

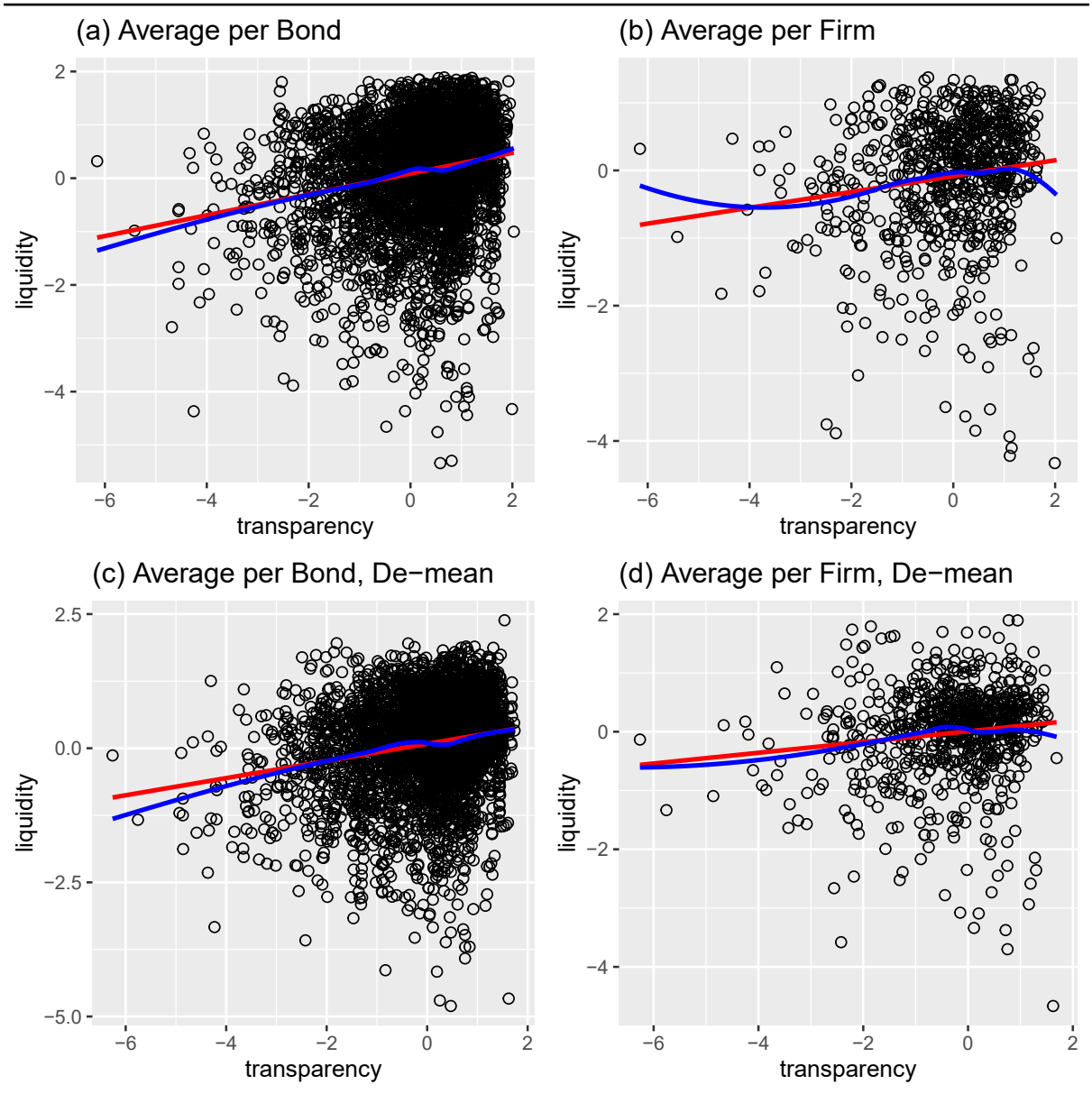


Figure 2: Time Series Plots of Liquidity Proxies

The figure presents the time series plots of the liquidity proxies described in Section 4 from Q1 2004 until Q2 2016. Figures (a) to (d) are the Amihud measure, the Roll measure, the Imputed Roundtrip Costs, and the first component from principal component analysis from the previous 3 measures, respectively. The mean value is plotted in red, the median in blue, the 25th percentile in grey, and the 75th percentile in black. The time period from Q3 2007 until Q4 2009 which we consider to be the Crisis period has witnessed significant drops across all measures.

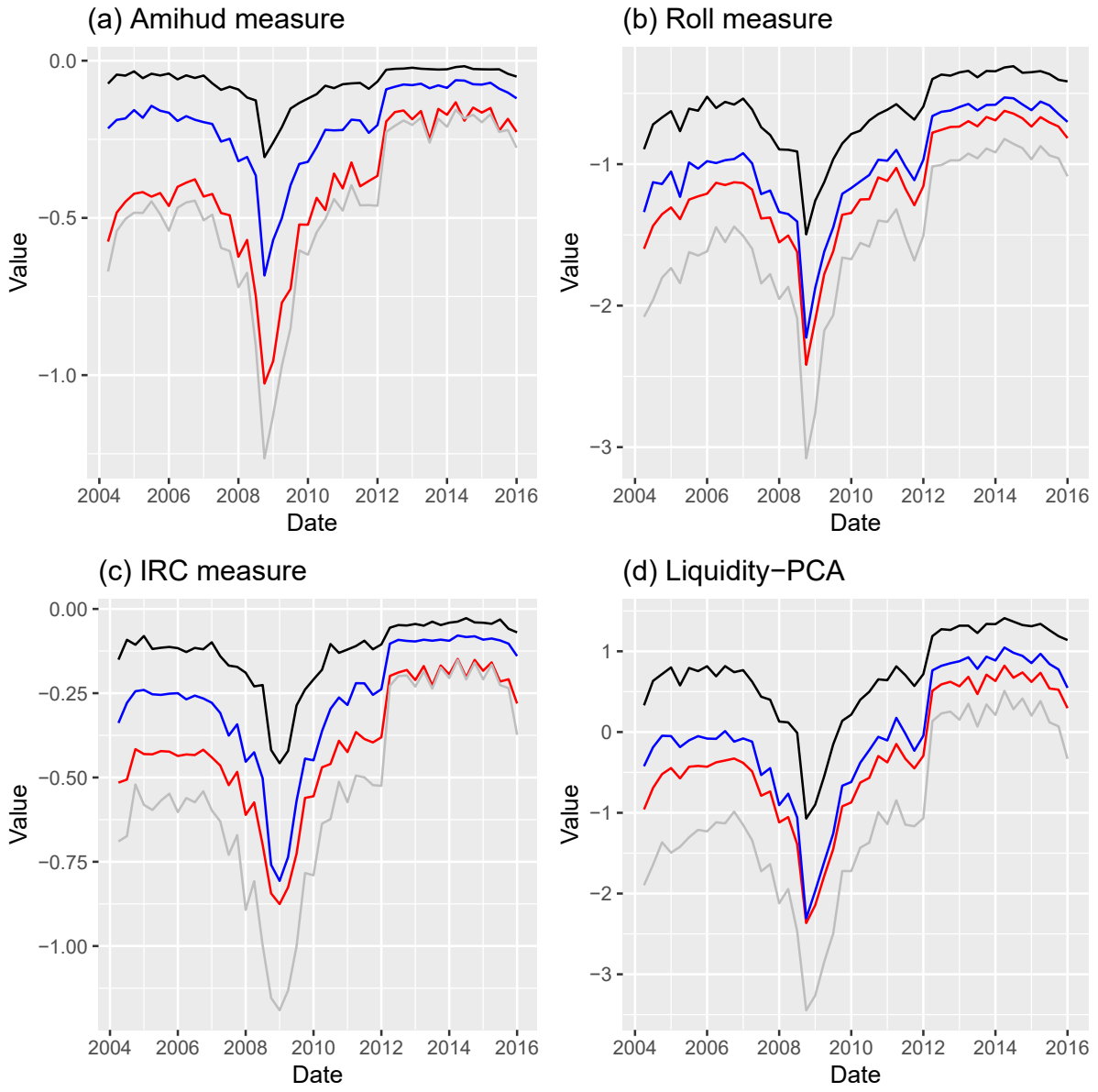
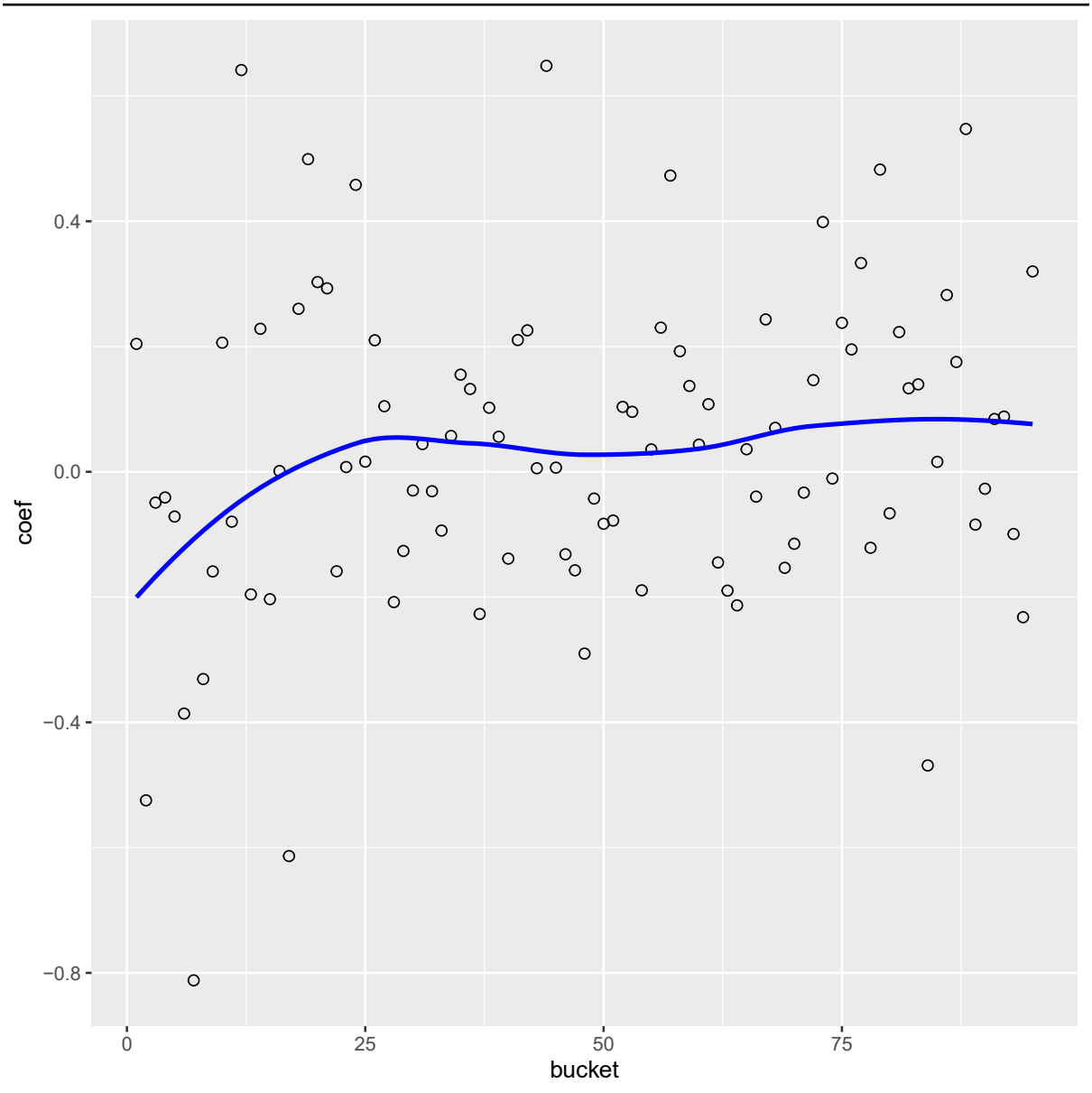


Figure 3: Scatterplot of transpanrecy-liquidity Coefficient by EDF quantile

The figure presents the scatterplot of the coefficients on Transparency by EDF quantile (100-quantiles) that can be graphically interpreted as falling into 4 buckets, low (0-25), median (25-50), high (50-75) and extreme(75-100) obtained from running the model:

$$\begin{aligned}\text{Liquidity}_{i,t} = \mathbf{a} \cdot \text{Transparency}_{i,t-1} + \mathbf{b} \cdot \text{Bond Controls}_{i,t-1} \\ + \mathbf{c} \cdot \text{Credit Risk Controls}_{i,t-1} + \alpha_i + \lambda_t + \epsilon_{i,t}.\end{aligned}$$



Internet Appendix for Corporate Transparency and Bond Liquidity

In this appendix, we provide additional information on the construction of the liquidity, liquidity risk, and transparency proxies. We further present results on the canonical correlations and loadings which serve as basis for our aggregated liquidity and transparency measures. In addition, disaggregated results for individual liquidity, liquidity risk, and transparency measures are presented. Finally, further estimation results conditional on different credit rating classifications are presented.

Contents:

Appendix A: Implementation of Liquidity Proxies
Appendix B: Implementation of Transparency Proxies
Appendix D: Canonical Correlations and Loadings
Appendix E: Summary Statistics by Credit Rating
Appendix F: Dynamic Fixed Effects Regression Models
Appendix C: Robust Principal Component Analysis

A Implementation of Liquidity Proxies

In this appendix we describe in detail the implementation of the individual liquidity measures used in the main text. We winsorize the 0.5% highest values of every liquidity variable, meaning that all values above the 99.5% percentile are set to the 99.5% percentile.

Amihud (2002) constructs an illiquidity measure based on the theoretical model of Kyle (1985) and we use a slightly modified version of this measure. It measures the price impact of a trade per unit traded. For each corporate bond, the measure is the daily average of absolute returns r_j divided by the trade size Q_j (in billion USD) of consecutive transactions:

$$\text{Amihud}_t = \frac{1}{N_t} \sum_{j=1}^{N_t} \frac{|r_j|}{Q_j}, \tag{A.1}$$

where N_t is the number of returns on day t. At least two transactions are required on a given day to calculate the measure, and we define a quarterly Amihud measure by taking the median of daily measures within the quarter.

Roll (1984) finds that under certain assumptions, the percentage bid–ask spread equals two times the square root of minus the covariance between consecutive price changes:

$$\text{Roll}_t = 2\sqrt{-\text{Cov}(\Delta p_i, \Delta p_{i-1})}, \tag{A.2}$$

where t is the time period for which the measure is calculated. If the covariance is positive, the observation is discarded. The intuition is that the bond price bounces back and forth between the bid and the ask price, and higher percentage bid–ask spreads lead to higher negative covariance between consecutive returns. We define a daily Roll measure on days with at least one transaction using a rolling window of 21 trading days, and the measure is only well-defined if there are at least four transactions in the window. We define a quarterly Roll measure by taking the median of daily measures within the quarter.

Feldhütter (2012) proposes an alternative measure of transaction costs based on what he calls Imputed Roundtrip Trades (IRT). The intuition is the following. Often, we see a corporate bond trading two or three times within a very short period of time after a longer period with no trades. This is likely to occur because a dealer matches a buyer and a seller and collects the bid–ask spread as a fee. When the dealer has found a match, a trade between seller and dealer along with a trade between buyer and dealer are carried out. Possibly, the matching occurs through a second dealer in which case there is also a transaction between the two dealers. If two or three trades in a given bond with the same trade size take place on the same day, and there are no other trades with the same size on that day, we define the transactions as part of

an IRT. For an IRT we define the imputed roundtrip cost (IRC) as

$$\mathrm{IRC}_t = \frac{P_{\max} - P_{\min}}{P_{\max}}, \tag{A.3}$$

where $P_{\max}$ is the largest price in the IRT and $P_{\min}$ is the smallest price in the IRT. A daily estimate of roundtrip costs is the average of roundtrip costs on that day for different trade sizes, and we estimate quarterly roundtrip costs by averaging over daily estimates. Feldhütter (2012) examines the properties of IRTs in detail, including how much of total trading volume is captured, and for a subsample of TRACE data with buy–sell indicators available, to what extent IRTs capture full roundtrip costs.

To measure liquidity risk, we take the standard deviation of the daily liquidity measures over a quarter. We require that there be at least six daily observations in a quarter to estimate the standard deviation.

B Implementation of Transparency Proxies

This section describes the details of the proxies for the transparency of the accounting information of a company. For each variable we require a time series of data with a minimum of four consecutive quarterly observations. We use a maximum of eight observations when available.

As suggested by Dechow and Dichev (2002) and Francis *et al.* (2005) accruals quality (AQ) may be an indicator of corporate transparency: Earnings with an accrual component that maps with less variability into the cash flow component may be considered more precise. Specifically, we use the procedure by Francis *et al.* (2005) and estimate the following cross-sectional regression for each of the Fama and French (1997) 48 industry groups with at least 20 firms in fiscal year t:

$$AC_t = \phi^0 + \phi^1 \mathrm{CFO}_{t-1} + \phi^2 \mathrm{CFO}_t + \phi^3 \mathrm{CFO}_{t+1} + \phi^4 \Delta\mathrm{Rev}_t + \phi^5 \mathrm{PPE}_t + v_t,$$

where $CFO_t = NIBE_t - TCA_t$ are cash flow from operations, $NIBE_t$ is net income before extraordinary items, ΔREV_t is the change in revenues, and PPE_t is net value of plant, property, and equipment, and AC_t are total current accruals defined as

$$\mathrm{AC}_t = \Delta\mathrm{CA}_t - \Delta\mathrm{CL}_t - \Delta\mathrm{Cash}_t + \Delta\mathrm{STDebt}_t - \mathrm{Depn}_t. \tag{B.1}$$

ΔCA is the change in current assets, ΔCL the change in current liabilities, $\Delta Cash$ the change in cash, $\Delta STDebt$ the change in debt in current liabilities, and $Depn$ the depreciation and amortization expense. The quarterly cross-sectional regression produces firm-quarter residuals. For each firm in each quarter, the residuals are scaled by total assets and then the standard deviation is computed. Given that a higher standard deviation represents lower information quality, we use the negative of this figure as the AQ measure. We measure earnings precision (EP) as the negative of the standard deviation of earnings, with earnings defined as earnings before extraordinary items deflated by total assets.

In a previous version of the paper, we also test two transparency measures which are commonly used in cross-country studies. For our first measure of transparency, we follow the approach by Lang *et al.* (2012) and use evidence of earnings management as a proxy. Their discretionary earnings smoothing (DES) proxy is based on two earnings smoothness measures commonly used in the literature. The first earnings smoothness measure (S_1) captures the volatility of earnings relative to the volatility of cash flows with the idea being that, the more firms use accruals to manage earnings, the smoother net income will be relative to cash flows (Leuz *et al.* (2003); Francis *et al.* (2004)). S_1 is measured as the standard deviation of net income

before extraordinary items divided by the standard deviation of cash flow from operations, where net income before extraordinary items and cash flow from operations are scaled by average total assets. Cash flow from operations is equal to net income before extraordinary items minus accruals.

The second earnings smoothness measure (S_2) is the correlation between the cash flow from operations scaled by total assets and total accruals scaled by total assets. The idea behind this measure is that, to the extent that managers create accrual reserves in good times and use them to compensate for poor cash flows in bad times, accruals and cash flows will be more negatively correlated (Lang *et al.* (2006); Barth *et al.* (2008)). Both smoothing measures (S_1, S_2) are multiplied by negative one so that larger values represent firms with smoother earnings.

The smoothness of earnings relative to cash flows is clearly a natural function of the fundamentals that affect a firm's operating environment. In order to determine how transparent earnings are we need to measure the portion in excess of naturally-occurring earnings smoothness. As a consequence, we draw from prior research on the determinants of earnings smoothness and specify an equation designed to capture, to the extent possible, the expected level of earnings smoothness for a firm. We then measure discretionary (excess) smoothing using the residual from the regression specified below:

$$\begin{aligned} S_{i,t} = \alpha &+ \beta_1 \text{LNTA}_t + \beta_2 \text{LEV}_t + \beta_3 \text{BM}_t + \beta_4 \text{STDSALES}_t + \beta_5 \text{PLOSS}_t + \\ &\beta_6 \text{OPCYCLE}_t + \beta_7 \text{SG}_t + \beta_8 \text{OPLEV}_t + \beta_9 \text{AVECFO}_t + \\ &\sum_{a=1}^{18} \alpha_a \text{IND}_a + \sum_{b=1}^{14} \alpha_b \text{QUARTER}_b + \epsilon_t \end{aligned} \tag{B.2}$$

The right hand side variables are: $LNTA$, the log of total assets measured in millions of U.S. dollars, a measure of firm size; LEV, total debt divided by total assets, to capture differences in financing choices; BM, the ratio of book value to market value of equity, to reflect the extent of the firm's intangible assets and expected earnings growth; $STDSALES$, the standard deviation of sales, to capture the volatility of a firm's underlying operating environment; $PLOSS$, the proportion of years that a firm experiences losses over the last three to five years, to capture differences in the accruals properties of loss observations; $OPCYLE$, the log of days of accounts receivable plus inventories, to capture the length of the firm's operating cycle; SG, the average sales growth to capture growth opportunities; $OPLEV$, net property, plant and equipment divided by total assets, to capture capital intensity; $AVECFO$, average cash flow from operations divided by total assets to capture a firm's general level of profitability; and indicator variables for a firm's industry IND because the properties of accruals are likely to depend on industry, as well as year indicator variables $YEAR$ to control for macroeconomic

cycles that could affect earnings cycles.

After we obtain each of the two discretionary smoothness regression residual measures for S_1 and S_2, they are then scaled into percentile ranks, and combined by taking the average. This figure is then subtracted from 1 (so that higher values indicate greater transparency). This variable is referred to as *DES* and is used to proxy for earnings management in our liquidity regressions. We follow the same procedure for the predicted values obtained from the model for S_1 and S_2 and scale them into ranks and average them. This variable is called fundamental earnings smoothing (*FES*).

Our previous analyses include both the portion of smooth earnings explained by the intrinsic fundamental factors (*FES*) as well as the excess portion (*DES*). Our primary interest was in *DES* as a measure of transparency, and we predict that greater discretionary smoothing will be indicative of greater earnings management and therefore associated with greater opacity. However, we expect *FES* to be positively correlated with liquidity to the extent that there is less potential for asymmetric information in firms whose profits are naturally smooth. Lang *et al.* (2012) show that *DES* captures elements of managerial discretion in that it is positively correlated with incentives to manage earnings (concentrated ownership and high book-tax accounting conformity) and negatively correlated with impediments to earnings management (high quality auditor, strong investor protection, global accounting standards, and high analyst following).

Table B1: Correlations

The table reports the correlations of among the international transparency proxies. The values above the diagonal are Bravais-Pearson correlations, the values below are Spearman rank correlations. Values in bold are significant at the 5% level.

	DES	EP	AQ	Analyst	Precision
DES		**−0.306**	**0.016**	**0.121**	**0.038**
EP	**−0.326**		**0.522**	**0.084**	**0.282**
AQ	**0.050**	**0.503**		**0.253**	**0.204**
Analyst	**0.126**	**0.090**	**0.277**		**0.103**
Precision	**0.050**	**0.380**	**0.230**	**0.125**	

Because DES is the only transparency variable that has a negative correlation with the transparency proxy EP, we refrain from using this measure in our analysis.

C Robust Principal Component Analysis

Table C1 presents the results of the robust PCA

Table C1: Principal Component Loadings

The table reports the (robust) principal component analysis loadings for each of the transparency proxies (Panel A), the liquidity proxies (Panel B), and the liquidity risk proxies (Panel C) along with the cumulative explanatory power of the components. To account for the skewness of the measures, we use the robust PCA by Hubert *et al.* (2005).

Panel A: PCA Loadings for Transparency Proxies			
	PC1	PC2	PC3
AQ	0.59	-0.53	-0.61
EP	0.65	-0.14	0.75
Precision	0.48	0.84	-0.26
Cum. % explained	0.60	0.27	0.13

Panel B: PCA Loadings for Liquidity Proxies			
	PC1	PC2	PC3
Amihud	0.58	0.79	-0.21
Roll	0.58	-0.21	0.79
IRC	0.58	-0.58	-0.58
Cum. % explained	0.73	0.14	0.13

Panel C: PCA Loadings for Liquidity Risk Proxies			
	PC1	PC2	PC3
Amihud Risk	0.5862	-0.4011	-0.7040
Roll Risk	0.5588	0.8293	-0.0072
IRC Risk	0.5866	-0.3892	0.7102
Cum. % explained	0.67	0.18	0.15

D Canonical Correlation Structure

Table D1: Structure of Canonical Correlations

Panel A reports the weights of the canonical functions from the CCA. Panel B reports the loadings of the canonical functions. These are the correlations of the canonical variates with the variables that make them up. Panel C reports the cross-loadings of the canonical functions. These are the correlations of the canonical variates with the other set of variables.

	Function 1	Function 2	Function 3
Panel A: Canonical Weights			
Standardized canonical coefficients for the independent variables			
AQ	0.001	0.001	-0.006
EP	0.001	-0.003	0.001
Precision	0.006	0.005	0.002
Standardized canonical coefficients for the dependent variables			
Amihud	0.000	0.002	0.002
Roll	0.001	0.004	-0.008
IRC	0.019	-0.011	0.003
Panel B: Canonical Loadings			
Correlations between the independent variables and their canonical variates			
AQ	0.462	-0.246	-0.852
EP	0.610	-0.793	-0.005
Precision	0.914	0.348	0.208
Correlations between the dependent variables and their canonical variates			
Amihud	0.410	0.799	0.440
Roll	0.477	0.695	-0.538
IRC	0.991	0.051	0.125
Panel C: Canonical Cross-Loadings			
Correlations between the independent variables and dependent canonical variates			
AQ	0.121	-0.009	-0.004
EP	0.159	-0.029	0.000
Precision	0.238	0.013	0.001
Correlations between the dependent variables and independent canonical variates			
Amihud	0.107	0.029	0.002
Roll	0.124	0.025	-0.003
IRC	0.258	0.002	0.001

D.1 Canonical Correlation Analysis

In this paper we are attempting to link corporate transparency and bond liquidity. Both concepts are difficult to measure empirically, which is why we use a set of different proxies for each. To obtain a picture of the relationship between the two sets of variables, we use canonical correlation analysis (CCA). CCA seeks to identify possible links between two sets of variables

$X \in \mathbb{R}^p$ and $Y \in \mathbb{R}^q$. As such, it is an extension of the classical bivariate correlation. The canonical correlations between X and Y are found by finding the linear combinations which result in the highest correlation. The first canonical correlation is the maximal correlation between any linear combinations of $\mathbf{X} \in \mathbb{R}^p$ and $\mathbf{Y} \in \mathbb{R}^q$:

$$\rho_c^1 = \max_{\mathbf{a}\in\mathbb{R}^p, \mathbf{b}\in\mathbb{R}^q} \text{corr}(\mathbf{a}'\mathbf{X}, \mathbf{b}'\mathbf{Y}). \tag{1}$$

The linear combinations produced are called first canonical variates. The successive canonical correlations, up to the smaller of p and q, are constructed in the same manner with the additional requirement that every canonical variate of each set of covariates is orthogonal to all prior canonical variates of that set. The square root of the canonical correlations, called canonical roots, represent the amount of variance in one canonical variate accounted for by the other canonical variate.

[Table D2 about here]

Table D2 presents the results of the canonical correlation analysis discussed in Section 5.3 on relationship between bond liquidity and firm-level transparency

Table D2: Results of Canonical Correlation Analysis

The table reports the coefficients and diagnostics for the CCA of the liquidity and transparency variables described in Section 4. Column 2 reports the canonical correlations. Wilk's lambda, reported in column 4, tests the null hypothesis that this and all following canonical correlations are equal to zero.

Canonical Function	Canonical Correlation	Canonical R^2	Wilk's Lambda	Rao's F-Approximation	P-Value
1	0.261	0.068	0.931	340.763	0.000
2	0.036	0.001	0.999	13.969	0.000
3	0.005	0.000	1.000	1.126	0.289

E Results by Credit Rating

There is a strong relationship between credit risk and bond liquidity on the one hand and credit ratings on the other. It is conceivable that accounting transparency also varies within different rating classes. At the same time, there is also evidence that accounting transparency has an impact on credit ratings Ashbaugh-Skaife *et al.* (2006). Table E1 below reports the summary statistics of the transparency and liquidity variable for each rating class. The statistics show that, in general, transparency and liquidity increase as ratings get better.

Table E1: Summary Statistics for Credit Rating

The table reports the cross-sectional descriptive statistics (5th, 25th, 50th, 75th, 95th percentiles, mean, and standard deviation) for the aggregate liquidity and transparency proxies. The variables are described in detail in Section 4.

	$Q_{0.05}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.95}$	Mean	Std. dev.
AAA-AA Rating							
Trans	-1.18	0.24	0.76	1.14	1.67	0.58	0.90
Liq	-2.32	-0.26	0.53	1.10	1.72	0.24	1.27
A Rating							
Trans	-0.98	0.20	0.73	1.11	1.62	0.58	0.80
Liq	-2.78	-0.51	0.43	1.09	1.76	0.09	1.44
BBB Rating							
Trans	-1.58	-0.10	0.61	1.17	1.70	0.40	1.03
Liq	-3.07	0.64	0.44	1.15	1.78	0.05	1.52
BB Rating							
Trans	-2.75	-0.97	0.00	0.67	1.39	-0.62	1.29
Liq	-2.65	-0.68	0.16	0.69	1.33	-0.14	1.24
B Rating							
Trans	-3.66	-1.64	-0.13	0.67	1.40	-0.58	1.64
Liq	-2.65	-0.67	0.19	0.71	1.40	-0.12	1.28
CCC-CC Rating							
Trans	-5.23	-3.46	-2.48	-1.24	-0.10	-2.60	1.84
Liq	-3.47	-1.60	-0.53	0.31	1.14	-0.78	1.56

We therefore re-estimate the regression (1) for each rating class separately. We only report the results for the aggregate Liquidity measure.[21]

[21] The results for the individual liquidity measures are qualitatively the same and are available upon request from the authors.

Table E2: Summary Statistics for Expected Default Frequency

The table reports the cross-sectional descriptive statistics (5th, 25th, 50th, 75th, 95th percentiles, mean, and standard deviation) for the aggregate liquidity and transparency proxies. The variables are described in detail in Section 4. We define the categories of EDF as follows: low EDF categlow EDF category $< 0.00001(0.001\%)$, medium EDF category $> 0.00001(0.001\%$ and $< 0.1(10\%)$, and high EDF category $> 0.1(10\%)$.

	$Q_{0.05}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.95}$	Mean	Std. dev.
Low EDF							
Trans	-1.54	-0.00	0.64	1.11	1.65	0.43	1.01
Liq	-2.31	-0.27	0.53	1.13	1.76	0.25	1.28
Medium EDF							
Trans	-2.95	-1.22	-0.04	0.79	1.52	-0.32	1.40
Liq	-3.41	-1.25	-0.25	0.46	1.25	-0.55	1.46
High EDF							
Trans	-4.29	-2.37	-1.08	0.05	1.22	-1.24	1.69
Liq	-4.42	-2.26	-1.02	-0.08	0.79	-1.30	1.62

Table E3: Summary Statistics for Expected Default Frequency

The table reports the cross-sectional descriptive statistics (5th, 25th, 50th, 75th, 95th percentiles, mean, and standard deviation) for the aggregate liquidity and transparency proxies. The variables are described in detail in Section 4. Low (high) expected default frequency (EDF) refers to observation with an EDF below the first (above the third) quartile and medium to observations within the interquartile range.

	$Q_{0.05}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.95}$	Mean	Std. dev.
Low EDF							
Trans	-0.79	-0.34	0.79	1.19	1.67	0.67	0.78
Liq	-1.85	0.07	0.78	1.33	1.88	0.52	1.20
Medium EDF							
Trans	-1.71	-0.20	0.53	1.07	1.65	0.32	1.07
Liq	-2.42	-0.41	0.42	1.01	1.67	0.13	1.29
High EDF							
Trans	-3.54	-1.62	-0.31	0.59	1.43	-0.62	1.57
Liq	-3.87	-1.59	-0.47	0.33	1.18	-0.79	1.56

Table E4: Summary Statistics for Distance to Default

The table reports the cross-sectional descriptive statistics (5th, 25th, 50th, 75th, 95th percentiles, mean, and standard deviation) for the aggregate liquidity and transparency proxies. The variables are described in detail in Section 4. Low (high) distance to default (DD) refers to observation with an DD below the first (above the third) quartile and medium to observations within the interquartile range.

	$Q_{0.05}$	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.95}$	Mean	Std. dev.
Low DD							
Trans	-3.53	-1.62	-0.31	0.59	1.43	-0.62	1.57
Liq	-3.87	-1.59	-0.47	0.33	1.80	-0.79	1.56
Medium DD							
Trans	-1.71	-0.20	0.53	1.07	1.65	0.32	1.07
Liq	-2.42	-0.41	0.42	1.01	1.67	0.14	1.29
High DD							
Trans	-0.79	0.34	0.79	1.19	1.67	0.67	0.78
Liq	-1.85	0.07	0.78	1.33	1.88	0.52	1.20

F Dynamic Fixed Effects Regression Models

Table F1: Dynamic Liquidity and Liquidity Risk Transparency Regressions

	Liquidity			Liquidity Risk		
	1	2	3	4	5	6
	(1)	(2)	(3)	(4)	(5)	(6)
Liq_1	0.554***	0.548***	0.545***			
	(0.016)	(0.017)	(0.017)			
LiqVol_1				0.447***	0.432***	0.430***
				(0.014)	(0.014)	(0.013)
Trans	0.040***	0.040***	0.024**	−0.033**	−0.035***	−0.022*
	(0.011)	(0.011)	(0.010)	(0.013)	(0.013)	(0.012)
age		−0.005	−0.005		0.011***	0.011***
		(0.004)	(0.004)		(0.004)	(0.004)
coupon		−0.034***	−0.035***		0.047***	0.048***
		(0.009)	(0.010)		(0.011)	(0.011)
log(offeringAmount)		0.043**	0.050**		−0.091***	−0.095***
		(0.021)	(0.021)		(0.027)	(0.027)
IC			−0.0002			0.002**
			(0.001)			(0.001)
IS			0.030			0.068
			(0.079)			(0.126)
DA			−0.472***			0.464***
			(0.112)			(0.120)
NIA			0.859***			−1.106**
			(0.276)			(0.534)
BM			−0.189***			0.193***
			(0.032)			(0.034)
log(vola)			−0.008			0.011*
			(0.005)			(0.006)
Observations	68,983	68,983	68,983	52,824	52,824	52,824
Adjusted R^2	0.597	0.599	0.600	0.512	0.516	0.517

Note: *p<0.1; **p<0.05; ***p<0.01

G Higher lag structure and Unique bond per firm

Higher Lag Structure. Our primary results are based on a one-quarter lag. It is conceivable that the true effects of accounting information transparency are not immediately reflected in trading of investors. To test for this possibility, we report the results of the panel regression including lags up to order four of the transparency measures. We report results with and without controls in Table G1. The main results are not affected by the addition of higher lags.

[Table G1 about here]

Unique Bond per Firm. A possible explanation for the non-linearity might be that, in general, each firm in our sample has multiple bonds outstanding at any point in time. With the exception of the bond control variables, all of our control variables and in particular our transparency measure are observed at the firm level. We therefore select one bond per company using the following procedure: For each firm, we select the bonds with the largest issue size. If multiple bonds qualify, we take the bonds with the largest coupon rate, then the shortest time to maturity, and finally the most recent offering date. In each case, we select a criterion that should increase the liquidity of the bond chosen.[22] This way we obtain a unique bond for each of the 693 firms in the sample with a total of 8,115 quarterly observations. The results are reported in Table G2. The significant linear effect of $Trans$ remains intact but decreases by adding more control variables. The results are quite robust and in line with the baseline regressions in Table 3. However, compared to the complete sample, we now find that the quadratic term is no longer statistically significant. Also, the interaction term between $Trans$ and the financial crisis dummy is insignificant for all specification.

[Table G2 about here]

[22] We have experimented with the selection procedure and obtained similar results in each case. For one, we have reversed the selection criterion thereby choosing the presumably least liquid bond for each firm. We have also used the medium value for each bond characteristic. Finally, we have used random selection.

Table G1: Liquidity Transparency Regressions with Higher Lags

The table reports the results of the fixed effects panel regression to explain the *level* of a bond's liquidity:

$$\text{Liquidity}_{i,t} = \sum_{j=1}^{4} a_j \cdot \text{Trans}_{i,t-j} + \mathbf{b} \cdot \text{Bond Controls}_{i,t-1} + \mathbf{c} \cdot \text{Credit Risk Controls}_{i,t-1} + \delta_t + \text{Industry}_i + \epsilon_{i,t}.$$

For each variable, its estimated coefficient with standard error in parenthesis below are reported. The final row reports the adjusted R^2 for the estimated model. Column (1) is our main regression with controls. Column (2) contain the results using only lagged terms without controls. Column (3) adds the lagged terms to our main regression with controls. The variables are described in Section 4 and the data set in Section 4.4. Each model is estimated using firm- and time fixed effects. We follow Petersen (2009) and calculate robust standard errors clustered at the *bond level* and *time dimension*.

	Liq			Liq Risk		
	1	2	3			
	(1)	(2)	(3)	(4)	(5)	(6)
Trans	0.089***	0.048**	0.054***	−0.074***	−0.048**	−0.041**
	(0.020)	(0.020)	(0.018)	(0.024)	(0.021)	(0.016)
age		−0.018**	−0.034***		0.026***	0.039***
		(0.008)	(0.008)		(0.007)	(0.008)
coupon		−0.071***	−0.062***		0.088***	0.079***
		(0.019)	(0.018)		(0.019)	(0.020)
log(offeringAmount)		0.075	0.079*		−0.178***	−0.160***
		(0.046)	(0.042)		(0.045)	(0.043)
IC		−0.0001	−0.0001		0.004**	0.002*
		(0.002)	(0.002)		(0.002)	(0.001)
IS		0.063	0.075		−0.008	0.079
		(0.143)	(0.133)		(0.163)	(0.152)
DA		−1.246***	−0.819***		1.050***	0.708***
		(0.200)	(0.188)		(0.174)	(0.154)
NIA		1.330***	1.753***		−0.917*	−1.540***
		(0.447)	(0.392)		(0.498)	(0.529)
BM		−0.356***	−0.337***		0.317***	0.296***
		(0.049)	(0.046)		(0.058)	(0.048)
log(vola)		−0.006	−0.009		0.010*	0.010
		(0.007)	(0.007)		(0.006)	(0.007)
Trans_2	0.002	0.011		−0.013	−0.019	
	(0.024)	(0.024)		(0.024)	(0.024)	
Trans_3	−0.016	−0.016		0.041	0.040	
	(0.031)	(0.031)		(0.028)	(0.027)	
Trans_4	0.013	0.012		−0.004	−0.002	
	(0.023)	(0.021)		(0.022)	(0.020)	
Observations	53,045	53,045	72,980	47,250	47,250	64,096
Adjusted R^2	0.440	0.451	0.424	0.391	0.409	0.392

Note: *p<0.1; **p<0.05; ***p<0.01

Table G2: Liquidity Transparency Regressions with Controls: One Bond per Company

The table reports the results of the fixed effects panel regression to explain the *level* of a bond's liquidity:

$$\begin{aligned}\text{Liquidity}_{i,t} = a \cdot \text{Trans}_{i,t-1} + \mathbf{b} \cdot \text{Bond Controls}_{i,t-1} \\ + \mathbf{c} \cdot \text{Credit Risk Controls}_{i,t-1} + \delta_t + \text{Industry}_i + \epsilon_{i,t}.\end{aligned}$$

For each variable, its estimated coefficient with standard error in parenthesis below are reported. The final row reports the adjusted R^2 for the estimated model. The regression is run using only one bond per company in the sample. Columns (1) and (2) shows the results without controls. Columns (3) and (4) the control variables are included. The variables are described in Section 4 and the data set in Section 4.4. Each model is estimated using firm- and time fixed effects. We follow Petersen (2009) and calculate robust standard errors clustered at the *bond level* and *time dimension*.

	Liq				Liq Risk			
	1	2	3	4				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trans	0.082***	0.092***	0.060**	0.071***	−0.091***	−0.069***	−0.063***	−0.044**
	(0.026)	(0.028)	(0.026)	(0.026)	(0.025)	(0.025)	(0.022)	(0.022)
Trans:dumCr		−0.038		−0.043		−0.085		−0.078*
		(0.049)		(0.048)		(0.053)		(0.046)
IC			0.001	0.001			0.003	0.003
			(0.002)	(0.002)			(0.002)	(0.002)
IS			0.006	−0.011			−0.281	−0.311
			(0.197)	(0.194)			(0.264)	(0.261)
DA			−0.166	−0.181			0.769**	0.745**
			(0.383)	(0.385)			(0.319)	(0.310)
NIA			2.051***	2.103***			−1.047	−0.940
			(0.534)	(0.527)			(0.767)	(0.693)
BM			−0.263***	−0.265***			0.381***	0.377***
			(0.065)	(0.065)			(0.075)	(0.073)
log(vola)			−0.010	−0.010			0.013	0.013
			(0.011)	(0.011)			(0.011)	(0.011)
Observations	12,265	12,265	12,265	12,265	10,717	10,717	10,717	10,717
Adjusted R^2	0.627	0.627	0.629	0.630	0.602	0.603	0.606	0.607

Note: *p<0.1; **p<0.05; ***p<0.01

Pricing the Location of Commercial Properties

Roland Füss* Wei Lin†

Abstract

We use an asset pricing model based on net present value to study the locational risk factors of private commercial properties. To accomplish this, we extend the approach of Korteweg and Nagel (2016) into a pricing setting where the objective is to minimize the pricing errors by a thorough examination of factors. We thus propose a framework that allows for joint consideration of various definitions of location. This framework also enables the construction of portfolios based upon ad hoc measures, a novel feature that mimics the pricing routines in the conventional time-series approach. Our results suggest that the stock market model works well compared to models including a physical-distance-based location factor and established stock market risk factors.

Keywords: *Commercial real estate*; *cash flow*; *asset pricing*; *location*; *risk factors*; *GMM*; *NPV*; *clustering.*
JEL Classification: ***G12*, *R32*, *C14***

Acknowledgements: We benefit from discussions with and comments from Gabriel Ahlfeldt, Kola Akinsomi, Maximilian von Ehrlich, Karl Frauendorfer, Roland Füss, Jeremy Gabe, Patrick Gagliardini, Tim Kronecke, Stephen Penman, Stefan Ruenzi, Daniel Ruf, Paul Söderlind, Michael Weber, and the participants of the 1st IRES Doctoral Syposium and the European Real Estate 25th Annual Conference.

*Swiss Institute of Banking and Finance (s/bf), University of St.Gallen, Unterer Graben 21, CH-9000 St. Gallen, Switzerland, Phone: +41 (0)71 224 7055, E-mail: roland.fuess@unisg.ch.
†University of St.Gallen, Phone: +41 (0) 76 445 6107, E-mail: wei.lin@unisg.ch.

1 Introduction and Motivation

"Location, location, location". Being the mantra in selection of property investments and oftentimes an important consideration in theoretical models[1], location as a risk factor has more potential than it is currently explored in empirical asset pricing of commercial real estate (CRE). Hence as a testing example of our pricing framework we choose to explore the potential of location measures as risk factors. Location has been defined differently in different settings. One direction is to distinguish social, economic, and political boundaries, yielding MSAs, parishes, and voting districts for instance. Kiel and Zabel (2008) define location as geographic clusters, narrowing from MSA to township to streets. Another is physical-distance-based definition, Clapp *et al.* (2002) follow the literature and pinpoint locations via the use of proximity to amenities and distance to points of interest. While we reckon that location is a multi-dimensional construct and should be examined with a more holistic approach, we focus on a physical-distance-based location measure to showcase our proposed pricing framework. However, we note that our pricing framework allows for joint consideration of various definitions of location, enabling future research to examine which components of locational variables - on both the macro- and micro-level- are priced in commercial properties.

To price individual commercial real estate investment payoffs, we adopt a cash-flow-based GMM asset pricing model that is proposed by Korteweg and Nagel (2016). Their *Generalized Public Market Equivalent* (GPME) methodology contain two attractive aspects from the data perspective for pricing commercial real estate investments. First, the use of cash flows allows us to circumvent potential limitations of appraisal-based returns in evaluating the performance of commercial property investments. Aggregated appraised-based index returns, used in several studies to analyze the pricing implications for real estate, could be subject to appraisal-based biases, aggregation issues, and measurement errors. Second, the framework allows for risk-adjustment of a portfolio of investments that feature infrequently observed cash flows and multiple overlapping holding periods. Third, the GPME provides statistical inference under cross-sectional dependence for investments with the above characteristics.

While what Korteweg and Nagel (2016) have in mind is performance evaluation, our inter-

[1]The central place theory hypothesizes a center that provides service to a certain area, where a given location could be defined by proximity to this center. The bid rent theory considers the relationship of location rent and the distance to such a center, thus motivating the distance-to-CBD measure. The location theory of production activities considered by Beckmann and Thisse (1987) treats the households as fixed and analyzes how firms choose their location. Under the location theory, the underlying spatial distribution of households is vital to the firms' choices. In addition to these theories, in practice we also seem to consider more thoroughly regarding surrounding amenities such as infrastructure than a simple measure such as the distance to the center. To adjust the risk for commercial real estate and to assess the location premium is thus particularly important for institutional investors and their investment decisions.

est lies in the determination of prices. This seemingly subtle but vital distinction with respect to the context has the ramification that we cannot simply apply the GPME in our context. The reason is that as more factors are added, the GPME would construct corresponding mimicking portfolios to match the added factors, thus changing the number of moment conditions on the left-hand-side to be minimized. That is, simply adding more factors into the GPME does not result in comparable pricing errors due to that the minimization task is now carried out amongst different sets of equations. To further illustrate on this important aspect. Korteweg and Nagel (2016) (KN) develop the GPME methodology in a performance evaluation context, where the left-hand-side (LHS) changes along with each additional variable added to the right-hand-side (RHS). To put this into perspective, Fama and French (1996) would have 25 portfolios on the LHS and they remain the same portfolios. In contrast, the context KN have in mind would have 3 portfolios or assets on the LHS if we deal with 3 factors, and 25 portfolios or assets would require 25 factors. To take one step further, these equally-sized clustered portfolios also serve some similar purposes as the FF-25 portfolios in that they should hold fix the things to be priced, hence allowing the test of different models on the same portfolios. To draw an analogy to the pricing exercise as in Fama and French (1996) is that the number of firms (cross-section) in each portfolio vary across time, while each portfolio has the same length of time. In terms of the moment function the t is the same, thus allowing computation of the sample average. Since the KN method is built upon the net-present-value idea, the time dimension could vary for each investment. Hence in our extension we instead hold the number of cross-section fixed and allow the time to vary.

Our contribution to the literature is threefold. First, we contribute to the asset pricing literature on cash flow based and net-present-value based approaches. We extend the GPME developed by Korteweg and Nagel (2016) from a performance comparison context where assets are not held fixed into a standard asset pricing context where assets are held fixed so results from the pricing factor models can be compared to see whether such models have been improved, thus drawing this novel method closer to the extant pricing literature. Our efforts put this methodology to fit into the standard asset pricing literature, in particular by our providing a pricing framework applicable to infrequently traded assets such as real estate or private equity. That is, our framework enables the testing of myriad factors developed in the asset pricing literature from the Fama and French (1993) factors, the Pástor and Stambaugh (2003) liquidity factor, to any recent addition to the factor zoo such as the price-to-cost margin factor as in D'Acunto *et al.* (2018).

Second, we contribute to the literature on pricing private commercial real estate by applying to this asset class an extension of the GPME method by Korteweg and Nagel (2016) in a private equity context that shares important characteristics of infrequently traded assets. Several papers have focused on macroeconomic risk and established stock market factors to

evaluate real estate index returns. Naranjo and Ling (1997) employ a multi-factor time series model for appraisal-based NCREIF index data sorted by geographic region and property type. They identify economic factors driving private commercial real estate returns, such as growth rate in real per capital consumption, the real T-bill rate, the term structure of interest rates and unexpected inflation. Ling and Naranjo (1999) explicitly test the exposure of private commercial real estate to the national stock market. Similarly, Ghysels *et al.* (2007) and Plazzi *et al.* (2010) study the time series variation of expected commercial real estate returns among MSAs in the U.S. given macroeconomic fundamentals. Exploiting the present discounted value approach, they use the capitalization rate as a predictor for future rent growth and expected returns. Peng (2016) applies a cross-sectional pricing model to estimate the loadings of individual property returns over their holding periods on the established stock market risk, the Fama and French (1993) factors, and the Pástor and Stambaugh (2003) liquidity factor. In comparison to the literature, our proposed pricing framework has two key features. On one hand, it enables the use of cash flows that are more accurately measured than appraisals, which can also be applied in other contexts such as private equity. On the other hand, it enables the evaluation and construction of real-estate specific risk factors.

Third, we contribute to the understanding of location in real estate markets. Location has been an important consideration in the extant literature. Pivo and Fisher (2011) find the increased walkability contribute to higher price premiums for office, retail, and apartment buildings while Ling *et al.* (2018) considers how REIT returns vary across MSA. Hayunga and Pace (2010) study how spatial distances down to the zip-code level influence portfolio returns of direct CRE property investments. We contribute to this literature by proposing a novel method to price properties and focusing on the use of location as a pricing factor for commercial real estate. Several other papers acknowledge the exposure of individual properties to aggregated macroeconomic fluctuations. For instance, Plazzi *et al.* (2008) link the cross-sectional dispersion of commercial real estate returns to macroeconomic fundamentals. Tuzel and Zhang (2017) compute an industry-weighted beta factor for each MSA to show that firms' production factors, i.e., wages, capital, and real estate, are exposed to this location-driven beta. In contrast, we analyze the relevance of the micro-level location value for the pricing of commercial real estate at the property level[2].

The remainder of this paper is organized as follows. Section 2 presents the cash-flow-based pricing approach that comprises the key methodological component of our pricing framework. Section 3 details our pricing framework. Section 4 describes our data. Section 5 documents our empirical results. Section 6 concludes.

[2]The property level is analogous to firm's individual project investments in the sense that the properties are held by institutional investors such as pension funds.

2 Methodology and Research Design

2.1 An cash-flow-based approach: the GPME and its extension into a pricing context

We extend into a pricing context the GPME methodology of Korteweg and Nagel (2016) that measures investment performance based on net present value (NPV). Our framework allows for risk-adjustment and provides a statistical test on the pricing errors. Our choice of methodology results from that commercial property payoffs, like other infrequently traded assets, are irregularly spaced, skewed, and endogenously timed. This presents major challenges to a spatial regression approach or a linear factor model that typically rely on strong distributional assumptions and appraisal values in the real estate context. The GPME method instead enables us to address these challenges by utilizing cash flows directly. Specifically, the GPME offers three attractive properties that suit the characteristics of private commercial property payoffs. First, it avoids the strong distributional assumption required by estimation methods such as OLS and maximum likelihood. Second, it preserves the compounding properties of the stochastic discount factor (SDF) through the specification of an exponentially affine SDF and thus wards off the potential specification errors in the linearized versions of the SDF. Third, it accounts for the cross-sectional correlation of the payoffs by using a spectral density matrix that treats the degree of overlap as a measure of distance, significantly reducing the severe over-rejection problem of the J-test.

The GPME uses an exponentially affine SDF and employs a generalized method of moments (GMM) estimator to estimate the SDF parameters. The baseline approach uses an SDF of the form

$$M_{t+1} = \exp(a - b \cdot f_{t+1}). \tag{1}$$

The time t value of an asset that pays out an expected cash flow C_{t+1} and has a continuation value V_{t+1} at time $t+1$, V_t, is the expected value of the sum of these two components discounted with an SDF, M_{t+1}:

$$V_t = E_t \left[M_{t+1} \cdot (C_{t+1} + V_{t+1}) \right]. \tag{2}$$

Dividing both sides of Eq.(2) by V_t yields the pricing relation, that is, under the null hypothesis of no abnormal performance, the present value of a one-dollar investment should equal one dollar:

$$1 = E_t \left[M_{t+1} \cdot R_{t+1} \right]. \tag{3}$$

For commercial real estate, the cash flows might occur at irregularly spaced points in

time due to changes in leases. Similarly, the timing of both acquisition and sales events of the held properties is irregular. The exponentially affine SDF suits this multi-period nature of commercial property payoffs because the pricing relation of Eq.(3) still holds for longer horizons:

$$1 = E_t \left[M_{t+h} \cdot R_{t+h} \right], \tag{4}$$

where M_{t+h}, the multi-period SDF from t to $t+h$, compounds the single-period SDF as shown in Eq.(1), is:

$$M_{t+h}^{h} \equiv \Pi_{i=1}^{h} M_{t+i} \tag{5}$$

$$= \exp(a \cdot h - b \cdot f_{t+h}^{h}), \tag{6}$$

$$where \quad f_{t+h}^{h} \equiv \Sigma_{i=1}^{h} f_{t+i} \tag{7}$$

To estimate the SDF parameters and conduct statistical inference with a J-test on zero pricing error, we follow the same GMM estimation approach used by Korteweg and Nagel (2016). The key elements are summarized as follows. Let θ denote the parameters of the SDF, its estimate $\hat{\theta}$ is:

$$\hat{\theta} = arg \min_{\theta} \left(\frac{1}{N} \Sigma_i u_i(\theta) \right)' W \left(\frac{1}{N} \Sigma_i u_i(\theta) \right), \tag{8}$$

$$where \quad u_i(\theta) \equiv \Sigma_{j=1}^{J} M_{t+h(j)}^{h(j)}(\theta) \cdot Y_{i,t+h(j)},$$

$$and \quad Y_{i,t+h(j)} \equiv \begin{pmatrix} C_{i,t+h(j)} \\ C_{if,t+h(j)} \\ C_{iM,t+h(j)} \end{pmatrix}.$$

The $C_{.,.}$'s are cash flows that are normalized by the initial investment amount reflecting the NPV approach. We use the $Y_{.,.}$ to put all cash flows into a vector. The above example is a one-factor model containing cash flows from the property investments, from investments into a risk-free asset, and from investments into the market portfolio.

Under the assumption that the SDF correctly prices the assets, the realized pricing errors are only correlated when they are measured over overlapping time windows. The degree of overlap is treated as a measure of distance in analogy to spatial GMM methods Conley (1999). To ensure that the spectral density matrix is positive semi-definite, Bartlett-type weights that decline with greater distance is applied.[3]

[3]For robustness tests there are two important parameters to show explicitly. One is the fund-life along with the typical distribution pattern of a property investment fund. We draw from the actual data as

2.2 Our extended-GPME

While what Korteweg and Nagel (2016) (KN) have in mind is performance evaluation, our interest lies in the determination of prices. This seemingly subtle but vital distinction with respect to the context has the ramification that we cannot simply apply the GPME in our context. The reason is that as more factors are added, the GPME would construct corresponding mimicking portfolios to match the added factors, thus changing the number of moment conditions on the left-hand-side to be minimized. That is, simply adding more factors into the GPME does not result in comparable pricing errors due to that the minimization task is now carried out amongst different sets of equations. To further illustrate on this important aspect. The KN paper developed in a performance evaluation context, where the left-hand-side (LHS) changes along with each additional variable added to the right-hand-side (RHS). To put this into perspective, Fama and French (1996) would have 25 portfolios on the LHS and they remain the same portfolios. In contrast, the context KN have in mind would have 3 portfolios or assets on the LHS if we deal with 3 factors, and 25 portfolios or assets would require 25 factors. To take one step further, these equally-sized clustered portfolios also serve some similar purposes as the FF-25 portfolios in that they should hold fix the things to be priced, hence allowing the test of different models on the same portfolios. To draw an analogy to the pricing exercise as in Fama and French (1996) is that the number of firms (cross-section) in each portfolio vary across time, while each portfolio has the same length of time. In terms of the moment function the t is the same, thus allowing computation of the sample average. Since the KN method is built upon the net-present-value idea, the time dimension could vary for each investment. Hence in our pricing context we instead hold the number of cross-section fixed and allow the time to vary.

To extend the GPME into a pricing context, we thus need to construct portfolios - more specifically, groups of properties - to maintain a fixed set of moment conditions that are evaluated. Unlike a portfolio of stocks that result in a time-series of returns in the traditional setting, the NPV approach dictates that in each portfolio or group we need to have the same number of individual properties, each of which would contribute a moment condition according to Eq. 4. A further clarification on our application of the GMM estimation is appropriate here. In the time-series regression setting, the time dimension has to be the same for each portfolio while the cross-section or the number of individual stocks included can vary. However, in the NPV setting as in our paper, the cross-section has to be of the same length while the time dimension can vary. Then we can take the average of these moment conditions from each of the group or portfolio, regardless of time instead of cross-section, to jointly minimize. Therefore, what we need is to cluster individual properties by some criteria and form groups that are equally-sized.

in the descriptive statistics to choose the fund-life at 7 years or 28 quarters. Another is the distance parameter of 1.5 in the Bartlett-type weight.

That is, each group contains the same number of properties. [4]

To illustrate formally and put the above in perspective, the key aspect of our extension lies in altering the moment conditions so as to enable a fixed set of assets or portfolios, which in turn allows for a comparison of different pricing models. In a standard time-series setting the unconditional moment restrictions (UMR) look like the following,

$$0 = E\left[g(X_{t+1};\theta_0)\right], \tag{9}$$

$$\begin{aligned} where \quad g(X_{t+1};\theta_0) &= Z_t \prod h(Y_{t+1};\theta_0), \\ where \quad h(Y_{t+1};\theta_0) &= M_{t,t+1}(\theta) * R_{t+1} - \tau, \end{aligned}$$

where τ represents a vector of 1s. It is then easy to find the empirical analog of the UMR the sample average,

$$\frac{1}{T} * \Sigma_{t=1}^{T} g(X_t;\theta) \tilde{=} 0, \tag{10}$$

where X_t represents the portfolios to be priced, e.g. the FF-25 portfolios, and θ include the parameters to be estimated. This estimation is typically over-identified and generally has no exact solutions. Hence the estimates are obtained by minimizing the sum of squared errors by having the Ω matrix to weight across equations as in Eq. (8):

$$\left[\frac{1}{T} * \Sigma_{t=1}^{T} g(X_t;\theta)\right]' \Omega \left[\frac{1}{T} * \Sigma_{t=1}^{T} g(X_t;\theta)\right],$$

With the standard case in mind and in comparison, our extension of KN's GPME - an NPV analog to the time-series setting by instead holding fixed the cross-section and allowing the time-dimension to vary - has the moment conditions whose sample average that looks like the following,

$$\frac{1}{N} * \Sigma_{i=1}^{N} g(X_i;\theta) \tilde{=} 0, \tag{11}$$

[4]For instance, our results are based upon clustering by physical distance, that is, by the closeness indicated by the latitude and longitude between properties. While our focus is on extending the GPME into a pricing framework, future research in this vein could also form clusters by other measures (e.g. size or income-price ratio), varying the number of clusters and the number of properties therein, and imposing contiguity constraints.

where X_i represents the portfolios to be priced, e.g. a portfolio of commercial properties like offices, and include all the cash flows from all periods of the investment. θ are the parameters to be estimated. This estimation stems from, as the standard case, the UMR in the NPV setting,

$$0 = E\left[g(X_i;\theta_0)\right], \tag{12}$$

$$\begin{aligned} where \quad & g(X_i;\theta_0) = Z_i \prod h(Y_i;\theta_0), \\ where \quad & h(Y_i;\theta_0) = \Sigma_{h=1}^{J} M_{t+h}(\theta) * C_{t+h} - \tau, \end{aligned}$$

where h is the number of periods of cash flows from the infrequently traded assets. Here τ also represents a vector of 1s but serves to set the net NPV governed by $\Sigma_{h=1}^{J} M_{t+h}(\theta) * C_{t+h} - \tau$ equal to 0 through normalizing the initial investments to 1 as in KN.

In sum, despite that in appearance our extension seemingly resembles Eq. (8) from KN's GPME, the key and critical difference is that the moment conditions contain very different drivers. In KN, the moment conditions include mimicking portfolios which hence change along with any additional factor into the pricing model, a desirable feature that is essential in the performance evaluation context. As for our extension, the moment conditions contain only the cash flows of assets to be priced, hence they do not change with the pricing model, which is a must-have in the pricing context to enable model comparison.

3 Pricing Framework

Our pricing framework consist of two main steps. First, we construct risk factors or obtain portfolio excess returns of interest. Then we apply the extended-GPME to investigate the risk premia of these factors and compare different model specifications.

A key component in our approach is to allow for the use of location risk factors and potentially other CRE-specific risk factors. We can summarize our approach to obtain factors or portfolio (excess) returns for CRE as follows. First, we find all repeated transactions. Second, we estimate the location values following Clapp *et al.* (2002) and compute other measures such as the book-to-market values. Third, we sort properties by the characteristics in the second step. Fourth, following Clapp and Giaccotto (1998) we determine the threshold percentile (e.g. 75th and 25th) values for the sorted properties from the previous step and use such values as our hedonic variables in the hedonic repeated-measures (HRM) model to obtain price indices. We can thus see whether the sorted portfolios have different price paths and decide whether the

respective characteristic is a feasible way to construct a risk factor. The returns along different price paths can then be used to compute excess returns across the percentiles.

Section 3.1 illustrates how we estimate the time-varying location value. Section 3.2 introduces the HRM to explain how we construct real-estate specific factors or obtain returns on the portfolios, which we employ in our factor models along with the factors from the established literature.

3.1 Estimating Location Value

The main idea in our first step of location risk factor construction is to separate out the value of location from the information available. To construct our location risk factor, we employ geocode information following Clapp *et al.* (2002) to parsimoniously extract the location values. Our rationale is as follows. First, this approach allows us to have time-varying locational values across different time frequencies. On the contrary, computing distances to points of interest could render the values of locations constant over time simply because most points of interest, for instance metro and bus stops, do not move much across even a time period of decades. Second, while the large neighborhood literature has identified various locational determinants of property prices[5], our interest is in the location risk premium that calls for aggregation of various determinants. However, many such determinants are difficult to measure and thus often unavailable. To aggregate them would incur further challenges such as spatial heterogeneity in the sense that the weightings of the determinants might differ across regions. Therefore, for the purpose of relative pricing we would prefer a parsimonious measure of location values.

Following Clapp *et al.* (2002), we estimate for each time t for properties within a city:

$$\ln\left(price_i\right) = X_{hedonics,i} \cdot \beta_h + \varepsilon_i, \tag{13}$$

where $\varepsilon_i = f(W_i) + \xi_i$. The $f(W_i)$ term includes first- and second-order polynomials in latitude and longitude, respectively.[6]

While Clapp and Wang (2006) group individual houses into homogenous neighborhoods by their location values, in the CRE context the following considerations lead us to conclude that we should skip this step for our construction of portfolios by location values. Unlike in

[5]For instance, access to subway, air quality, crime rates, and noise levels are all found to influence property prices.

[6]The inclusion of a physical location vector into the standard hedonic equation is important both theoretically and empirically. As Clapp and Wang (2006) point out, to omit the $f(W_i)$ term is equivalent to imposing the hypothesis that location values are constant across a city. Thus not surprisingly, the empirical results in forming neighborhood boundaries change significantly. Such theoretical and empirical relevance directly motivates us to use geocode information at the property level.

the housing market where properties are grouped into contiguous neighborhoods before being combined into submarkets, in the CRE setting we should just form submarkets by combining the properties directly. That is, to form submarkets in the housing market we should combine class-A neighborhoods but in the CRE market class-A properties. Our motivation is two-fold. First, the CRE market is much less liquid than the housing market and thus we might only have a few data points in an area at a given point in time.

Based on the above arguments, we skip the step of combing individual properties into neighborhoods as Clapp and Wang (2006) do. Instead, we sort directly commercial properties by their location values and calculate portfolio returns using price indices generated by the hedonic repeated-measures model. This approach allows us to calculate our (unattractive minus attractive, or UMA) location risk factor.

3.2 Factor Construction by Estimating Portfolio Returns

To construct real-estate specific factors or obtain returns on our sorted portfolios, we resort to the hedonic repeated-measures (HRM) approach proposed by Clapp and Giaccotto (1998). The HRM offers two attractive properties compared to the repeat-sales regression (RSR) without hedonics.[7] First, the added hedonic variables allow the price paths to vary with respect to these variables. This is very convenient and efficient for our purposes of obtaining portfolio returns since we can obtain different indices by characteristics or sorted portfolios directly with the HRM rather than estimate returns on each portfolio separately. That is, the risk factors of location value, size, and book-to-market ratio (BM) can all serve as inputs of characteristics once we assign a percentile to each property. Second, it allows for changes in explicitly modelled characteristics whereas the RSR without hedonics would require the researcher to find pairs of transactions that do not show changes in characteristics. This is important for the CRE market as we expect that since commercial properties are only re-sold so infrequently their characteristics are likely to change across such long period of time. The HRM also thus admits a larger sample size and reduces the sample selection bias of the RSR.

To introduce the HRM, we start with an equation aimed to estimate implicit prices of hedonic characteristics:

$$p_{it} = F_t + \alpha_t^{'} S_{it} + \beta_t^{'} L_{it} + \Sigma_{j=1}^{n_t} \delta_{jt} D_j + \varepsilon_{it}, \tag{14}$$

where $p_i t$ is the natural logarithm of the transaction price for the i-th property sold at time t, $S_i t$ and $L_i t$ are column vectors of structural and location characteristics for the subject

[7] Clapp and Giaccotto (1998) show that the indices of HRM converges to those of Bailey *et al.* (1963), who formalize the RSR, when the hedonic characteristics are evaluated at their averages in the HRM.

property, while $\alpha_t^{'}$ and $\beta_t^{'}$ are row vectors of implicit prices at time t for the elements in S_it and L_it respectively, D_j is a house-specific dummy variable that can be seen as unmeasured characteristics such as maintenance quality and where $D_j = 1$ for the j-th property and zero otherwise, and n_t is the number of properties sold during time period t.

For properties with repeated sales at time t_1 and t_2, the difference in log prices $r_i = p_{it_2} - p_{it_1}$ is thus:

$$\begin{aligned} r_i = F_{t_2} - F_{t_1} + \alpha_{t_2}^{'} S_{it_2} - \alpha_{t_1}^{'} S_{it_1} + \beta_{t_2}^{'} L_{it_2} - \beta_{t_1}^{'} L_{it_1} + \\ \delta_{it_2} - \delta_{it_1} + \varepsilon_{it_2} - \varepsilon_{it_1}. \end{aligned} \tag{15}$$

In order to distinguish the region-wide price change $F_{t_2} - F_{t_1}$ from the change in unmeasured characteristics $\delta_{it_2} - \delta_{it_1}$, we would assume that the latter be constant over time[8] and use Qt_i^* to write the + and – pairs in a compact and general way:

$$\begin{aligned} r_i = \alpha_0^{'}(Q0_i^* S_{i0}) + \cdots + \alpha_T^{'}(QT_i^* S_{iT}) + \beta_0^{*'}(Q0_i^* L_{i0}) + \beta_1^{'}(Q1_i^* L_{i1}) \\ + \cdots + \beta_T^{'}(QT_i^* L_{iT}) + C_1 Q1_i^* + \cdots + C_T QT_i^* + \varepsilon_i^*, \end{aligned} \tag{16}$$

where Qt_i^* is $+1$ for the time of the second sale, is -1 for the time of the first sale, and is 0 otherwise; $\varepsilon_i^* = \varepsilon_{it_2}^* - \varepsilon_{it_1}^*$.

Hence we will test our location risk factor constructed by the above method against established stock market risk factors. Motivated by the established asset pricing literature, we start with a simple CAPM, include risk factors following Fama and French (1993), and then our CRE-specific location risk factor. [9]

[8] If δ_{it} does change over time, then we would not be able to distinguish the change from F_t. However, for our purpose of estimating the returns on sorted portfolios, we only need to use α_t and β_t.

[9] The investigation of risk premia is an avenue that we leave to future research endeavour as our paper focuses on developing a pricing framework befitting infrequently traded assets such as real estate. However, we provide a glance on how one might gauge the risk premia or to test whether the risk factors are economically sensible in the context of an exponentially-affine SDF. While in a linearized version of the SDF one can use the FMB (by Fama and MacBeth (1973)) cross-sectional regression to find a conventional risk premium λ, in the exponentially affine version of the SDF, to our best knowledge, one can only resort to the following general form to gauge the risk premium.

$$E\left[R_{t+1}\right] - R_f = -R_f * Cov(R_{t+1}, M_{t+1}), \tag{17}$$

where one uses sample analogues on the right hand side for the estimation. The economic intuition prescribes two outcomes: a pro-cyclical asset such as a commercial property should have a positive risk premium and that the size of the risk premium should be reasonable. One can also use the time-series average of the SDF to see whether the estimates are reasonable:

$$E\left[M_{t+1} * R_{t+1}\right] = 1, \tag{18}$$

4 Data Description

We use un-levered property investment data provided by the National Council of Real Estate Investment Fiduciaries (NCREIF) that contains a large sample of US private commercial property cash flows between 1978 and the first quarter of 2019. The data contributing members of the NCREIF database are institutional real estate investment managers, institutional investors, academics, and professional businesses that provide services to institutional investors - public accountants, pension real estate consultants, and appraisers. In the commercial real estate markets, institutional investors accounted for about 10% of all private commercial real estate equity Ling and Archer (2012) and about 20% of all acquisitions of commercial properties that sold for greater than $5 million over the 2001-2006 period Fisher *et al.* (2009). The original quarterly data contains various features, but we would require the following variables in our analysis: market values (appraisal or transaction prices), income (as cash flows), address (we use google map API to acquire the corresponding geo-code information, that is, latitude and longitude), MSA code, zip code, age, and net rentable area (NRA).[10]

Table 1 reports the number of properties by time.

[Table 1 about here]

Figure 1 illustrates the geographic distribution of the number of properties aggregated across time.

[Figure 1 about here]

Table 2 reports the number of properties by holding periods in the full dataset (upon removing outliers) to guide the choice of property-life used in the GPME.

[Table 2 about here]

---

when one has a risk-free return which should typically be close to 1, then

$$E\left[M_{t+1}\right] = \frac{1}{R_f} \approx 1, \tag{19}$$

That is, the time-series averages of the SDF estimates should be close to 1 if they are economically reasonable.

[10]The structural variables age and NRA allow us to control for the influences of property structure in our construction of the portfolio returns with the HRM. The geo-code information is indispensable for us to evaluate the potential attractiveness of a given location for different uses of properties. Cash flow data are essential to the GPME methodology.

Table 3 reports the mean and standard deviation on property attributes and prices by time. That is, net rentable area and age that are employed in the LRM as well as market value that indicates the size of properties in our dataset.

[Table 3 about here]

5 Empirical Results

While we present our results in a logistical order for consistency of the previous presentation, we note that for economic interpretation our results can be considered in the following by order of interest. We are mostly interested in the pricing errors, then the excess returns of the various portfolios from the HRM, then the estimated location values of the LRM. The large cross-section compared to the time-series of our data results in too much over-lapping that hinders the direct application of our pricing framework at a nation-wide level. (Since the GPME provides good small-sample property in T), we thus run our pricing exercises on individual MSA levels. This also allows us to see whether different regions contain varying risk-premia or are exposed to the risk factors differently.

5.1 Location Value Estimations

Since we use log-price in the LRM as in (13), the location values we obtain from the model are not price levels, that is, to convert back into prices we have

$$\begin{aligned} Price_i &= \exp(X_{hedonics,i} \cdot \beta_h + \varepsilon_i) \\ &= \exp(X_{hedonics,i} \cdot \beta_h) \cdot \exp(\varepsilon_i), \end{aligned} \tag{20}$$

where we might interpret the location values (exponentiated) as multipliers about the hedonics. That is, the location influences on the price of a property in the sense that it magnifies around the structural characteristics of a property. For instance, building a log cabin versus a modernist concrete duplex on the land might fetch radically different prices. Further, that the LRM back-fits an intercept indistinguishable from 0 allows for a better economic interpretation of the model. Namely, the price of a property would consist only of the structure and the location - when there is no structure nor location the price would be 0.

Table 4 provides one cross-sectional example from 2018 Q4 of the results from the LRM.

[Table 4 about here]

We can thus also look at how location value estimates distribute across geographic regions (by zip code), both in absolute terms (exponentiated to be deemed as multipliers as in Eq. (20) and as percentages of the prices (in logarithms as in Eq. (13). Figures in 2 show the above, respectively.

[Figure 2 about here]

5.2 Real Estate Portfolio Returns from the HRM

Table 5 reports the estimated coefficients of the HRM as in (16) where the variables are $\ln(NRA)$, Age, and the estimated location values from the LRM.

[Table 5 about here]

Table 6 reports the annual returns of the constructed portfolios along with the Fama-French SMB and HML factors following the format of Table XI in Fama and French (1996).

5.3 Equal-size clustering outcome

To enable the GMM estimation of our NPV-based approach in the pricing context, we form 10 clusters consisting each of 1000 properties regardless of time. Figure 3 displays the clustering outcomes of our algorithm that assigns our final dataset comprising 10,000 properties into 10 equally-sized clusters, each of which contains 1000 properties. It can be seen that some properties could deviate quite far away from its clustered centroid (yellow dots for instance) since we have yet to impose any contiguity constraint in the current algorithm. While such constraint would certainly improve on the reasonableness of our clustering algorithm, as long as the deviations are not too drastic on an aggregate level, it should not pose a fundamental problem to our investigation. In particular, this clustering algorithm can be used to cluster by neighborhood or other non-physical measures such as economic prosperity. Our motivation to cluster by physical distance - the most straightforward useage - is to test the validity of our pricing framework. As explained in the previous sections, we would attempt to cluster properties using other measures for robustness.

[Figure 3 about here]

5.4 GPME estimates: CAPM

We follow the classic asset pricing literature and start with the pricing errors or abnormal returns of sorting based upon characteristics. That is, whether the capital asset pricing model

(CAPM) could explain the cross-section of returns on commercial property. A common sort in the CRE literature is based upon MSA.[11] Therefore, we use the CAPM with the stock market to test whether there are cross-sectional differences that remain unexplained.

We start with the performance evaluation context as in Korteweg and Nagel (2016) to empirically corroborate our line of reasoning regarding our equally-sized clusters that do not follow the traditional MSA-clusters. Table 6 reports the abnormal returns using the GPME with the CAPM across the MSAs that contain at least 10 properties.

[Table 6 about here]

Since in the long table the pattern of the average excess return is difficult to observe, we plot the pricing errors onto the map as in figure 4:

[Figure 4 about here]

We note that the abnormal performance should be interpreted as an NPV value under the GPME performance valuation framework. That is, a positive 0.3 GPME would represent a 30% higher return accumulated across the whole sample period rather than a single quarter. While the above figure shows that there might be patterns of abnormal returns from the CAPM associated with the MSA sort, that pattern is not uniform from a geographic point of view. That is, while in some coastal areas the pricing errors are large, other areas along the coast can also exhibit small pricing errors. Therefore, this adds to our intuition that the MSA sorts, while being able to motivate a multi-factor model from the CAPM, are not so intuitive in the sense of showing a pattern of average excess returns compared to sorts such as the size and the BE/ME in the stock market literature. Hence, we believe that this exercise serves as evidence to validate our non-MSA clustering.

5.5 GPME estimates: multi-factor

Table 8 reports our empirical results utilizing our pricing framework with successive factor addition. These results are mixed in the sense that our HRM-constructed asset-specific factors, while reducing pricing errors upon the FF-3 factor model, do not pose a monotonic picture. However, considering the size of the errors, it might be due to that they are too small to be

[11] A natural question, having the stock market sorting in mind, would be what the MSA sorting represents. Since an MSA is defined by common economic linkage within certain geographical proximity, an intuition is that this is a sorting criteria both on the economic environment and on the geographic proximity. While the MSA sorts are common practice, we think that perhaps a sorting on a specific and explicit variable that could capture the MSA sorts would be more intuitive in contemplating an economic story.

distinguishable. This would point us to conduct robustness tests such as building more clusters or change the clustering measure, along to check whether there might be room to improve on our optimization algorithm for the non-linear GMM estimation.

6 Conclusion

We propose a pricing framework that uses cash flows and enables asset-specific risk factors of commercial properties. Specifically, We adopt a pricing framework that builds upon net present value to circumvent the appraisal problems in such markets, extending the Korteweg and Nagel (2016) approach to a context of price determination. We also showcase this framework through a pricing exercise of private commercial property investments using our own location risk factors. To estimate time-varying physical-distance-based location values we resort to a parsimonious method and then estimate portfolio excess returns with an approach befitting the characteristics of property investments.

Our empirical results show that a one-factor stock market model works rather well for commercial property pricing in comparison to multi-factor models including the factors of Fama and French (1996) and a physical-distance-based location risk factor. This provides some hints on location's usefulness considered as a risk factor, and points to further efforts to exploit the other aspects of locational definitions.

References

Bailey, M. J., Muth, R. F. and Nourse, H. O. (1963). A regression method for real estate price index construction. *Journal of the American Statistical Association*, **58** (304), 933–942.

Beckmann, M. J. and Thisse, J.-F. (1987). The location of production activities. In *Handbook of Regional and Urban Economics*, Elsevier, pp. 21–95.

Clapp, J. M. and Giaccotto, C. (1998). Price indices based on the hedonic repeat-sales method: Application to the housing market. *The Journal of Real Estate Finance and Economics*, **16** (1), 5–26.

—, Kim, H.-J. and Gelfand, A. E. (2002). Predicting spatial patterns of house prices using LPR and bayesian smoothing. *Real Estate Economics*, **30** (4), 505–532.

— and Wang, Y. (2006). Defining neighborhood boundaries: Are census tracts obsolete? *Journal of Urban Economics*, **59** (2), 259–284.

Conley, T. (1999). GMM estimation with cross sectional dependence. *Journal of Econometrics*, **92** (1), 1–45.

D'Acunto, F., Liu, R., Pflueger, C. and Weber, M. (2018). Flexible prices and leverage. *Journal of Financial Economics*, **129** (1), 46–68.

Fama and French (1996). Multifactor explanations of asset pricing anomalies. *The Journal of Finance*, **51** (1), 55–84.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, **33** (1), 3–56.

— and MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, **81** (3), 607–636.

Fisher, J., Ling, D. C. and Naranjo, A. (2009). Institutional capital flows and return dynamics in private commercial real estate markets. *Real Estate Economics*, **37** (1), 85–116.

Ghysels, E., Plazzi, A. and Valkanov, R. (2007). Valuation in US commercial real estate. *European Financial Management*, **13** (3), 472–497.

Hayunga, D. K. and Pace, R. K. (2010). Spatial statistics applied to commercial real estate. *The Journal of Real Estate Finance and Economics*, **41** (2), 103–125.

Kiel, K. A. and Zabel, J. E. (2008). Location, location, location: The 3l approach to house price determination. *Journal of Housing Economics*, **17** (2), 175–190.

Korteweg, A. and Nagel, S. (2016). Risk-adjusting the returns to venture capital. *The Journal of Finance*, **71** (3), 1437–1470.

Ling, D. and Archer, W. (2012). *Real estate principles: a value approach*. McGraw-Hill Higher Education.

Ling, D. C. and Naranjo, A. (1999). The integration of commercial real estate markets and stock markets. *Real Estate Economics*, **27** (3), 483–515.

—, — and Scheick, B. (2018). Asset location, timing ability and the cross-section of commercial real estate returns. *Real Estate Economics*, **47** (1), 263–313.

Naranjo, A. and Ling, D. C. (1997). Economic risk factors and commercial real estate returns. *The Journal of Real Estate Finance and Economics*, **14** (3), 283–307.

Pástor, Ľ. and Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, **111** (3), 642–685.

Peng, L. (2016). The risk and return of commercial real estate: A property level analysis. *Real Estate Economics*, **44** (3), 555–583.

Pivo, G. and Fisher, J. D. (2011). The walkability premium in commercial real estate investments. *Real Estate Economics*, **39** (2), 185–219.

Plazzi, A., Torous, W. and Valkanov, R. (2008). The cross-sectional dispersion of commercial real estate returns and rent growth: Time variation and economic fluctuations. *Real Estate Economics*, **36** (3), 403–439.

—, — and — (2010). Expected returns and expected growth in rents of commercial real estate. *Review of Financial Studies*, **23** (9), 3469–3519.

Tuzel, S. and Zhang, M. B. (2017). Local risk, local factors, and asset prices. *The Journal of Finance*, **72** (1), 325–370.

Table 1: Summary Statistics: Number of Properties by Time

This table reports descriptive statistics for the NCREIF property data upon filters, which comprises U.S. commercial properties from NCREIF in the periods 1997:3 to 2019:1. Panel A reports the number of properties in each year-quarter, which is relevant for the LRM analysis where we run cross-sectionally quarter by quarter. Panel B reports the number of properties that start in each year-quarter. Panel C reports the number of properties that end in each year-quarter. Both panels A and B help to gauge the overlaps of the property investments.

YYYYQ	Nr.Prop	YYYYQ	Nr.Prop	YYYYQ	Nr.Prop	YYYYQ	Nr.Prop
Panel A: number of properties by year-quarter							
1997 Q3	1263	2003 Q1	2757	2008 Q3	4364	2014 Q1	6259
1997 Q4	1299	2003 Q2	3023	2008 Q4	4456	2014 Q2	6342
1998 Q1	1381	2003 Q3	2904	2009 Q1	4547	2014 Q3	6481
1998 Q2	1410	2003 Q4	2847	2009 Q2	4621	2014 Q4	6372
1998 Q3	1471	2004 Q1	3050	2009 Q3	4660	2015 Q1	6474
1998 Q4	1432	2004 Q2	2984	2009 Q4	4682	2015 Q2	6458
1999 Q1	1481	2004 Q3	3095	2010 Q1	4702	2015 Q3	6399
1999 Q2	1489	2004 Q4	2998	2010 Q2	4771	2015 Q4	6375
1999 Q3	1560	2005 Q1	3100	2010 Q3	4742	2016 Q1	6476
1999 Q4	1440	2005 Q2	3189	2010 Q4	5006	2016 Q2	6574
2000 Q1	1516	2005 Q3	3263	2011 Q1	5172	2016 Q3	6558
2000 Q2	1768	2005 Q4	3285	2011 Q2	5413	2016 Q4	6539
2000 Q3	1797	2006 Q1	3360	2011 Q3	5692	2017 Q1	6740
2000 Q4	1835	2006 Q2	3425	2011 Q4	5823	2017 Q2	6604
2001 Q1	1835	2006 Q3	3538	2012 Q1	6068	2017 Q3	6478
2001 Q2	1949	2006 Q4	3656	2012 Q2	6172	2017 Q4	6359
2001 Q3	2178	2007 Q1	3940	2012 Q3	6135	2018 Q1	6248
2001 Q4	2406	2007 Q2	3884	2012 Q4	6092	2018 Q2	6129
2002 Q1	2475	2007 Q3	3995	2013 Q1	6120	2018 Q3	6154
2002 Q2	2710	2007 Q4	4137	2013 Q2	6110	2018 Q4	6028
2002 Q3	2530	2008 Q1	4184	2013 Q3	6098	2019 Q1	5970
2002 Q4	2513	2008 Q2	4304	2013 Q4	6139		NA
Panel B: number of properties by starting date							
1997 Q3	1263	2003 Q1	237	2008 Q3	104	2014 Q1	269
1997 Q4	128	2003 Q2	438	2008 Q4	134	2014 Q2	244
1998 Q1	140	2003 Q3	112	2009 Q1	100	2014 Q3	315
1998 Q2	105	2003 Q4	64	2009 Q2	109	2014 Q4	204
1998 Q3	62	2004 Q1	153	2009 Q3	120	2015 Q1	214
1998 Q4	74	2004 Q2	77	2009 Q4	101	2015 Q2	163
1999 Q1	82	2004 Q3	137	2010 Q1	46	2015 Q3	150
1999 Q2	70	2004 Q4	114	2010 Q2	146	2015 Q4	167
1999 Q3	103	2005 Q1	179	2010 Q3	44	2016 Q1	283
1999 Q4	67	2005 Q2	329	2010 Q4	302	2016 Q2	260
2000 Q1	165	2005 Q3	224	2011 Q1	212	2016 Q3	197
2000 Q2	201	2005 Q4	194	2011 Q2	263	2016 Q4	201
2000 Q3	91	2006 Q1	181	2011 Q3	240	2017 Q1	380
2000 Q4	99	2006 Q2	197	2011 Q4	235	2017 Q2	111
2001 Q1	124	2006 Q3	155	2012 Q1	325	2017 Q3	21
2001 Q2	153	2006 Q4	207	2012 Q2	180	2017 Q4	12
2001 Q3	317	2007 Q1	349	2012 Q3	146	2018 Q1	7
2001 Q4	198	2007 Q2	145	2012 Q4	162	2018 Q2	2
2002 Q1	97	2007 Q3	196	2013 Q1	167	2018 Q3	12
2002 Q2	310	2007 Q4	207	2013 Q2	132	2018 Q4	8
2002 Q3	90	2008 Q1	323	2013 Q3	131	2019 Q1	3
2002 Q4	51	2008 Q2	176	2013 Q4	284		NA

Table 1 continues.

YYYYQ	Nr.Prop	YYYYQ	Nr.Prop	YYYYQ	Nr.Prop	YYYYQ	Nr.Prop
Panel C: number of properties by ending date							
1997 Q3	74	2003 Q1	122	2008 Q3	28	2014 Q1	161
1997 Q4	48	2003 Q2	124	2008 Q4	15	2014 Q2	191
1998 Q1	41	2003 Q3	89	2009 Q1	48	2014 Q3	285
1998 Q2	35	2003 Q4	104	2009 Q2	65	2014 Q4	146
1998 Q3	77	2004 Q1	129	2009 Q3	64	2015 Q1	184
1998 Q4	41	2004 Q2	78	2009 Q4	27	2015 Q2	211
1999 Q1	74	2004 Q3	198	2010 Q1	46	2015 Q3	200
1999 Q2	42	2004 Q4	77	2010 Q2	68	2015 Q4	168
1999 Q3	70	2005 Q1	232	2010 Q3	56	2016 Q1	158
1999 Q4	41	2005 Q2	166	2010 Q4	52	2016 Q2	219
2000 Q1	56	2005 Q3	172	2011 Q1	51	2016 Q3	227
2000 Q2	37	2005 Q4	81	2011 Q2	83	2016 Q4	111
2000 Q3	82	2006 Q1	104	2011 Q3	99	2017 Q1	138
2000 Q4	97	2006 Q2	66	2011 Q4	82	2017 Q2	225
2001 Q1	52	2006 Q3	101	2012 Q1	80	2017 Q3	132
2001 Q2	73	2006 Q4	89	2012 Q2	181	2017 Q4	121
2001 Q3	69	2007 Q1	142	2012 Q3	204	2018 Q1	122
2001 Q4	45	2007 Q2	100	2012 Q4	126	2018 Q2	94
2002 Q1	75	2007 Q3	96	2013 Q1	154	2018 Q3	144
2002 Q2	82	2007 Q4	142	2013 Q2	143	2018 Q4	69
2002 Q3	126	2008 Q1	49	2013 Q3	249	2019 Q1	5970
2002 Q4	103	2008 Q2	53	2013 Q4	139		NA

Table 2: Summary Statistics: Number of Properties by Holding Period

This table reports descriptive statistics for the NCREIF property data upon filters, which comprises U.S. commercial properties from NCREIF in the periods 1997:3 to 2019:1. Panel A reports the number of properties by holding period, that is, the number of quarters a property is held before disposition.

Quarters.Held	Nr.Prop	Quarters.Held	Nr.Prop	Quarters.Held	Nr.Prop	Quarters.Held	Nr.Prop
0	118	22	288	44	160	66	36
1	101	23	266	45	113	67	36
2	103	24	286	46	91	68	25
3	118	25	253	47	93	69	31
4	147	26	192	48	135	70	47
5	111	27	274	49	92	71	23
6	386	28	288	50	76	72	17
7	543	29	205	51	60	73	12
8	865	30	179	52	73	74	9
9	588	31	277	53	77	75	27
10	555	32	188	54	143	76	25
11	624	33	201	55	157	77	13
12	669	34	70	56	142	78	16
13	510	35	188	57	29	79	14
14	521	36	74	58	46	80	13
15	434	37	159	59	35	81	5
16	417	38	109	60	72	82	6
17	422	39	120	61	23	83	11
18	540	40	90	62	39	84	10
19	434	41	95	63	88	85	11
20	428	42	80	64	74	86	48
21	411	43	98	65	12	NA	NA

Table 3: Summary Statistics: Property Attributes and Prices

YYYYQ	meanMV	sdMV	meanNRA	sdNRA	meanAge	sdAge
1997 Q3	24	35	313	424	36	10
1997 Q4	26	40	274	311	36	10
1998 Q1	27	43	296	333	36	10
1998 Q2	27	42	265	295	36	10
1998 Q3	27	44	268	308	36	10
1998 Q4	27	45	291	361	36	10
1999 Q1	28	45	264	307	35	11
1999 Q2	29	45	272	310	35	11
1999 Q3	29	45	275	334	35	11
1999 Q4	31	48	273	328	35	11
2000 Q1	30	48	277	328	34	11
2000 Q2	30	45	270	328	34	11
2000 Q3	30	45	270	329	34	11
2000 Q4	29	41	268	306	33	12
2001 Q1	30	42	266	301	33	12
2001 Q2	32	44	276	308	33	12
2001 Q3	35	51	284	349	33	13
2001 Q4	34	50	283	362	33	13
2002 Q1	34	50	290	364	33	13
2002 Q2	33	51	279	352	33	13
2002 Q3	33	51	279	359	33	13
2002 Q4	34	54	279	357	33	13
2003 Q1	33	53	281	348	32	13
2003 Q2	31	50	268	333	32	12
2003 Q3	31	52	266	332	32	12
2003 Q4	32	55	266	331	32	12
2004 Q1	32	54	267	324	32	13
2004 Q2	32	54	263	306	31	13
2004 Q3	33	55	261	304	31	13
2004 Q4	34	58	254	296	31	13
2005 Q1	34	54	254	305	31	13
2005 Q2	35	62	255	303	30	13
2005 Q3	37	65	247	295	30	13
2005 Q4	39	70	244	293	30	13
2006 Q1	39	71	245	293	30	14
2006 Q2	40	72	252	313	30	14
2006 Q3	42	73	246	289	30	14
2006 Q4	43	78	247	289	30	14
2007 Q1	45	79	244	276	30	14
2007 Q2	46	84	244	280	30	15
2007 Q3	48	87	244	281	30	15
2007 Q4	48	92	243	274	29	16
2008 Q1	47	90	244	265	29	15

Table 3: Summary Statistics: Property Attributes and Prices

2008 Q2	47	89	244	266	29	15
2008 Q3	46	89	247	285	29	15
2008 Q4	42	80	247	282	29	15
2009 Q1	40	75	244	263	29	15
2009 Q2	37	71	246	271	29	15
2009 Q3	36	69	246	270	29	15
2009 Q4	35	68	248	270	29	15
2010 Q1	35	68	249	275	28	15
2010 Q2	36	71	243	269	29	16
2010 Q3	37	72	243	266	29	16
2010 Q4	38	75	236	257	29	16
2011 Q1	38	76	238	257	28	16
2011 Q2	40	80	240	260	28	16
2011 Q3	40	79	236	252	28	16
2011 Q4	42	86	235	250	28	16
2012 Q1	42	86	235	260	28	16
2012 Q2	43	88	234	261	28	16
2012 Q3	43	89	234	263	28	16
2012 Q4	45	92	236	270	28	16
2013 Q1	47	96	237	271	28	17
2013 Q2	48	98	236	264	28	17
2013 Q3	50	101	239	265	28	17
2013 Q4	52	104	241	267	28	17
2014 Q1	54	112	241	268	28	18
2014 Q2	55	115	241	267	28	18
2014 Q3	56	117	240	267	28	19
2014 Q4	60	122	244	272	28	19
2015 Q1	62	130	246	276	28	19
2015 Q2	64	134	247	286	27	19
2015 Q3	67	138	251	291	27	19
2015 Q4	68	141	251	293	27	20
2016 Q1	69	143	246	289	27	20
2016 Q2	70	144	247	293	27	20
2016 Q3	72	148	249	293	27	20
2016 Q4	74	156	250	294	27	20
2017 Q1	74	157	247	290	27	21
2017 Q2	76	161	250	296	26	21
2017 Q3	78	162	252	305	26	21
2017 Q4	79	164	251	305	26	21
2018 Q1	79	165	251	298	26	21
2018 Q2	81	167	251	300	26	21
2018 Q3	80	167	249	301	26	21
2018 Q4	81	168	251	303	26	21
2019 Q1	82	170	252	305	26	21

Table 4: Local Regression Model: base and backfitting results

	ln(Price)	
	Y	Y1_1_i
	Model 1: Base	Model 2: LRM Backfitted
	(1)	(2)
ln(NetRentableArea)	-0.056^{***}	-0.061^{***}
	(0.010)	(0.010)
ln(SquareFeet)	0.919^{***}	0.916^{***}
	(0.013)	(0.013)
Age	-0.018^{***}	-0.017^{***}
	(0.001)	(0.001)
AgeSquared	0.0003^{***}	0.0003^{***}
	(0.00001)	(0.00001)
latitude	0.070^{***}	
	(0.019)	
longitude	0.278^{***}	
	(0.009)	
latitudeSqaured	-0.001^{***}	
	(0.0003)	
longitudeSquared	0.001^{***}	
	(0.00005)	
Constant	19.402^{***}	-0.048
	(0.575)	(0.115)
Observations	7,789	7,789
Adjusted R^2	0.572	0.540
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 5: Hedonic Repeat-Sales Model: coefficients

	QT coefficient	ln(NRA) coefficient	Age coefficient	ln(LRM) coefficient
1997 Q4	0.099	−0.016	−0.003	0.018
1998 Q1	2.439	−0.097	0.001	−0.170
1998 Q2	0.888	−0.025	0.023	−0.214
1998 Q3	0.444	0.014	0.006	−0.114
1998 Q4	1.893	−0.057	0.004	−0.202
1999 Q1	1.020	0.032	−0.004	−0.184
1999 Q2	1.207	−0.034	0.009	−0.151
1999 Q3	0.642	0.004	0.012	−0.150
1999 Q4	0.103	0.027	0.011	−0.098
2000 Q1	1.418	0.034	−0.0004	−0.272
2000 Q2	2.459	−0.187	0.016	−0.061
2000 Q3	1.234	0.014	0.008	−0.243
2000 Q4	2.151	−0.121	0.004	−0.102
2001 Q1	−0.494	−0.024	0.007	0.077
2001 Q2	0.930	−0.057	0.006	−0.042
2001 Q3	1.263	−0.022	0.005	−0.158
2001 Q4	0.693	−0.049	−0.002	0.020
2002 Q1	1.380	−0.231	0.001	0.199
2002 Q2	0.737	−0.031	0.007	−0.056
2002 Q3	−0.309	−0.015	0.001	0.071
2002 Q4	2.713	−0.050	−0.005	−0.248
2003 Q1	1.678	−0.172	0.011	0.037
2003 Q2	0.250	−0.067	0.001	0.080
2003 Q3	0.620	−0.037	−0.002	−0.011
2003 Q4	0.257	−0.016	−0.001	0.005
2004 Q1	−1.630	0.006	0.009	0.218
2004 Q2	−0.204	0.037	0.005	−0.035
2004 Q3	−1.105	−0.079	0.001	0.326
2004 Q4	−0.967	−0.006	−0.004	0.196
2005 Q1	−0.700	−0.028	−0.001	0.194
2005 Q2	0.974	−0.035	0.0002	−0.054
2005 Q3	−0.137	0.015	0.009	−0.012
2005 Q4	0.903	−0.022	0.002	−0.060
2006 Q1	−0.528	−0.037	0.006	0.170
2006 Q2	0.801	−0.091	0.006	0.079
2006 Q3	−0.451	−0.067	0.006	0.221
2006 Q4	−0.021	−0.034	0.006	0.107
2007 Q1	−0.778	0.014	0.002	0.137
2007 Q2	0.115	−0.012	0.002	0.058
2007 Q3	0.141	−0.008	0.004	0.042
2007 Q4	−1.248	−0.030	0.007	0.274
2008 Q1	0.786	−0.111	0.007	0.127
2008 Q2	−1.400	−0.001	0.005	0.249

Table 5: Hedonic Repeat-Sales Model: coefficients

2008 Q3	−0.798	−0.029	0.005	0.196
2008 Q4	0.338	−0.071	0.005	0.097
2009 Q1	1.601	−0.053	−0.003	−0.087
2009 Q2	1.115	−0.084	−0.003	0.017
2009 Q3	−1.341	0.017	0.005	0.194
2009 Q4	0.622	−0.054	0.003	0.020
2010 Q1	−0.331	−0.013	0.007	0.054
2010 Q2	0.453	−0.010	0.0003	−0.032
2010 Q3	−0.839	0.111	−0.001	−0.042
2010 Q4	−1.814	0.010	0.003	0.257
2011 Q1	−2.130	0.042	0.011	0.237
2011 Q2	−0.533	−0.027	0.009	0.134
2011 Q3	−1.005	−0.011	0.005	0.178
2011 Q4	−1.068	0.003	0.005	0.170
2012 Q1	−1.060	−0.003	0.003	0.191
2012 Q2	−0.250	−0.010	0.004	0.083
2012 Q3	−1.311	0.028	0.004	0.165
2012 Q4	−1.674	0.056	0.007	0.165
2013 Q1	−0.366	0.006	0.004	0.075
2013 Q2	−1.001	0.024	0.005	0.132
2013 Q3	0.561	−0.004	0.003	−0.034
2013 Q4	−0.725	−0.031	0.004	0.200
2014 Q1	−1.249	0.030	0.003	0.173
2014 Q2	−1.770	0.078	0.006	0.156
2014 Q3	0.373	−0.012	0.002	0.002
2014 Q4	6.592	0.001	0.012	−1.049
2015 Q1	−0.314	−0.022	−0.004	0.160
2015 Q2	0.576	0.041	0.004	−0.113
2015 Q3	1.558	0.021	0.006	−0.249
2015 Q4	−3.250	0.344	0.008	−0.109
2016 Q1	−0.593	0.053	0.012	0.003
2016 Q2	−3.349	0.060	0.003	0.458
2016 Q3	−1.706	−0.069	0.007	0.425
2016 Q4	−3.535	−0.004	−0.006	0.644
2017 Q1	−0.948	−0.070	0.007	0.304
2017 Q2	−5.063	−0.038	0.005	0.923
2017 Q3	−3.808	0.047	0.005	0.498
2017 Q4	1.760	−0.067	−0.002	−0.046
2018 Q1	3.649	0.046	−0.009	−0.462
2018 Q2	3.514	0.044	0.001	−0.473
2018 Q3	−3.571	−0.014	0.005	0.585
2018 Q4	−8.993	0.123	0.003	1.118
2019 Q1	−3.274	0.013	0.004	0.517

Table 6: Annual Explanatory Returns: 1998-2018

This table reports the annual returns. Negative is the number of negative annual returns.

Year	$R_m - R_f$	SMB	HML	LRM	NRA	Age
1998	18.71	-20.07	-8.7	-7.636	-17.84	31.44
1999	19.85	13.01	-24.8	-6.386	3.75	32.59
2000	-16.86	-5.19	39.2	-8.570	-26.07	36.02
2001	-14.87	19.75	15.9	-1.710	-15.94	23.54
2002	-22.49	5.54	8.6	-0.288	-31.54	5.69
2003	30.52	20.68	3.8	1.454	-28.83	14.45
2004	10.66	4.86	7.1	9.835	-4.83	18.90
2005	3.02	-1.43	7.8	-0.075	-8.29	17.92
2006	10.24	0.42	12.5	16.942	-25.81	43.94
2007	0.99	-6.90	-13.6	17.018	-4.64	27.37
2008	-37.83	5.74	1.7	18.839	-23.64	38.51
2009	28.25	8.05	-4.3	2.512	-19.77	3.29
2010	17.37	13.12	-3.9	4.442	13.07	15.24
2011	0.41	-5.05	-8.2	14.423	0.83	64.19
2012	16.25	-0.88	8.4	10.482	9.75	33.86
2013	35.17	5.47	1.3	5.460	-0.58	31.09
2014	11.71	-7.00	-1.9	-9.859	13.34	49.73
2015	0.06	-4.09	-9.9	-4.623	66.67	29.08
2016	13.29	6.18	20.8	22.671	5.60	34.70
2017	21.39	-4.10	-11.1	31.200	-15.85	32.41
2018	-6.85	-3.32	-10.2	19.953	30.34	0.17
Mean	6.6	2.1	1.5	6.5	-3.8	27.8
s.d.	18.5	9.7	14.0	11.6	23.0	15.5
Negative	5.0	10.0	10.0	8.0	13.0	0.0

Table 7: GPME with CAPM

nameRow	colGPME	colAlpha	colBeta1
Los Angeles-Riverside-Orange County, CA	0.275	0.028	-2.734
	(0.187)	(0.015)	(0.691)
Washington-Baltimore, DC-MD-VA-WV	0.225	0.022	-2.476
	(0.303)	(0.015)	(0.745)
Chicago-Gary-Kenosha, IL-IN-WI	0.139	0.026	-2.648
	(0.325)	(0.016)	(0.722)
New York-Northern New Jersey-Long Island, NY-NJ-PA	0.137	0.037	-3.101
	(0.379)	(0.018)	(0.732)
Dallas-Fort Worth, TX	0.227	0.030	-2.786
	(0.086)	(0.016)	(0.702)
San Francisco-Oakland-San Jose, CA	0.203	0.023	-2.527
	(0.109)	(0.016)	(0.786)
Atlanta, GA	0.084	0.018	-2.220
	(0.373)	(0.012)	(0.639)
Houston-Galveston-Brazoria, TX	0.261	0.025	-2.608
	(0.110)	(0.018)	(0.863)
Seattle-Tacoma-Bremerton, WA	0.205	0.030	-2.819
	(0.075)	(0.017)	(0.742)
Boston-Worchester-Lawrence, MA-NH-ME-CT	0.116	0.024	-2.586
	(0.400)	(0.017)	(0.830)
	0.183	0.021	-2.426
	(0.186)	(0.016)	(0.792)
Denver-Boulder-Greeley, CO	0.279	0.027	-2.618
	(0.098)	(0.016)	(0.716)
Phoenix/Mesa, AZ	0.128	0.015	-2.055
	(0.327)	(0.014)	(0.780)
Austin/San Marcos, TX	0.163	0.020	-2.359
	(0.143)	(0.016)	(0.797)
San Diego, CA	0.173	0.013	-1.982
	(0.178)	(0.012)	(0.737)
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD	0.212	0.034	-2.937
	(0.139)	(0.018)	(0.738)
Minneapolis/St. Paul, MN/WI	0.123	0.014	-2.023
	(0.283)	(0.012)	(0.691)
Portland-Salem, OR-WA	0.298	0.028	-2.693
	(0.122)	(0.014)	(0.587)
Raleigh/Durham/Chapel Hill, NC	0.158	0.022	-2.462
	(0.100)	(0.015)	(0.774)
Orlando, FL	0.232	0.022	-2.440
	(0.197)	(0.018)	(0.865)
Tampa/St. Petersburg/Clearwater, FL	0.246	0.018	-2.191
	(0.120)	(0.013)	(0.658)
Charlotte/Gastonia/Rock Hill, NC/SC	0.280	0.015	-2.081

Table 7: GPME with CAPM

	(0.041)	(0.014)	(0.798)
West Palm Beach/Boca Raton, FL	0.042	0.019	-2.322
	(0.747)	(0.012)	(0.591)
Indianapolis, IN	0.273	0.008	-1.703
	(0.053)	(0.012)	(0.882)
Kansas City, MO/KS	0.163	0.025	-2.565
	(0.246)	(0.022)	(1.032)
Nashville, TN	0.478	0.028	-2.716
	(0.127)	(0.019)	(0.805)
St. Louis, MO/IL	0.308	0.017	-2.150
	(0.185)	(0.016)	(0.826)
Memphis, TN/AR/MS	0.138	0.014	-2.012
	(0.200)	(0.016)	(0.891)
Detroit-Ann Arbor-Flint, MI	0.073	0.013	-1.964
	(0.233)	(0.010)	(0.597)
Las Vegas, NV/AZ	0.013	0.034	-2.897
	(0.936)	(0.016)	(0.599)
San Antonio, TX	0.162	0.036	-3.032
	(0.249)	(0.020)	(0.812)
Sacramento-Yolo, CA	0.162	0.008	-1.646
	(0.169)	(0.012)	(0.786)
Cincinnati-Hamilton, OH-KY-IN	0.116	0.029	-2.806
	(0.351)	(0.023)	(1.058)
Richmond/Petersburg, VA	0.324	0.024	-2.506
	(0.107)	(0.018)	(0.791)
Columbus, OH	0.177	0.000	-1.018
	(0.025)	(0.007)	(0.821)
Jacksonville, FL	0.181	0.017	-2.175
	(0.287)	(0.015)	(0.742)
Greenville/Spartanburg/Anderson, SC	0.353	0.047	-3.220
	(0.107)	(0.022)	(0.724)
Salt Lake City/Ogden, UT	0.282	0.027	-2.642
	(0.071)	(0.018)	(0.761)
Louisville, KY/IN	0.237	0.015	-2.167
	(0.024)	(0.015)	(0.876)
Hartford, CT	0.432	0.014	-2.000
	(0.089)	(0.016)	(0.884)
Reno, NV	0.367	0.017	-2.265
	(0.046)	(0.016)	(0.868)
Harrisburg/Lebanon/Carlisle, PA	-0.023	0.054	-4.137
	(0.856)	(0.023)	(1.027)
Milwaukee-Racine, WI	0.193	0.017	-2.182
	(0.045)	(0.016)	(0.854)
Pittsburgh, PA	0.619	0.002	-1.222
	(0.062)	(0.012)	(1.071)

Table 7: GPME with CAPM

Stockton/Lodi, CA	0.202	0.052	-3.548
	(0.417)	(0.025)	(0.838)
Norfolk/Virginia Beach/Newport News, VA/NC	0.358	0.030	-2.731
	(0.202)	(0.016)	(0.658)
Greensboro/Winston-Salem/High Point, NC	0.097	0.021	-2.387
	(0.429)	(0.018)	(0.819)
Fort Myers/Cape Coral, FL	0.201	0.040	-3.146
	(0.602)	(0.020)	(0.741)
Charleston/North Charleston, SC	0.097	0.014	-2.038
	(0.517)	(0.022)	(1.137)
Knoxville, TN	0.214	0.094	-4.915
	(0.120)	(0.033)	(0.965)
Cleveland-Akron, OH	-0.026	0.013	-1.917
	(0.788)	(0.014)	(0.785)
Tucson, AZ	0.074	0.021	-2.391
	(0.393)	(0.026)	(1.321)
Birmingham, AL	-0.003	0.021	-2.425
	(0.981)	(0.029)	(1.398)
Honolulu, HI	0.360	0.007	-1.664
	(0.008)	(0.015)	(1.161)
Naples, FL	0.108	-0.003	-0.320
	(0.771)	(0.001)	(0.802)
Santa Barbara/Santa Maria/Lompoc, CA	0.298	0.025	-2.737
	(0.001)	(0.027)	(1.328)
Colorado Springs, CO	0.077	0.008	-1.625
	(0.334)	(0.008)	(0.540)
Allentown/Bethlehem/Easton, PA	0.266	0.026	-2.590
	(0.077)	(0.023)	(1.020)
Columbia, SC	0.048	0.052	-3.436
	(0.634)	(0.027)	(0.810)
New Orleans, LA	0.121	0.020	-2.291
	(0.136)	(0.011)	(0.526)
Fort Pierce/Port St. Lucie, FL	-0.008	0.000	-0.986
	(0.963)	(0.007)	(0.803)
Melbourne/Titusville/Palm Bay, FL	-0.030	0.007	-1.573
	(0.805)	(0.011)	(0.708)
Oklahoma City, OK	0.233	0.008	-1.660
	(0.129)	(0.021)	(1.363)
Eugene/Springfield, OR	-0.087	0.080	-5.153
	(0.106)	(0.025)	(0.987)
Albany/Schenectady/Troy, NY	0.095	-0.001	-0.867
	(0.224)	(0.004)	(0.642)
Albuquerque, NM	0.197	0.000	-0.974
	(0.082)	(0.009)	(0.793)
El Paso, TX	0.279	0.039	-2.962

Table 7: GPME with CAPM

	(0.151)	(0.024)	(0.827)
Omaha, NE/IA	0.139	0.006	-1.487
	(0.092)	(0.008)	(0.593)
Lakeland/Winter Haven, FL	-0.195	0.014	-2.064
	(0.000)	(0.014)	(0.732)
Providence/Fall River/Warwick, RI/MA	0.100	0.037	-2.951
	(0.382)	(0.016)	(0.588)

Table 8: extended GPME pricing errors: multifactor models

The table reports the pricing errors with multi-factor models using clusters by physical distance. The row names are the additionally added factor, for example, the second row reports the results of having both Mkt and SMB in the model. Mkt, SMB, HML are the CRSP returns, small-minus-big returns, and high-minus-low returns as in Fama and French (1996), while NRA, Age, LRM are the portfolio excess returns constructed using the HRM of Clapp and Giaccotto (1998) as the spreads between the 25th and 75th percentiles.

	Physical distance clusters
Mkt	0.0032
SMB	0.0016
HML	0.0047
NRA	0.0040
Age	0.0027
LRM	0.0041

Figure 1: Aggregated number of properties across US

The figure shows the spatial distribution of the total number of properties aggregated over time.

Aggregated number of properties across US

Number of properties aggregated across time

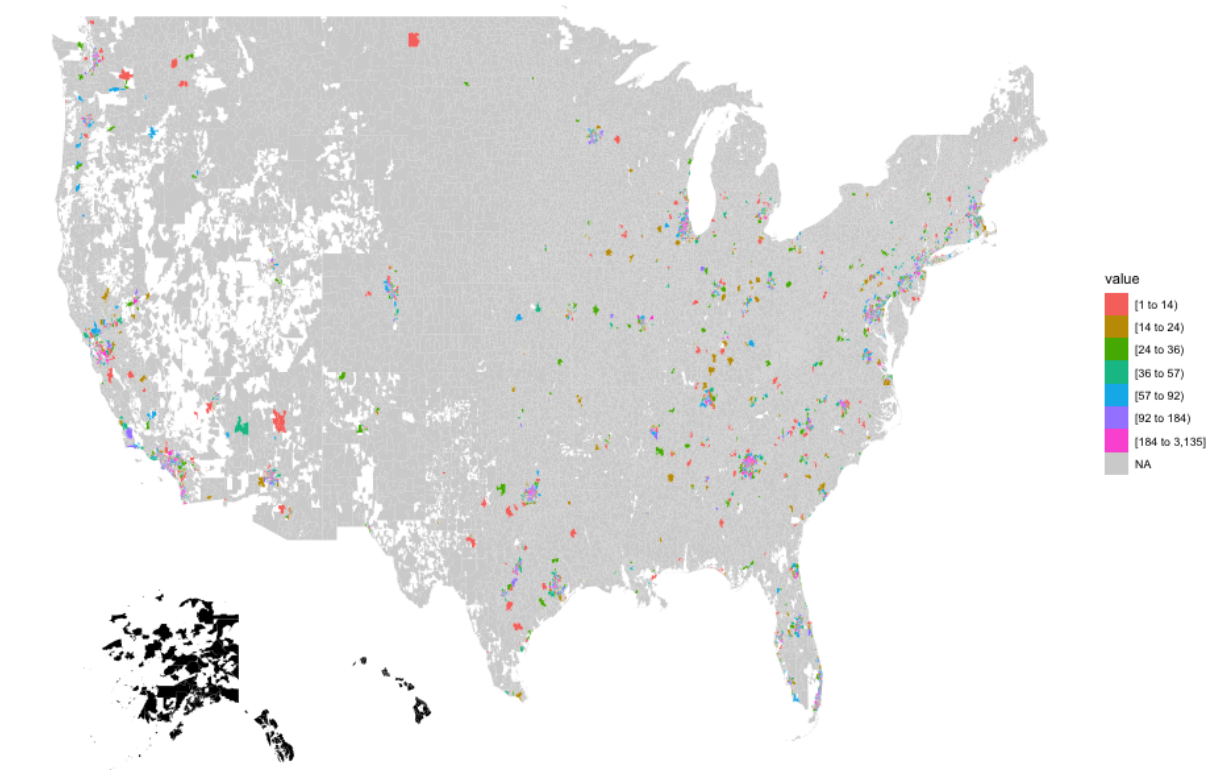
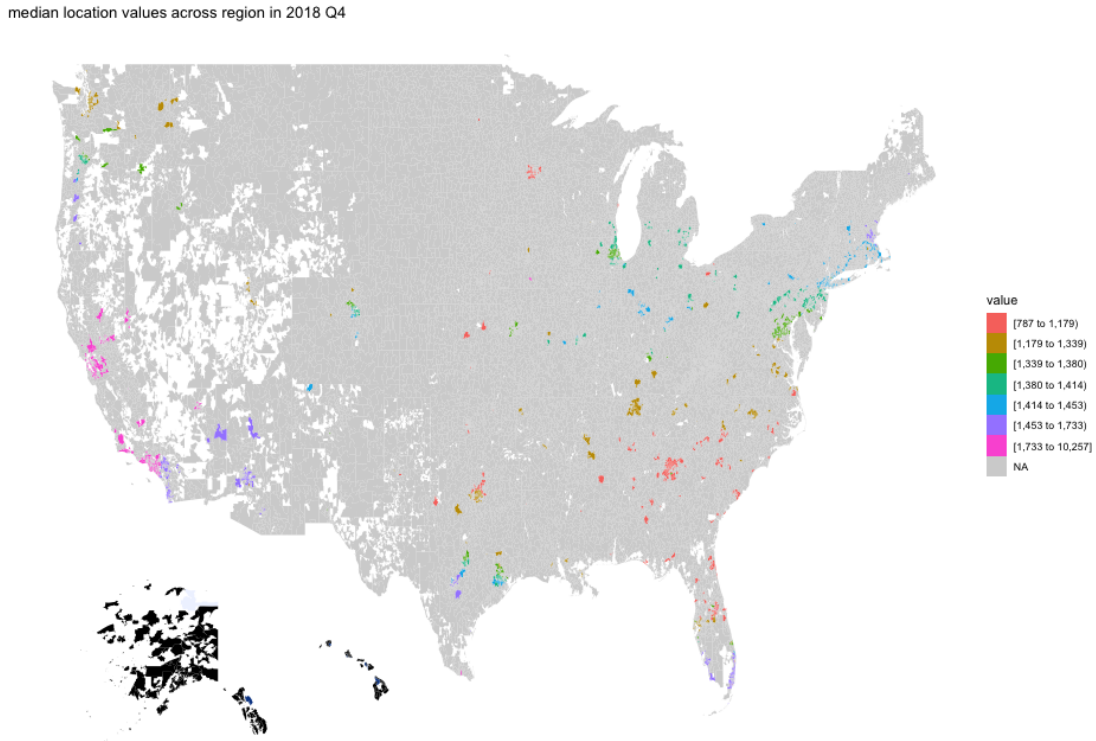


Figure 2: Median location values across region in 2018 Q4

Figure (a) shows the median of location value estimates while figure (b) shows the median of location value estimates as percentage of prices, both by zip-coded regions in the US in 2018 Q4.

(a) Median location values across region in 2018 Q4



(b) Median location values as percentage of prices across region in 2018 Q4

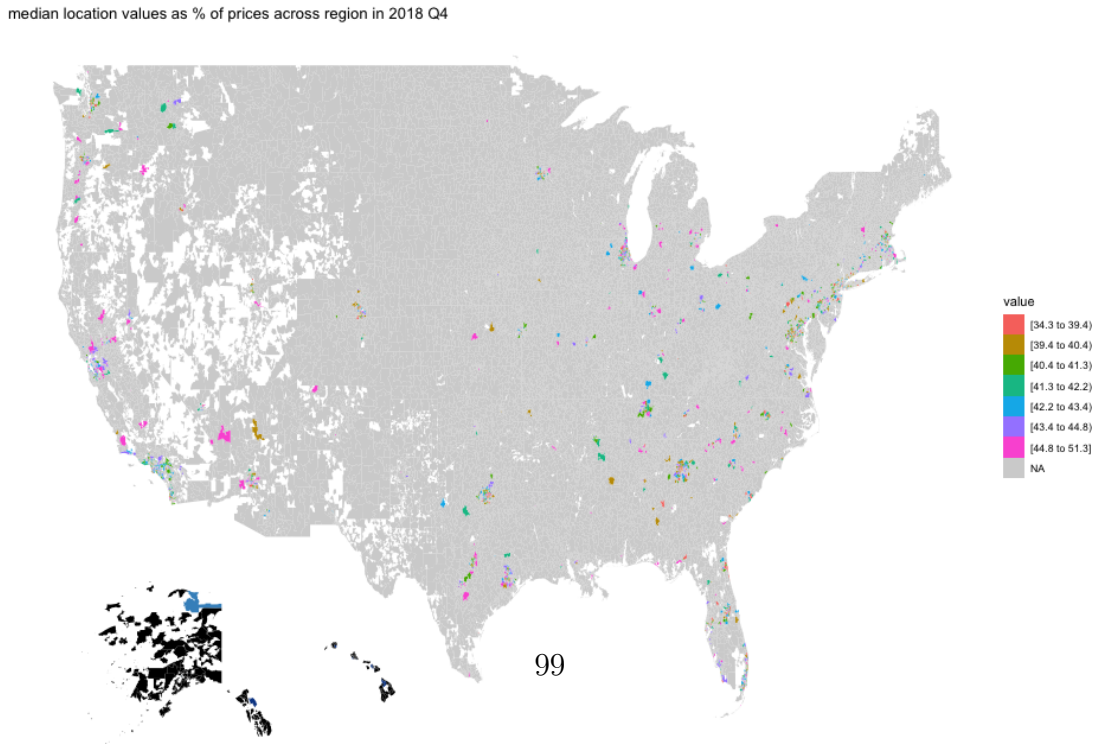


Figure 3: Equally-sized clusters with respective centroids

The figure displays the centroids of the clusters that are equal in size, constructed to enable the GMM estimation under our NPV approach.

Equally-sized clusters with respective centroids

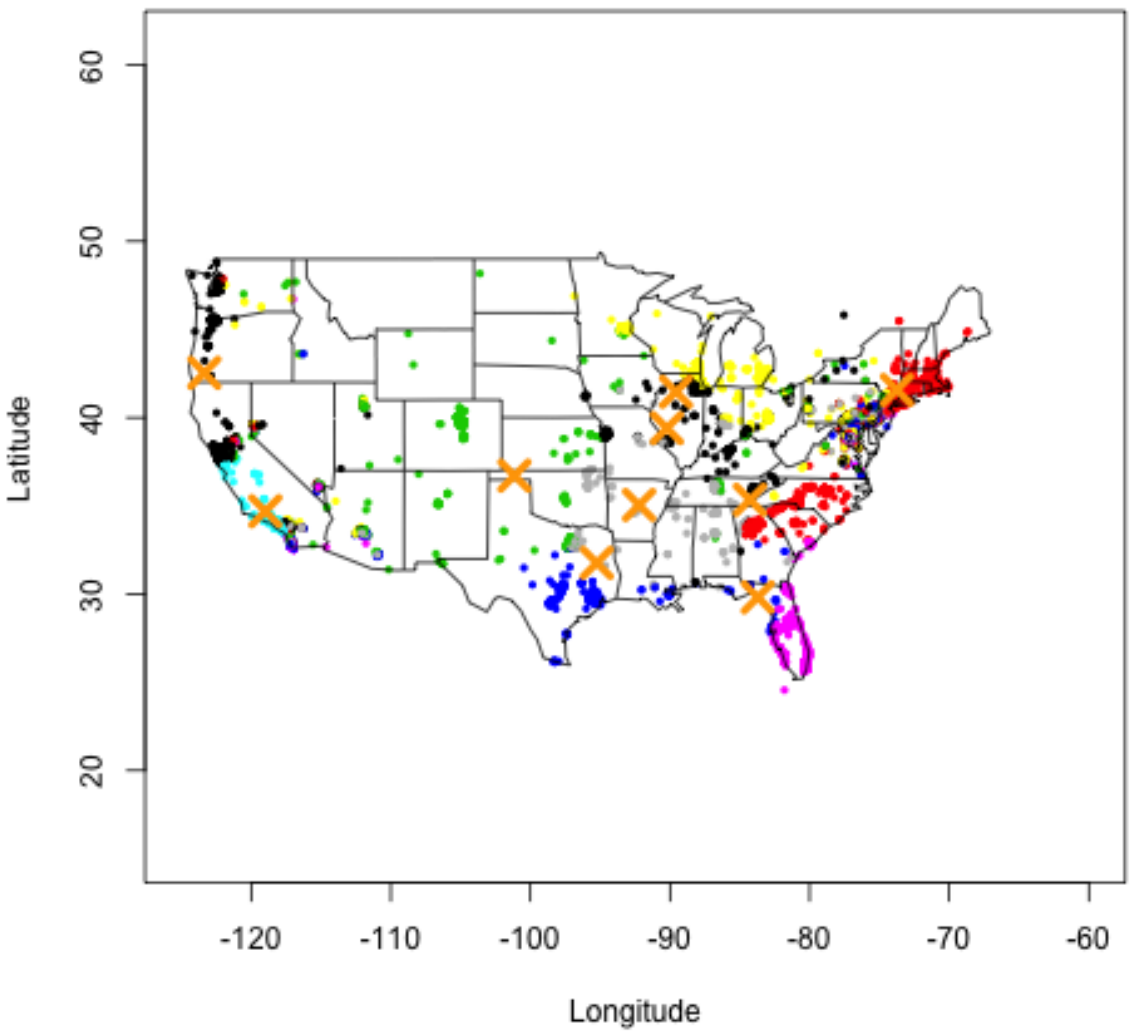
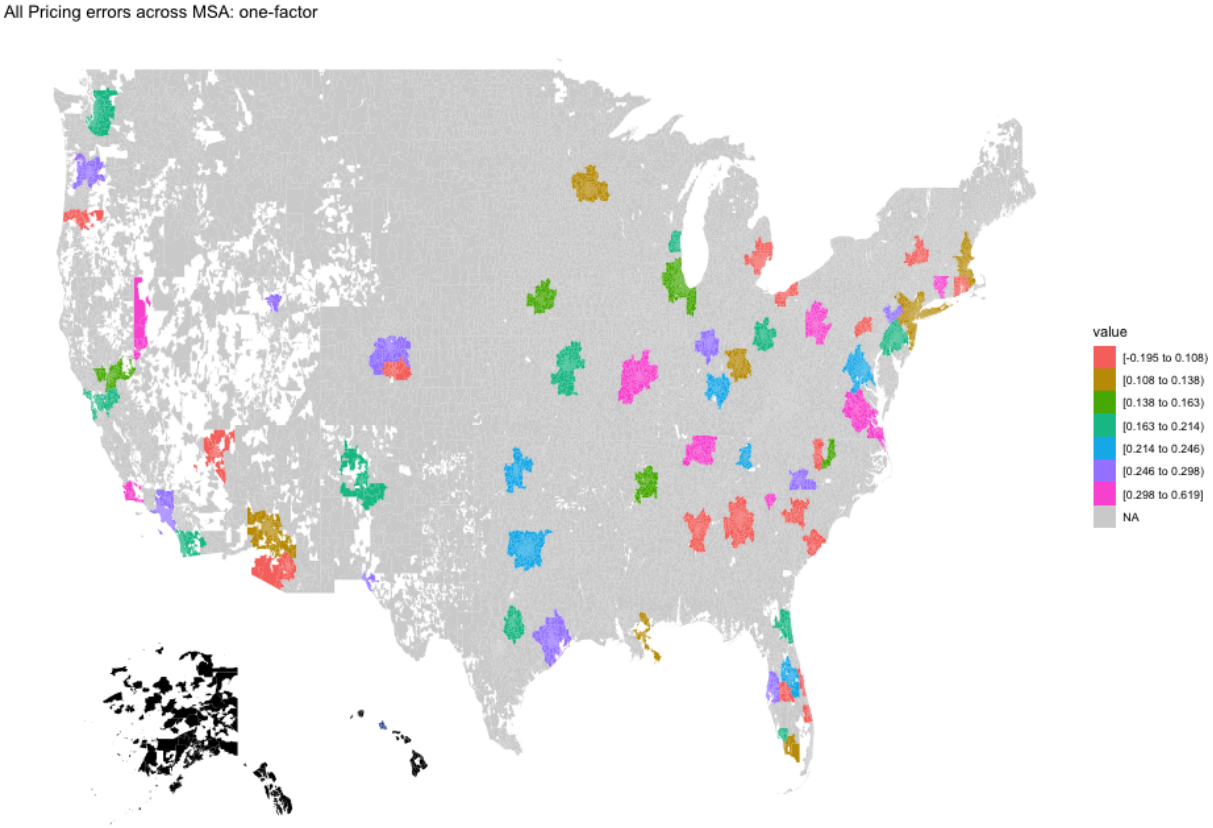


Figure 4: All Pricing errors across MSA: CAPM using the GPME

The figure shows the geographic distribution of the pricing errors with the CAPM using the GPME.

All Pricing errors across MSA: CAPM using the GPME



Do Investor Protection Laws Benefit Investors? Evidence from a Natural Experiment on Cross-listed Firms *

Wei Lin†

Abstract

Corporate governance in emerging economies centers around principal-principal conflicts that stem from concentrated ownership. We exploit a natural experiment setting where legislators in China revise the Securities Law aiming at improved minority shareholder protection. Specifically, we employ a propensity-score-matched (PSM) difference-in-differences (DiD) design. To implement this, we first match firms that are cross-listed in mainland China and Hong Kong to peer firms listed in Hong Kong by firm size, industry, board size, and board independence. Then we investigate the outcomes concerning the treated firms that are subject to the revised law compared to the control firms. First, we find that independent directors in cross-listed firms turn over significantly more. Second, the newly appointed to replace the resigned directors tend to be younger and include more female. We argue that these two findings suggest firms have taken the opportunity to appoint directors more befitting to the new environment, bringing in long turn benefits. Third, we find no evidence of significant changes in board independence in the short run. Combined with the first two findings, we argue that our evidence provides reconciliation on the arguments advanced by the finance and the strategy literature on the effects of strengthened institutions in that strengthened shareholder-friendly corporate governance at the firm level and symbolic adoption of certain governance practices could take place jointly.

Keywords: Corporate Governance, Legal Reforms, Principal-Principal Conflicts, Independent Director, Cross-Listed Firms, Emerging Economy, China.
JEL classification: G34, K40, P26.

*We thank Marc Arnold, Martin Brown, Karl Frauendorfer, Roland Füss, Marcin Kacperczyk, Nikos Kavadis, Jonathan Karpoff, Alberto Manconi, Felix von Meyerinck, Clemens Müller, Adair Morse, Christopher Polk, Zacharias Sautner, Paul Söderlind, Tereza Tykvova, Cong Wang, and participants at the Academy of International Business (AIB) Annual Meeting 2022, the International Corporate Governance Society (ICGS) Conferene 2021, and the PiF seminar at the University of St. Gallen for valuable comments and helpful suggestions.

†University of St.Gallen, Unterer Graben 21, CH-9000 St. Gallen, E-mail: wei.lin@unisg.ch

1 Introduction

The classic agency theory centers on the principal-agency (P-A) conflicts between corporate managers and shareholders (Eisenhardt (1989)). Such conflicts result from the separation between ownership and control (Jensen and Meckling (1976); Fama and Jensen (1983)). In line with this theoretical perspective, traditional corporate governance mechanisms such as board of directors, performance-related and equity-based incentives (Lin and Chuang (2011)) are designed to reduce agency costs derived from managerial opportunism and information asymmetry (Jensen and Meckling (1976); Eisenhardt (1989)). Emerging economies, however, have lower levels of market efficiency and ownership dispersion compared to where agency theory was first developed (Firth *et al.* (2016)). In such economies, the most pronounced corporate governance issues are the principal-principal (P-P) conflicts between controlling shareholders and minority shareholders (Shleifer and Vishny (1997); Young *et al.* (2008)).

Three notable aspects distinguish emerging economies from more advanced ones. First, formal institutions that protect investors' property rights tend to be weak, incomplete, or missing in emerging economies (Young *et al.* (2008); Hou and Moore (2010); Lin and Chuang (2011); Zhang *et al.* (2014); Huyghebaert and Wang (2012)). Further, the law enforcement typically varies substantially from one region to another despite a uniform legal framework being in place in these economies (Jiang *et al.* (2010)). Second, a typical publicly listed firm in an emerging economy adopts a concentrated ownership structure (Firth *et al.* (2016)). Its controlling shareholder can easily exploit the wealth of minority shareholders by means of related-party transactions or asset transfer (Berkman *et al.* (2009); Zhang *et al.* (2014))). Third, prevalent state ownership (La Porta *et al.* (1999)) exacerbates the expropriation of minority shareholders in emerging economies. In such circumstances the states tend to use firms as a tool to pursue political and social objectives that divert resources from economic value maximization for minority shareholders (He and Rui (2016); Shan (2013)). In sum, minority shareholders are especially disadvantageous in emerging economies where ownership concentration, ineffective institutions, and pervasive state ownership coexist.

Blending the perspectives of board independence and regulatory intervention together, we study whether legislative efforts towards greater investor protection materialize as intended, and how such efforts work out by influencing the level and quality of board in-

dependence. On the one hand, despite the identified effectiveness of board independence in resolving P-P conflicts, there is a lack of enthusiasm and demand for independent directors in emerging markets. Listed firms therein rarely appoint independent directors beyond the minimum threshold of regulatory mandates (Firth *et al.* (2016)). This weak demand for independent directors should not come as a surprise, however, considering the pervasiveness of agency problems among controlling and minority shareholders and the assumed duties of independent directors to mitigate such problems. Limited supply of competent independent directors accompanies such lackluster demand. In China, for instance, the majority of independent directors are academics (Firth *et al.* (2016)) who hold decorative board seats as friendly observers rather than diligent monitors (Huyghebaert and Wang (2012)). On the other hand, a series of works by La Porta and coauthors (La Porta *et al.* (1997), La Porta *et al.* (1998), La Porta *et al.* (1999), La Porta *et al.* (2000), La Porta *et al.* (2002)) demonstrate how legal origins and rules determine the size of capital markets (1997), the effectiveness of investor protection (1998), the concentration of ownership (1999), and the valuation of firms (2002). Further, studies on the impact of the Sarbanes-Oxley Act (SOX) of 2002 in the US, passed in response to a number of major corporate and accounting scandals, show that the legal reform can have both intended and unintended consequences (Arping and Sautner (2013); Linck *et al.* (2009)).

Aware of the PP conflicts facing firms in emerging economies, legislators in China came to revise the Securities Law with a focus on minority shareholder protection. In particular, the revised law enhances the accountability of the actual controller of a firm and attributes enhanced rights of shareholder representation to independent directors. The revised law were voted pass by the legislative body in December 28, 2019 and went into effect on March 1, 2020. While the debates surrounding the revision has been ongoing since 2014, the room for policy lobbying is generally small in China (Calomiris *et al.* (2010)). Further, the uncertainty evolving around the finality and implementation of the revision is only settled when it gets officially stamped out. Hence we argue that the anticipation effect on director turnovers would be minimal for our study for the following reason. Most important, given the temporal gap between the passage and enactment of law, directors could simply resign shortly before the enactment of the law if they are concerned about the impact of the new law. That is, most directors would not resign before the passage of the law to escape the potential impact of a law undergoing discussion due to the uncertainty on whether and when the law will be passed as well as the content

of the new legislature. Based upon these grounds, we argue that the law revision can be taken as an exogenous shock to listed firms in mainland China.

The legal revision presents as an exogenous shock and hence provides an opportunity to investigate the research questions in a natural experiment setting. Specifically, our treatment group consists of firms that are cross-listers on stock exchanges in both mainland China and Hong Kong. This is because the Securities Law applies only to firms listed in mainland China, explicitly excluding Hong Kong. To ensure comparability across treatment and control, we use propensity score matching (PSM) to identify similar peer firms in Hong Kong by firm size, industry, board size, and board independence. The first two variables capture important firm characteristics and are common in the literature. We employ the latter two variables of internal governance characteristics to further ensure the institutional comparability in our sample, as firms tend to list on foreign host markets befitting their own internal governance structures (Moore *et al.* (2012)). Moreover, while these two variables might correlate with firm size, they reflect monitoring costs and constraints on managerial influence, respectively (Boone *et al.* (2007)).

Using a difference-in-differences (DiD) technique on the PSM-matched firms, we find significantly higher independent director turnovers among the cross-listers. We attribute this to both the increased accountability of the actual controllers and the enhanced responsibility of the independent directors. In terms of board independence, we find no evidence of significant changes among the cross-listers. While our current post-revision observation window is limited, this might indicate that firms resort more to compliance of the revised law in the short-term as the revision puts no emphasis on this metric.

Our setting in China brings out two further aspects that pertain to the transferability of our study. First, The legal system in China traces its origin to the German civil law while borrowing substantially from common law systems, in particular the US and the UK, a common feature among East Asian countries (La Porta *et al.* (1998)). The legal origin of that system matters because the establishment and enforcement of formal institutions are heavily influenced by a country's legal system. In this aspect, countries with civil law origin accounts for about 80% of the 88 countries investigated by Djankov *et al.* (2008). Second, the two-tier board structure in China, where the board chair enjoys official empowerment by law, deviates from that in the US. Indeed, Krause *et al.* (2019) find that the board chair effects on firm performance in China and Germany is comparable

to the CEO effects in the US and the UK. That is, while our findings might have limited implications to common-law advanced economies such as the US, they might generalize to civil-law advanced economies such as Germany in addition to other emerging economies.

Our contributions to the literature are three-fold. First, we offer causal evidence on how country-level institution affect firm-level corporate governance practices by exploiting a unique natural experimental setting. Our findings contribute to bridge the distinctive arguments advanced by the finance literature and the strategy literature (Zattoni *et al.* (2020)). That is, strengthening investor protection could both induce shareholder-friendly firm-level corporate governance practices and induce symbolic adoption of certain practices. Further, we contribute to inform the debates on whether and how country-level institutions substitute firm-level governance (e.g. Melis and Rombi (2021)) as well as on if the above two can have complimentary effects. Second, we bring significant evidence to the literature on the interplay between investor protection and corporate governance from a legal perspective brought to trend by La Porta *et al.* (2000). That is, we explicitly investigate the causal effects of laws on firm corporate governance. Third, we shed light on corporate governance in emerging markets from a legal perspective. Specifically, our findings are informative to policy design in such markets by investigating the causality and effectiveness of a major legal revision.

We organize the remainder of this paper as follows. Section 2 discusses the related literature. Section 3 introduces our research setting and develops our hypotheses. Section 4 describes our data and details our empirical methodology Section 5 discusses our empirical results. Section 6 concludes.

2 Related Literature and Institutional Background

There is a vast and flourishing literature on corporate governance. In particular, our work is most closely related to two streams of literature. First is the literature on addressing Principal-Principal (PP) conflicts as the major concern in emerging economies. Young *et al.* (2008) summarize the cause, prevalence, and consequences of PP conflicts across emerging economies. They show concentrated ownership is a root cause of principal-principal (PP) conflicts: over 50% of equity ownership is typical in emerging economies, while 5% qualifies as blockholders in advanced economies. Further, listed firms in emerg-

ing economies look similar in form but not in substance compared to those in developed economies. That is, the tripod of modern governance mechanisms - shareholders, board of directors, professional managers - is adopted but rarely function as in advanced economies. Moreover, monitoring costs of a different nature arise, resulting from that concentrated ownership is a substitute of poor external governance mechanisms. Further, despite the identified effectiveness of board independence in resolving P-P conflicts, there is a lack of enthusiasm and demand for independent directors in emerging markets. Listed firms therein rarely appoint independent directors beyond the minimum threshold of regulatory mandates (Firth *et al.* (2016)). This weak demand for independent directors should not come as a surprise, however, considering the pervasiveness of agency problems among controlling and minority shareholders and the assumed duties of independent directors to mitigate such problems. Limited supply of competent independent directors accompanies such lackluster demand. In China, for instance, the majority of independent directors are academics (Firth *et al.* (2016)) who hold decorative board seats as friendly observers rather than diligent monitors (Huyghebaert and Wang (2012)). The prevalence of P-P conflicts in emerging markets and the consequent ineffectiveness of traditional corporate governance mechanisms have inspired scholars to explore alternative governance options. Using a pooled sample of 917 listed firms from 2003 to 2006 in China, Xu *et al.* (201) find that regional tax enforcement efforts reduce agency costs between blockholders and minority shareholders, and thus improve a firm's market performance. Based a natural experiment setting of China's split-share structure reform, Sun *et al.* (2017) validate the importance of regulatory intervention in enhancing investor protection and information disclosure. To further illustrate the prominence of PP conflicts in emerging economies, we note three aspects that distinguish emerging economies from their more advanced peers.

Formal institutions that protect investors' property rights tend to be weak, incomplete, or missing in emerging economies (Young *et al.* (2008); Hou and Moore (2010); Lin and Chuang (2011); Zhang *et al.* (2014)). Specifically, the takeover market is absent or inactive, the threat of bankruptcy for defaulting firms is minimal, and the financial market too nascent to regulate supply and demand efficiently (Huyghebaert and Wang (2012)). Further, the law enforcement typically varies substantially from one region to another despite a uniform legal framework being in place in these economies (Jiang *et al.* (2010)).

Concentrated ownership structure is adopted by a typical publicly listed firm in an emerging economy (Firth *et al.* (2016)). This structure allows the largest shareholder to exercise substantial control over firms through manipulating board composition and managerial incentives (Zhang *et al.* (2014)). The board hence acts as the representative of the controlling shareholders (Firth *et al.* (2016); Sun *et al.* (2017)) rather than an effective fiduciary of the firm (Jensen and Meckling (1976)). In such firms, controlling shareholders can easily exploit the wealth of minority shareholder by means of related-party transactions or asset transfer (Berkman *et al.* (2009)). Zhang *et al.* (2014)) document the collusion between managers and controlling shareholders on tunneling. Using a Chinese sample, the authors find that blockholders with excessive control rights are less likely to advocate performance-based incentives that direct managerial actions towards shareholder value maximization. In this vein, Huyghebaert and Wang (2012) find that as the fraction of directors affiliated with the dominant owner increases in a firm, so does its amount of related-party transactions.

Prevalent state ownership (La Porta *et al.* (1999)) exacerbates the expropriation of minority shareholders in emerging economies. A typical manifestation of P-P conflicts emerges when states are controlling owners of a firm. In such circumstances the states tend to use firms as the tool to pursue political and social objectives that divert resources from economic values maximization for minority shareholders (He and Rui (2016)). For example, Shan (2013) has identified a positive correlation between state ownership and the occurrences of type I tunnelling that features outward transfers of firm resources for the benefit of controlling shareholders (Shleifer and Vishny (1997))

In sum, minority shareholders are especially disadvantageous in emerging economies where ownership concentration, ineffective institutions, and pervasive state ownership coexist. That is, traditional corporate governance bundles that align ownership with control (Lin and Chuang (2011)) are ineffective in shielding minority investors from managerial opportunism. Worse, these bundles tend to aggravate P-P conflicts that eventually lead to further value extraction by blockholders (Young *et al.* (2008)). With a sample of 525 listed firms in Taiwan, Lin and Chuang (2011) find that internal corporate governance mechanisms, such as increasing family ownership and institutional ownership and introducing CEO duality, do not reduce the risks of IPO underpricing that harms primarily minority shareholders. In contrast, they find evidence that employing independent outsider directors mitigate the extent of IPO underpricing (Lin and Chuang (2011)). Sim-

ilarly, Shan (2013) find that the frequency of board meetings reduces the extent of type I tunneling and board independence mitigates expropriation of minority shareholders.

Second is the literature on legal approach to corporate governance pioneered through a series of works by La Porta and coauthors. (La Porta *et al.* (1997), La Porta *et al.* (1998), La Porta *et al.* (1999), La Porta *et al.* (2000), La Porta *et al.* (2002)) They demonstrate how legal origins and rules determine the size of capital markets (1997), the effectiveness of investor protection (1998), the concentration of ownership (1999), and the valuation of firms (2002). Further, studies on the impact of the Sarbanes-Oxley Act (SOX) of 2002 in the US, passed in response to a number of major corporate and accounting scandals, show that the legal reform can have both intended and unintended consequences. For instance, Arping and Sautner (2013) find that SOX Section 404 resulted in more accurate and less dispersed analyst earnings forecasts, proxies for improved accounting transparency. However, Linck *et al.* (2009) demonstrate the costs thus associated with the mandates on directors' workload and firms' board independence – doubled premiums on director and officer (D&O) insurance along with significant increases in directors' pay and overall costs. In this vein two streams of literature emerge: the finance literature often suggests that strengthening national institutions (e.g. investor protection) tend to induce shareholder-friendly firm-level corporate governance practices, while the strategy literature tends to argue that most new CG practices outside the US and the UK are adopted symbolically to increase firm's or country's legitimation (Zattoni *et al.* (2020)). The latter argument thus indicates that the strengthened institutions might either be symbolic or brings additional monitoring costs without additional benefits (Hermalin and Weisbach (2012)). However, the void of one type of institutions might be filled or substituted by others in a complex interplay between both formal and informal institutions. The finance literature argues for substitution effects between national institutions and corporate governance mechanisms while the strategy literature promotes complimentary effects.

The institutional background related to directors' appointment and departure is relevant and thus introduced as follows. In mainland China, each elected director must receive shareholder approval through e.g. annual general meeting (AGM). Independent directors cannot be dismissed except for unusual circumstances. If their resignations lead to board independence lower than 1/3, such resignations shall come into effect when their replacements are found. In Hong Kong, the HKSE Rules and Guidance states that "all directors appointed to fill a casual vacancy should be subject to election by sharehold-

ers at the first general meeting after appointment". In sum, while the shareholders are entitled to approve or reject the election of a director, the appointment of a director can occur and become effective any time before shareholder meetings. This procedural practice means that director appointment and departure can take place any time around the year.

3 Research Setting and Hypotheses Development

Aware of the PP conflicts facing firms in emerging economies, legislators in China came to revise the Securities Law with a focus on minority shareholder protection. Particularly relevant to our study, the revised law enhances the accountability of the actual controller (she who has the de facto control rights) of a firm and attributes enhanced rights of shareholder representation to independent directors. Under the revised Securities Law, individual investors can file class lawsuit against firms that exploit shareholder rights in the forms of theft, fraud, accounting manipulation, and related-party transactions and independent directors are held accountable. With the new revision, independent directors are exposed to greater legal, financial and reputational risks which are expected to encourage them to act more responsibly in supervising firm operations and strategies. The revised law were voted pass by the legislative body in December 28, 2019 and went into effect on March 1, 2020. While the debates surrounding the revision has been ongoing since 2014, the room for policy lobbying is generally small in China (Calomiris *et al.* (2010)). Further, the uncertainty evolving around the finality and implementation of the revision is only settled when it gets officially stamped out. Hence we argue that the anticipation effect on director turnovers would be minimal for our study for the following reason. Most important, given the temporal gap between the passage and enactment of law, directors could simply resign shortly before the enactment of the law if they are concerned about the impact of the new law. That is, most directors would not resign before the passage of the law to escape the potential impact of a law undergoing discussion due to the uncertainty on whether and when the law will be passed as well as the content of the new legislature. Based upon these grounds, we argue that the law revision can be taken as an exogenous shock to listed firms in mainland China.

The legal revision as an exogenous shock hence provides a unique opportunity to investigate our research questions in a natural experiment setting. To exploit this setting to a full extent, we concern ourselves on the causal effects the law revisions have

on firm and director behavior. Specifically, we employ the difference-in-differences (DiD) methodology, taking as treatment firms that are cross-listed in mainland China and Hong Kong, and as control firms that are listed in Hong Kong but not mainland China. The cross-listed firms are a natural choice in such a setting since they are affected by the Securities Laws in both markets, thus allowing us to control by design any impact attributable to regulations in Hong Kong where the control firms are listed. Notably, we can have such treatment and control groups thanks to that the mainland Securities Law applies only to firms listed in mainland China, explicitly excluding firms listed in Hong Kong.

The articles of interest for our study in the revised Securities Law pertain to the increased accountability of the controlling shareholders and the enhanced rights of independent directors. We give a brief summary as follows.

- Article 24 and 85: The burden of proof in cases of misconduct reside on the "critical minorities", including controlling shareholders and the actual controllers, board of directors, and other members of the top management team. The inclusion of controlling shareholders and actual controllers marks a critical shift from the previous version of the law whose language puts the burden of proof on the law enforcement.

- Article 94: The critical minorities can be legally pursued when they practice misconducts resulting to investor losses. The statue of limitation expands well over that specified in Corporation Law and there is no limitation on shareholding percentage. Combined with Article 78 that specifies the obligation of the critical minorities to disclose information, they are accountable if any undisclosed information leads to investors' losses. Combined with Article 95, this marks a resemblance to class action lawsuits pertaining to stock investments in the US.

- Article 90: Independent directors have been explicitly identified as having the rights to collect proxy votes from shareholders, allowing them to submit proposals and vote on behalf of the shareholders.

These articles are intended to improve corporate governance through explicitly holding accountable the critical minorities, including controlling shareholders and the actual controllers, board of directors, and other members of the top management team. Hence, we formulate accordingly the following hypotheses.

Hypothesis 1: Firms' corporate governance improve under the new Law, evidenced by increased board independence.
The revised law's emphasis on holding the critical minorities accountable, in particular putting the burden of proof in cases of misconduct on the controlling shareholders, incentivizes strengthened corporate governance practices. The finance literature suggests that strengthening national institutions (e.g. investor protection) tend to induce shareholder-friendly firm-level corporate governance practices, hence we expect to see increased board independence under the revised law and a more shareholder-friendly board (Zattoni *et al.* (2020). However, this effect might not be strong at least in the short run as firms are already obliged to have at least one third of its board composed of independent directors. Given the substitution effects between country-level institutions and firm-level governance (Melis and Rombi (2021)), firms might have fewer incentives to pursue voluntary improvements on board independence when such institutions are strengthened. Further, board independence might be tampered by tokenism or form over substance (Young *et al.* (2008)). That is, firms might have hired independent board members that do not have any actual involvement with the firms' affairs, thereby hampering the effectiveness of independent boards. We expect such practices to be mitigated under the revised law that explicitly attributes more rights to the independent directors, leading to our next hypothesis.

Hypothesis 2: Firms' composition of independent board shifts toward more involved members, marked by increased turnover on the independent board directors. Those previously sinecure independent board memberships should become much less attractive due to the increase responsibility of these members under the revised law. In China, for instance, the majority of independent directors are academics (Firth *et al.* (2016)) who hold decorative board seats as friendly observers rather than diligent monitors (Huyghebaert and Wang (2012)). Changing environments and external pressure contribute to increased director turnovers as they alter the needs of both firms and directors (Cotugno *et al.* (2020); Banerjee *et al.* (2020)). Moreover, changes in board size and composition matter to investors (Vallelado and García-Olalla (2021)) and relate to firm risks (Feng and Xiao

(2021). The above combined motivates us to investigate independent director turnovers. In particular, we expect to see a higher turnover due to the nudging effects on the independent board members. We further expect a large part of this increased turnovers to be attributed to resignations from such sinecure positions.

4 Data and Methodology

We obtain firm-level fundamentals data from Thomson Retuers' Worldscope, director list and turnover from Hong Kong Stock Exchange's HKEXnews, and director information from firms' annual reports. We also utilize data from the China Stock Market and Accounting Research Database (CSMAR). Our final sample contains 86 cross-listed firms with annual data from 2017 to 2020, that is, 3 years before the revised Securities Law went into effect. We focus our discussions on a matched sample comprising 86 matched pairs of firms and use a sample of all Hong-Kong-listed firms as a baseline test.

Our unique dataset features a natural experimental setting that allows us to investigate the causal effects of legal revisions on firm and director behavior. Such a unique setting is difficult to come across as we can only await the occurrence of appropriate events. Further, our setting threads through both emerging and advanced markets, which enables myriad intriguing observations and comparisons. The detailed variables included empowers our inquiry in that we can study various aspects of interest and at the same time control for effects established from the extant literature. However, such a setting, like most other natural experiments on cross-listed firms, has the following downside of a double-edged sword. There is an apparent bias towards larger-sized firms and the matched sample is of limited size. In addition, cross-listed firms might contain distinct attributes that limit the generalization of our findings.

To arrive at our matched sample, we match, in year 2017, each firm cross-listed on the stock exchanges of both mainland and Hong Kong to a similar firm listed on the Hong Kong Stock Exchange. Our matching variables include firm size (total assets in billion HKD), industry (25 major industry group from Worldscope), board size, and board independence. The first two variables capture important firm characteristics and are commonly used in firm-level matching in the literature. We employ the latter two variables of internal governance characteristics to further ensure the institutional comparability

within our sample, as firms tend to list on befitting foreign host markets (Moore *et al.* (2012)). Moreover, while these two latter variables might correlate with firm size, they reflect monitoring costs and constraints on managerial influence, respectively (Boone *et al.* (2007)).

Out set of control variables include firm age, return on assets (ROA), financial leverage (total liabilities over total shareholders' equity), strategic change, and industry- and year- fixed effects. In particular, the variable strategic change includes resource allocation in 6 domains in response to organizational decline, according to Crossland *et al.* (2014) and Wowak *et al.* (2016). We include this measure as director turnover might be closely related to organizational change. More specifically, this variable is constructed by summing the log of absolute changes from the previous year among the following 6 variables. Advertising is the ratio of advertising (proxied by selling, administrative, and general expenses) over sales (net sales or revenue). R&D is the ratio of research and development expenses over sales. Overhead Efficiency is the ratio of overhead costs over sales. We use as overhead costs – ongoing expenditures of running a business that cannot be conveniently traced to any particular cost unit – the sum of SG&A expenses, R&D expenses, and interest expenses. Capital Intensity is the ratio of net fixed assets over the total number of employees. Plant and Equipment Newness is the ratio of net fixed assets over gross fixed assets, where the difference comes from accumulated depreciation and impairment provision. Financial Leverage is the ratio of total liabilities over total shareholder's equity. Further, we control for industry- and year- fixed effects.

To examine the nudging effects of the law regarding sinecure positions, we look at the number of independent directors that resigned upon the enactment of the law. We treat a turnover of an independent director as a resignation in a given year if the following two conditions are satisfied: (a) the director has left the firm. (b) the director has served on the position for a period shorter than the maximum 6 years in mainland for cross-listed firms or the maximum 9 years in Hong Kong for control firms. Our use of this crude measure is due to that the exact reasons related to a director's turnover are rarely disclosed. We reckon that a director might have left the firm for reasons unrelated to the firm. For instance, a director might take on other commitments or become sick. However, we rely on that such idiosyncratic departures remain arbitrary across firm and time. Therefore, if we see a sudden overall surge in premature turnovers as identified above, we regard that this results from exogenous shocks.

4.1 Summary Statistics

Table 1 reports the summary statistics of the main variables across our samples. As discussed above, the cross-listed firms are quite different from a typical listed firm in the Hong Kong Stock Exchange in that they are much larger in size by total assets, have a larger board, are much older with higher leverage. Despite our efforts to find similar peers to them through matching, such tasks are difficult with weighting tradeoffs on what to match. Our matched peers are further in size (unreported balance test significance below 1%), but closer in board size and board independence (unreported balance test significance at 5%).

[Table 1 about here]

Table 2 reports the correlations among our variables employed in the matched sample.

[Table 2 about here]

Table 1: Summary Statistics

This table reports descriptive statistics of the main variables across our samples. The variables from top to bottom are total assets, board size, board independence, firm age, return on assets, financial leverage, and a measure of strategic change. Panel A relates to all Hong-Kong-listed firms during our sample period. Panel B relates to cross-listed firms. Panel C relates to matched firms from HK to the cross-listers by propensity-score-matching using total assets, board size, board independence, and industry.

	Panel A: All HK firms			Panel B: Cross-listed firms			Panel C: Matched Firms from HK		
	median	mean	st.dev	median	mean	st.dev	median	mean	st.dev
totAssets	1.98	130.7	2289.6	83.69	207.42	392.15	2.5	68.4	338.75
boardSize	7.00	7.4	3.1	9.00	9.34	2.00	8.0	8.8	3.14
boardInd	0.43	0.4	0.1	0.38	0.40	0.08	0.4	0.4	0.08
ageFirm	9.00	9.9	7.5	21.00	20.37	5.16	14.0	15.2	13.86
ROA	0.02	5.7	607.3	0.03	0.03	0.09	3.1	1.2	21.25
finLev	0.74	2.7	78.1	1.39	1.56	2.66	0.8	2.0	13.47
strategicChg	-10.41	-10.4	5.5	-7.61	-7.62	6.04	0.0	4.8	7.37

Table 2: Correlation matrix of of variables

The table reports the Pearson correlation coefficients among variables from the final matched sample.

	ageFirm	totAssets	ROA	boardSize	boardInd	finLev	strategicChg
ageFirm	1						
totAssets	0.36	1					
ROA	-0.02	0	1				
boardSize	0.11	0.08	0.05	1			
boardInd	-0.03	0.17	-0.11	-0.54	1		
finLev	0.04	0.04	-0.07	0.05	-0.04	1	
strategicChg	-0.15	-0.20	-0.07	-0.06	0.01	-0.01	1

5 Empirical Results

5.1 Difference in differences

To draw causal inference from the effects of revised law, we resort to the difference-in-differences (DiD) technique. We first report empirical results using DiD on cross-listed firms against all Hong Kong listed firms as our baseline results. Then we focus our discussions after we introduce our matching method to match cross-listed firms one-to-one against their peer listed firms on the Hong Kong stock market. Our rationale to focus on results upon matching is that cross-listed firms are generally much larger both in size and market cap than an average listed firm, hence the comparison should be made with more similar firms. To exploit our natural experimental setting, we run our regressions on the following specifications:

$$\begin{aligned} \text{Outcome}_{i,t} = {} & \delta \cdot \mathbb{1}_{Cross-Listed} \cdot \mathbb{1}_{After2019} \\ & + \gamma_1 \cdot \mathbb{1}_{Cross-Listed} + \gamma_2 \cdot \mathbb{1}_{After2019} \\ & + X\beta + \alpha_i + \lambda_t + \epsilon_{i,t}, \end{aligned} \tag{1}$$

where δ is our coefficient of interest, that is, the causal effect of the revised law on the treated firms. $\text{Outcome}_{i,t}$ is the outcome variable of interest defined in our working hypotheses. $\mathbb{1}_{Cross-Listed}$ is a dummy variable that indicates whether a firm is cross-listed or not. $\mathbb{1}_{After2019}$ is a dummy variable that indicates whether the current year t is after

2019 or not. X is our set of control variables. α_i is the industry fixed effect and λ_t the year fixed effect. As we are using a panel of data we use double clustered standard errors, at the firm level and the time dimension following Petersen (2009).

5.2 Propensity score matching

To arrive at our final sample with treatment and control firms that are as comparable as possible, we resort to propensity score matching, conducted in year 2017. The matching procedure can be broken down into 3 steps. First, we run a logistic regression on the dummy variable of interest, that is, whether a firm is cross-listed or not, using a set of covariates, i.e. total assets, industry, board size, and board independence. This regression sample includes firms with the interested dummy being both ones or zeros. Second, we use the coefficients from the first step to predict, using a logistic function, the likelihoods – the propensity scores - of the firms in the sample to end up having a cross-listing dummy of value 1. Third, we find the nearest neighbours using these propensity scores of the firms with a dummy of 0 to those firms with a dummy of 1. That is, we find the counterpart non-cross-listed firm that has the closest propensity score to each cross-listed firm. Employing a one-to-one matching scheme, we end up with a final sample of matched pairs with each treatment firm corresponding to a non-treatment or control firm.

We check for the trend by depicting the dependent variables of interest by treated and control firms across time. Figure 1 and figure 2 illustrate the board independence and independent director turnover of the matched sample, respectively. Figure 3 depict the independent director turnover as percentage of the total number of independent directors. From visual inspection the parallel trend assumption for DiD, which is arguably the most difficult to fulfill, might be violated for board independence and independent director turnover. That is, with a visual counterfactual we would expect even fewer director turnover, hence this suggests the strong effects of the law, though potentially with a bias of the estimate. Nonetheless, Ryan *et al.* (2018) find that DiD with matching outperforms the standard DID or interrupted time-series analysis models. Hence we proceed to focus our discussions on the PSM-DiD results.

[Figure 1 about here]

[Figure 2 about here]

[**Figure 3 about here**]

We also report market-wide averages of the interested dependent variables from the stock exchanges in mainland. We do so to think of these averages as the "natural rate" that serves as benchmarks for considering our results economically. Figures 4, 5, and 6 illustrate the board independence, independent director turnover, and independent director fees over time, respectively.

[**Figure 4 about here**]

[**Figure 6 about here**]

5.3 Propensity-score-matched difference in differences

We start by reporting DiD results with cross-listed firms against all firms on the Hong Kong stock market. We do so because this benchmark does not change while the PSM has the disadvantage of being subject to changes dependent upon matching variables chosen. Tables 3 and 4 report our baseline DiD empirical results on board independence and independent director turnover, respectively. We focus our discussions of results from the panel regression with both firm- and year- fixed effects as they represent the most stringent set of controls and that the results are generally robust across specifications. First, the coefficient of interest measuring effects on board independence is close to 0, suggesting that board independence does not change due to the law revision at least in the short term. Second, the coefficient estimates on total independent director turnovers and percentage of such turnovers per firm are economically and statistically significant.

[**Table 3 about here**]

[**Table 4 about here**]

Tables 5 and 6 report our PSM-DiD empirical results on board independence and independent director turnover, respectively. The two observations from our baseline DiD on board independence and independent director turnover hold also in the PSM-DiD. In particular, the 0.53 coefficient estimate on total turnovers suggests that the law revision result in about a 50% increase in likelihood of having an independent director turning over. The 0.16 coefficient estimate on percentage of turnovers combined with average number

of independent directors at 3 helps validate this finding, also ensuring the stationarity of the dependent variable.

The increased turnover among directors could be beneficial to firms under certain conditions. Hauser (2018) offers causal evidence that focused directors contribute to higher profitability and market-to-book valuations in the focal firms. Firms with directors whose outside appointments that are far from HQ benefit most from directors' having fewer multiple directorships. Following this vein, Moursli (2019) find that increased business of independent directors lead to decreases in firm value. Extra demand imposed by regulations is met with shortage in the supply of directors' labour market, hence the already extant independent directors must join multiple boards, thereby increasing their business and reduing committments at any single firm. Further, were a firm to take opportunity in appointing directors more befitting to the new environment, such increased board turnover might be conducive to the firm. For instance, if board education level increases (Cotugno *et al.* (2020)) or more female directors come on board (Boutchkova *et al.* (2020)).

However, such increased resignation might also open doors to detrimental changes in the firms. Ingratiation behavior by corporate leaders toward independent directors and the tendency to appoint deferential individuals as independent directors combine to mitigate the effectiveness of an independent board (Westphal and Zajac (2013)). The resignation boom that we find across the director labor market might result in further justification in appointing swiftly new replacements who are deferential, thence leading to corrosion of independent board monitoring in the long run (Fracassi and Tate (2012). From a resource dependence theory perspective, management is endowed with a co-optation opportunity by appointing their own representatives onto the board in the face of difficulties finding appropriate candidates. Li *et al.* (2021) document that independent directors that are appointed due to favourtism would reciprocate by pampering the insides in terms of expropriation and tunnelling. Feng and Xiao (2021) find that higher director turnover rates lead to higher risk, but if new directors are demographically and experiencially different from their predecessors, such risks are reduced. In a similar vein, Vallelado and García-Olalla (2021) find that investors react negatively to board changes in banks across the EU.

As Zattoni *et al.* (2020) conclude, the finance literature often suggests that strengthening investor protection tend to induce shareholder-friendly firm-level corporate governance practices, while the strategy literature tends to argue that most new CG practices

outside the US and the UK are adopted symbolically to increase firm's or country's legitimation. The latter argument thus indicates that the strengthened institutions might either be symbolic or brings additional monitoring costs without additional benefits (Hermalin and Weisbach (2012)). Our findings on the inert board independence in the face of increase investor protection thus would seem to favor the argument advanced by the strategy literature. However, combined with increased director turnovers - should they meet the conditions to benefit firms - our findings might also support the thesis of the finance literature on strengthened shareholder-friendly corporate governance at the firm level, hence uniting these two streams of literature.

[Table 5 about here]

[Table 6 about here]

5.4 Supplementary analyses: board composition upon turnover

Tables 9 and 10 report, for cross-listers and their matched counterparts respectively, the age and gender of independent director replacements before and after the law revision. Notably, there are about twice more turnovers in the cross-listed firms compared to their matched counterparts. For cross-listers who are directly impacted by the law revision, newly appointed independent directors to replace their resigned predecessors tend to be younger compared to before the law revision. Further, such replacements tend to include more female both pre- and post- law revision. As for the matched firms, this pattern is even more pronounced. Such pattern might benefit the firms in the long run as gender-diversified boards reduce male directors' attendance problem, increases CEO turnover probability in the face of poor firm performance; and that male directors who are exposured to female directors also benefit in the same direction outside the focal board ((Boutchkova *et al.* (2020)).

[Table 9 about here]

[Table 10 about here]

6 Conclusion

Exploiting a natural experimental setting where cross-listed firms are the sole subjects targeted by legal changes, we study whether and how legal revisions of investor protec-

tion laws benefit investors. First, we find that independent directors in cross-listed firms turn over significantly more. The increased turnover alone could be both beneficial and detrimental to firms depending on certain conditions. Second, the newly appointed to replace the resigned directors tend to be younger and include more female. Combined with the increased turnover, we argue that our evidence suggests that firms have taken the opportunity to appoint directors more befitting to the new environment, hence increased board turnover might be conducive to the firm in the long run. Third, we find no evidence of significant changes in board independence in the short run. Combined with increased director turnovers, and as we argue that they lean towards the conditions to benefit firms, our findings reconcile the arguments advanced by the finance and the strategy literature on the effects of strengthened institutions in that strengthened shareholder-friendly corporate governance at the firm level and symbolic adoption of certain governance practices could take place jointly.

Table 3: Difference-in-Differences baseline results: board independence

This table reports the regression results on board independence of cross-listed firms against all Hong Kong listed firms using the difference-in-differences technique. Columns under OLS include industry- and year- fixed effects. Columns under panel linear include firm- and year- fixed effects.

	board independence		
	OLS		*panel linear*
	(1)	(2)	(3)
hkCrossDum:time	−0.032	−0.046***	−0.021*
	(0.009)	(0.013)	(0.011)
hkCrossDum	−0.014	−0.008	
	(0.011)	(0.014)	
time	0.059***	0.081***	
	(0.001)	(0.002)	
ageFirm		0.001**	
		(0.001)	
totAssets		−0.00000	−0.00000**
		(0.00000)	(0.00000)
ROA		0.00000***	0.00000***
		(0.00000)	(0.00000)
boardSize		−0.001	0.034***
		(0.009)	(0.002)
finLev		−0.00002***	−0.00001
		(0.00000)	(0.00001)
strategicChg		0.002***	−0.00003
		(0.001)	(0.0004)
Constant	0.402***	0.381***	
	(0.010)	(0.064)	
R^2	0.054	0.086	0.188
Adjusted R^2	0.052	0.083	-0.063
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4: Difference-in-Differences baseline results: independent director turnover

This table reports the regression results on independent director turnover of cross-listed firms against all Hong Kong listed firms using the difference-in-differences technique. Columns under OLS include industry- and year- fixed effects. Columns under panel linear include firm- and year- fixed effects.

	total turnover			percentage of turnovers		
	OLS		*panel linear*	*OLS*		*panel linear*
	(1)	(2)	(3)	(4)	(5)	(6)
hkCrossDum:time	0.451	0.396***	0.326*	0.124***	0.111***	0.091*
	(0.066)	(0.060)	(0.178)	(0.022)	(0.019)	(0.050)
hkCrossDum	0.276***	0.278***		0.065***	0.080***	
	(0.037)	(0.027)		(0.012)	(0.011)	
time	−0.076***	−0.082***		−0.030***	−0.035***	
	(0.004)	(0.008)		(0.001)	(0.002)	
ageFirm		0.002			−0.00001	
		(0.002)			(0.001)	
totAssets		0.00002***	0.00001***		0.00000***	0.00000***
		(0.00000)	(0.00000)		(0.00000)	(0.00000)
ROA		−0.00001***	−0.00001***		−0.00000***	−0.00000***
		(0.00000)	(0.00000)		(0.00000)	(0.00000)
boardSize		0.010*	−0.029*		−0.010***	−0.038***
		(0.006)	(0.017)		(0.003)	(0.008)
boardInd		0.059	−0.205		−0.241***	−0.722***
		(0.152)	(0.182)		(0.052)	(0.145)
finLev		−0.0001***	−0.00005***		−0.00003***	−0.00002***
		(0.00002)	(0.00001)		(0.00001)	(0.00001)
strategicChg		0.015***	−0.001		0.005***	−0.0004
		(0.003)	(0.004)		(0.001)	(0.001)
Constant	0.360***	0.360***		0.107***	0.342***	
	(0.058)	(0.081)		(0.009)	(0.056)	
R^2	0.017	0.032	0.005	0.013	0.034	0.027
Adjusted R^2	0.015	0.027	-0.436	0.011	0.029	-0.420
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 5: Difference-in-Differences results with matched firms: independent director turnover

This table reports the regression results on independent director turnover of cross-listed firms against matched Hong Kong listed firms using the difference-in-differences technique. Columns under OLS include industry- and year- fixed effects. Columns under panel linear include firm- and year- fixed effects.

	board independence		
	OLS		*panel linear*
	(1)	(2)	(3)
hkCrossDum:time	−0.005	0.021***	0.002
	(0.004)	(0.003)	(0.007)
hkCrossDum	−0.008	−0.017*	
	(0.010)	(0.009)	
time	0.027***	−0.011***	
	(0.002)	(0.002)	
ageFirm		−0.0001	
		(0.0003)	
totAssets		0.00004***	0.0003***
		(0.00002)	(0.0001)
ROA		−0.0004**	−0.0002***
		(0.0002)	(0.0001)
boardSize		−0.017***	−0.024***
		(0.002)	(0.004)
finLev		−0.0003**	−0.00005
		(0.0001)	(0.0001)
strategicChg		−0.0004	−0.0002
		(0.0005)	(0.0004)
Constant	0.335***	0.583***	
	(0.007)	(0.029)	
R^2	0.180	0.434	0.361
Adjusted R^2	0.146	0.401	0.091
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 6: Difference-in-Differences results with matched firms: independent director turnover

This table reports the regression results on independent director turnover of cross-listed firms against matched Hong Kong listed firms using the difference-in-differences technique. Columns under OLS include industry- and year- fixed effects. Columns under panel linear include firm- and year- fixed effects.

	total turnover			percentage of turnovers		
	OLS		*panel linear*	*OLS*		*panel linear*
	(1)	(2)	(3)	(4)	(5)	(6)
hkCrossDum:time	0.426	0.482***	0.531***	0.136***	0.170***	0.160***
	(0.135)	(0.160)	(0.178)	(0.032)	(0.025)	(0.058)
hkCrossDum	0.253*	0.201*		0.037	0.032	
	(0.135)	(0.120)		(0.028)	(0.044)	
time	−0.078	−0.160		−0.043***	−0.087***	
	(0.069)	(0.145)		(0.014)	(0.026)	
ageFirm		0.001			0.002	
		(0.005)			(0.001)	
totAssets		0.0001	−0.004***		−0.00003	−0.0004
		(0.0002)	(0.001)		(0.00003)	(0.0003)
ROA		−0.005	−0.003***		−0.002	−0.002***
		(0.006)	(0.001)		(0.002)	(0.0003)
boardSize		0.005	−0.102		−0.007	−0.022
		(0.025)	(0.074)		(0.007)	(0.021)
boardInd		0.053	−1.887		−0.092	−0.679
		(0.597)	(1.334)		(0.168)	(0.416)
finLev		−0.001	−0.001		−0.0003	−0.0001
		(0.003)	(0.001)		(0.001)	(0.0004)
strategicChg		−0.005	−0.014*		−0.001	−0.002
		(0.011)	(0.008)		(0.003)	(0.003)
Constant	0.917***	0.828*		0.207**	0.326***	
	(0.269)	(0.454)		(0.084)	(0.098)	
R^2	0.088	0.104	0.046	0.115	0.139	0.033
Adjusted R^2	0.050	0.049	-0.360	0.068	0.067	-0.647
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 7: Cumulative abnormal returns around event dates: cross-listers and matched firms on Hong Kong Stock Exchange

This table reports the cumulative abnormal returns around an event date. For instance, CAR_5 indicates a window of (-5, 5). The abnormal return is computed using a one-factor market model with the Hang Seng Index (HSI) as the market portfolio. The parameters of the model are estimated using day -250 to day -50 of an event.

	treatment2020	control2020	treatment2019	control2019
mean(CAR_1)	-0.49	**-4.12**	0.16	1.76
mean(CAR_3)	-0.78	**-8.03**	-1.25	0.61
mean(CAR_5)	-0.72	**-6.46**	**-2.65**	0.51

Table 8: Cumulative abnormal returns around event dates: cross-listers on mainland Stock Exchanges

This table reports the cumulative abnormal returns around an event date. For instance, CAR_5 indicates a window of (-5, 5). The abnormal return is computed using a one-factor market model with the CSI 300 Index as the market portfolio. The parameters of the model are estimated using day -250 to day -50 of an event.

	treatment2020	treatment2019
mean(CAR_1)	-0.10	0.30
mean(CAR_3)	0.69	0.64
mean(CAR_5)	1.03	1.09

Table 9: Independent directors resigned and replaced among firms cross-listed in mainland and Hong Kong, pre- and post- law revision

This table reports the mean age and gender (1 for female and 0 for male) for independent directors resigned and replaced among cross-listed firms before and after the law revision. Time indicator is 1 for post- law revision and 0 for pre- law revision. Replacement dummy is 1 for directors that are newly appointed to replace the resigned directors who are indicated by 0.

time indicator	replacement dummy	age	gender
0.00	0.00	58.74	0.07
0.00	1.00	57.59	0.18
1.00	0.00	57.76	0.09
1.00	1.00	53.80	0.20

Table 10: Independent directors resigned and replaced among matched listed firm in Hong Kong, pre- and post- law revision

This table reports the mean age and gender (1 for female and 0 for male) for independent directors resigned and replaced among matched listed firms in Hong Kong before and after the law revision. Time indicator is 1 for post- law revision and 0 for pre- law revision. Replacement dummy is 1 for directors that are newly appointed to replace the resigned directors who are indicated by 0.

time indicator	replacement dummy	age	gender
0.00	0.00	55.04	0.18
0.00	1.00	54.65	0.16
1.00	0.00	56.30	0.12
1.00	1.00	44.00	1.00

Figure 1: Time-series plot of board independence of Propensity Score matched Treated and Control firms

The figure plots the annual average of the board independence of Propensity Matched Treated and Control firms over the study period. Treated and control are plotted in solid and dashed lines (triangle and circle points), respectively. The dashed vertical line is for visual separation between pre- and post- treatment period.

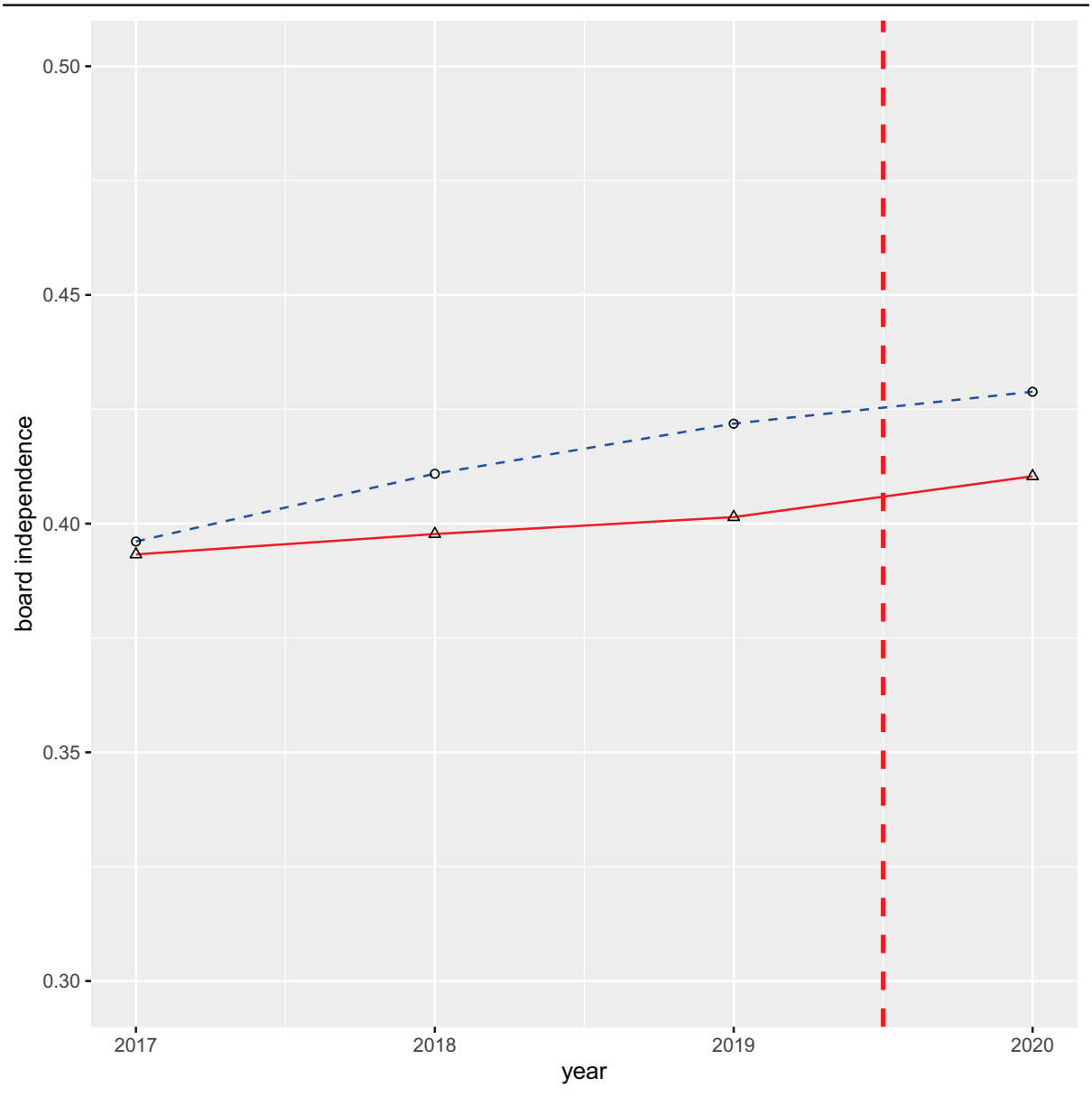


Figure 2: Time-series plot of independent director turnover per firm of Propensity Score matched Treated and Control firms

The figure plots the annual average of the number of independent director turnover by firm of Propensity Matched Treated and Control firms over the study period. Treated and control are plotted in solid and dashed lines (triangle and circle points), respectively. The dashed vertical line is for visual separation between pre- and post- treatment period.

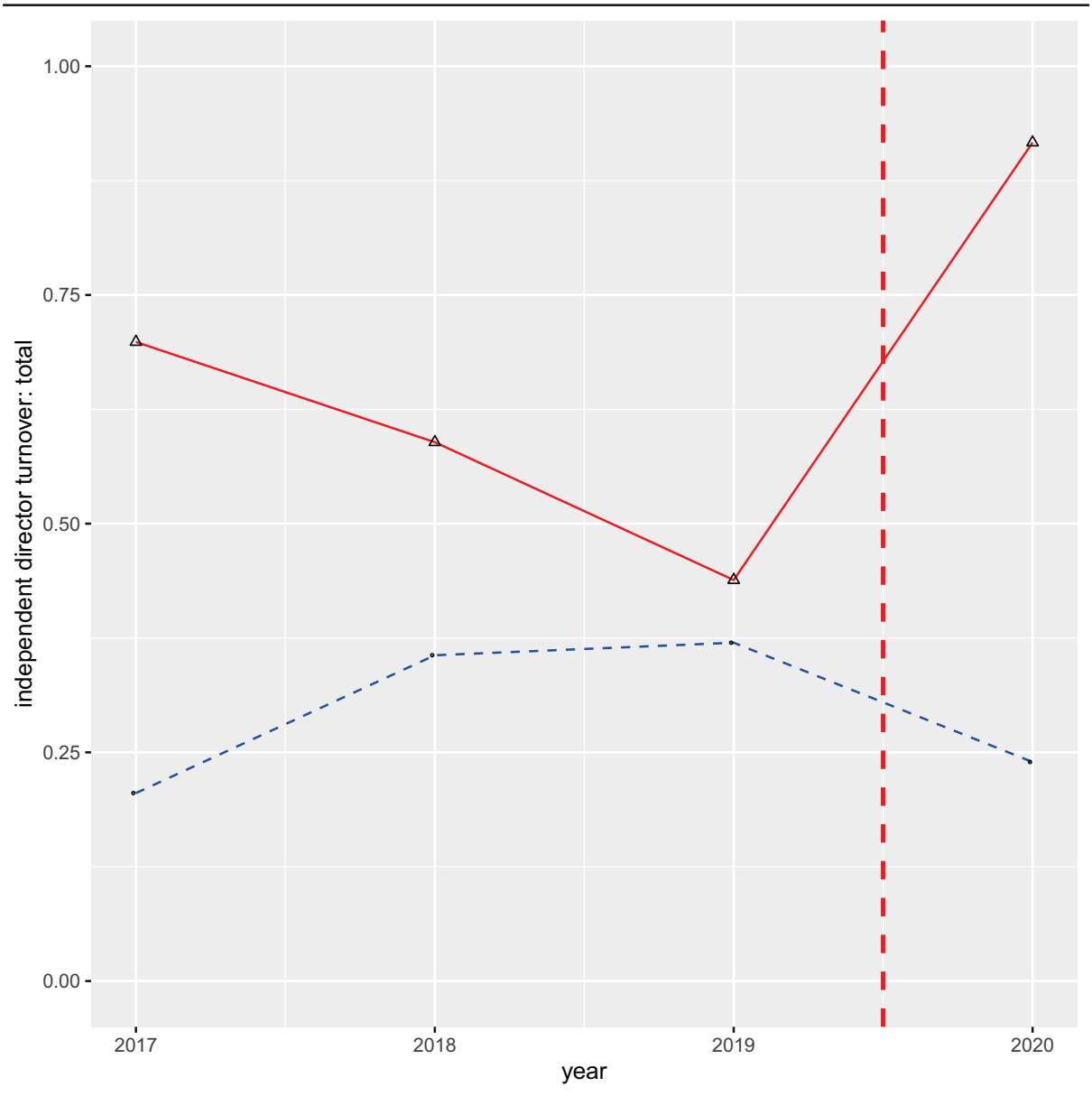


Figure 3: Time series plot of percentage of independent director turnover per firm of Propensity Score matched Treated and Control firms

The figure plots the annual average of the percentage of independent director turnover by firm of Propensity Matched Treated and Control firms over the study period. Treated and control are plotted in solid and dashed lines (triangle and circle points), respectively. The dashed vertical line is for visual separation between pre- and post- treatment period.

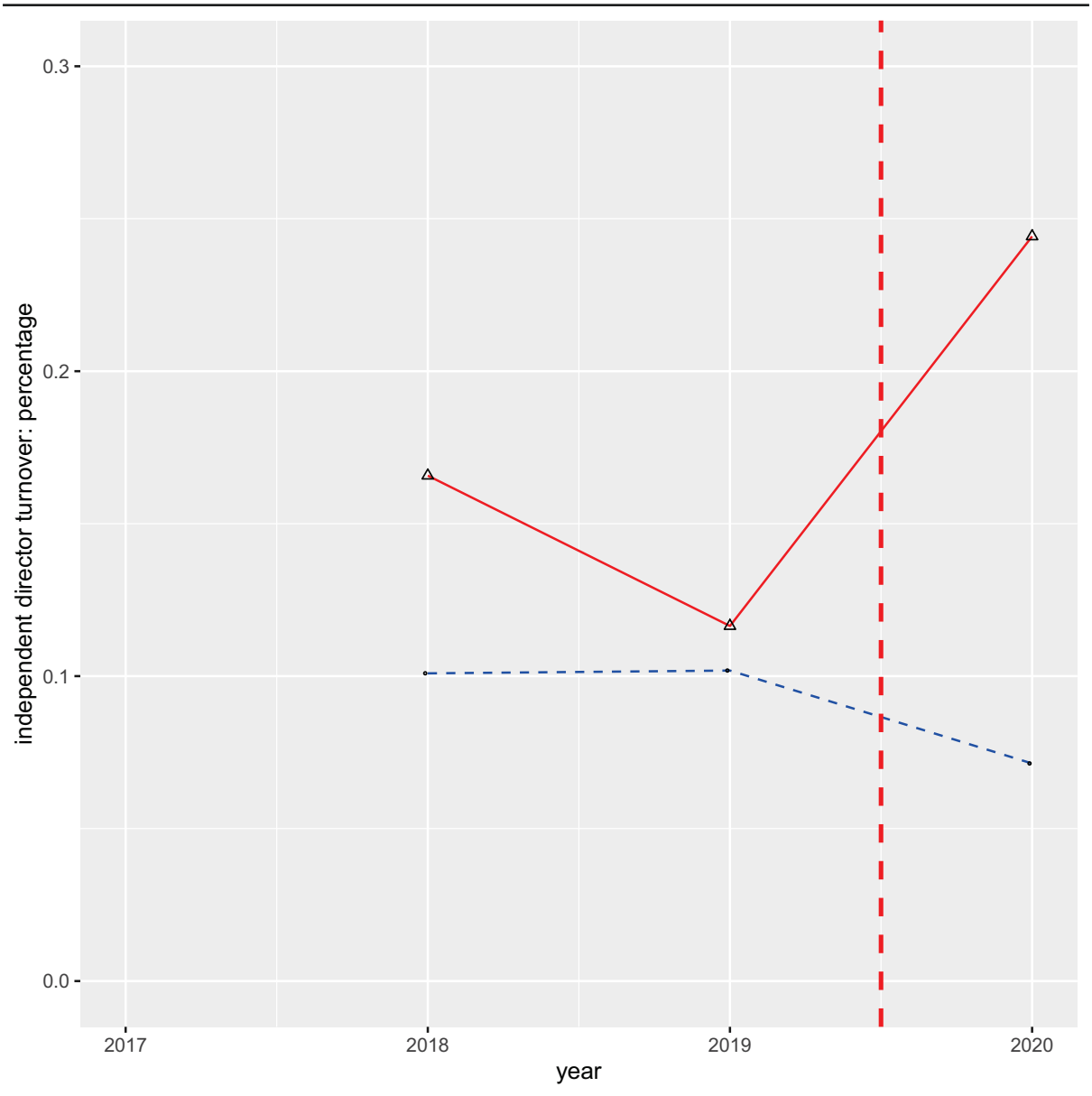


Figure 4: Time series plots: board independence among mainland firms

The figure presents the time series plots of the mean and median board independence in solid and dashed lines, respectively.

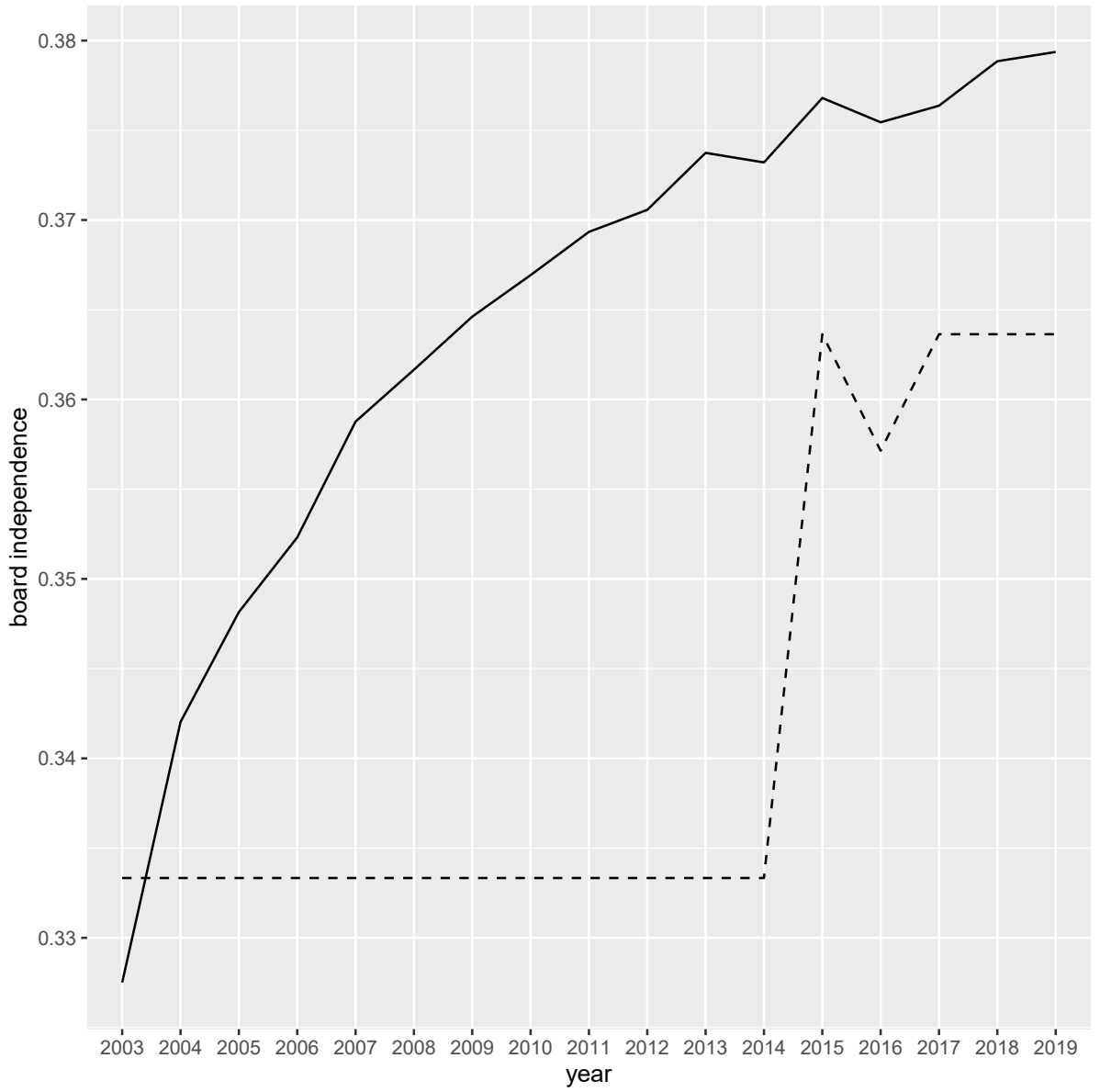


Figure 5: Time series plots: independent director resignations among mainland firms

The figure presents the time series plots of the independent director resignations per firm and per independent director.

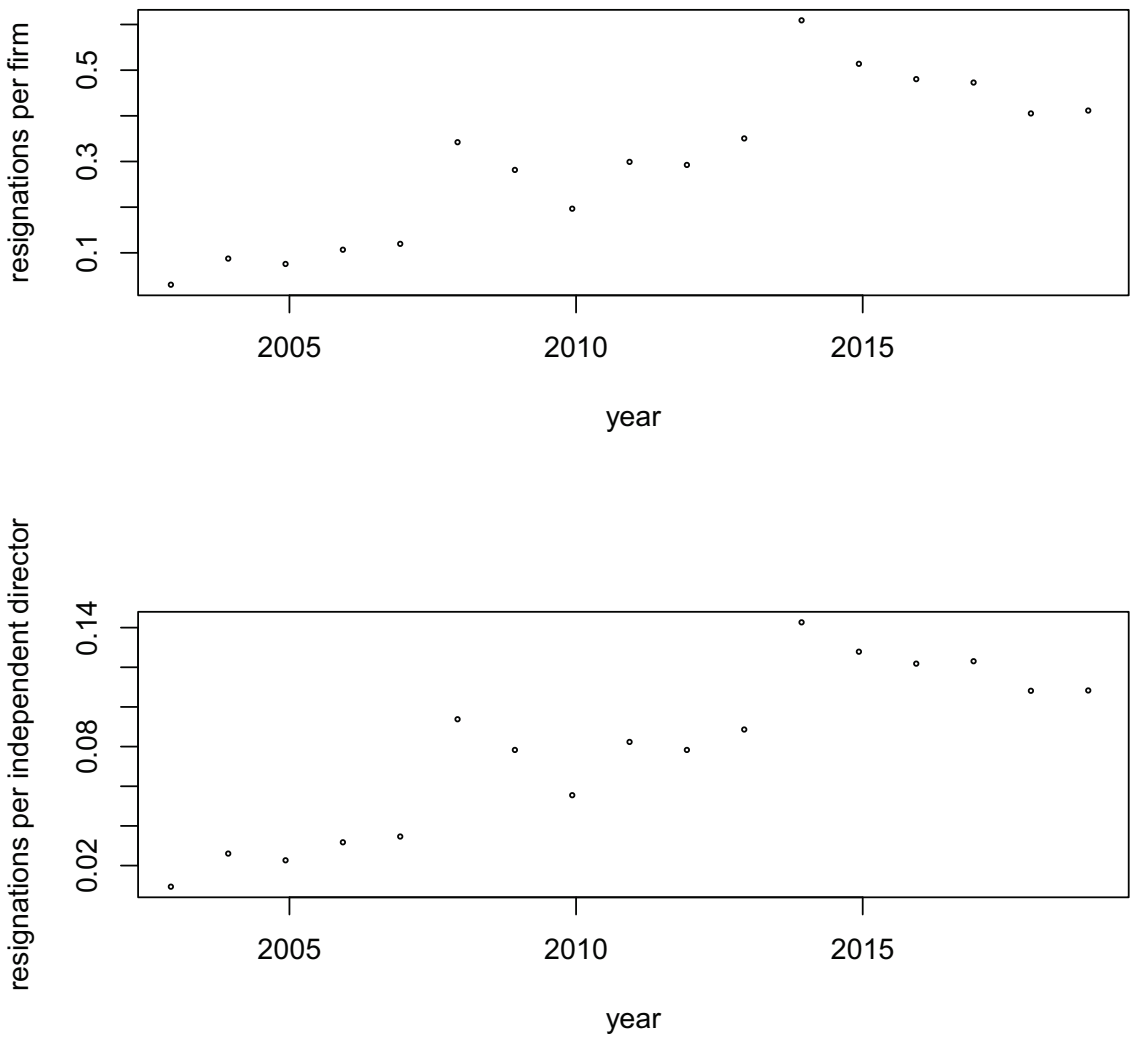
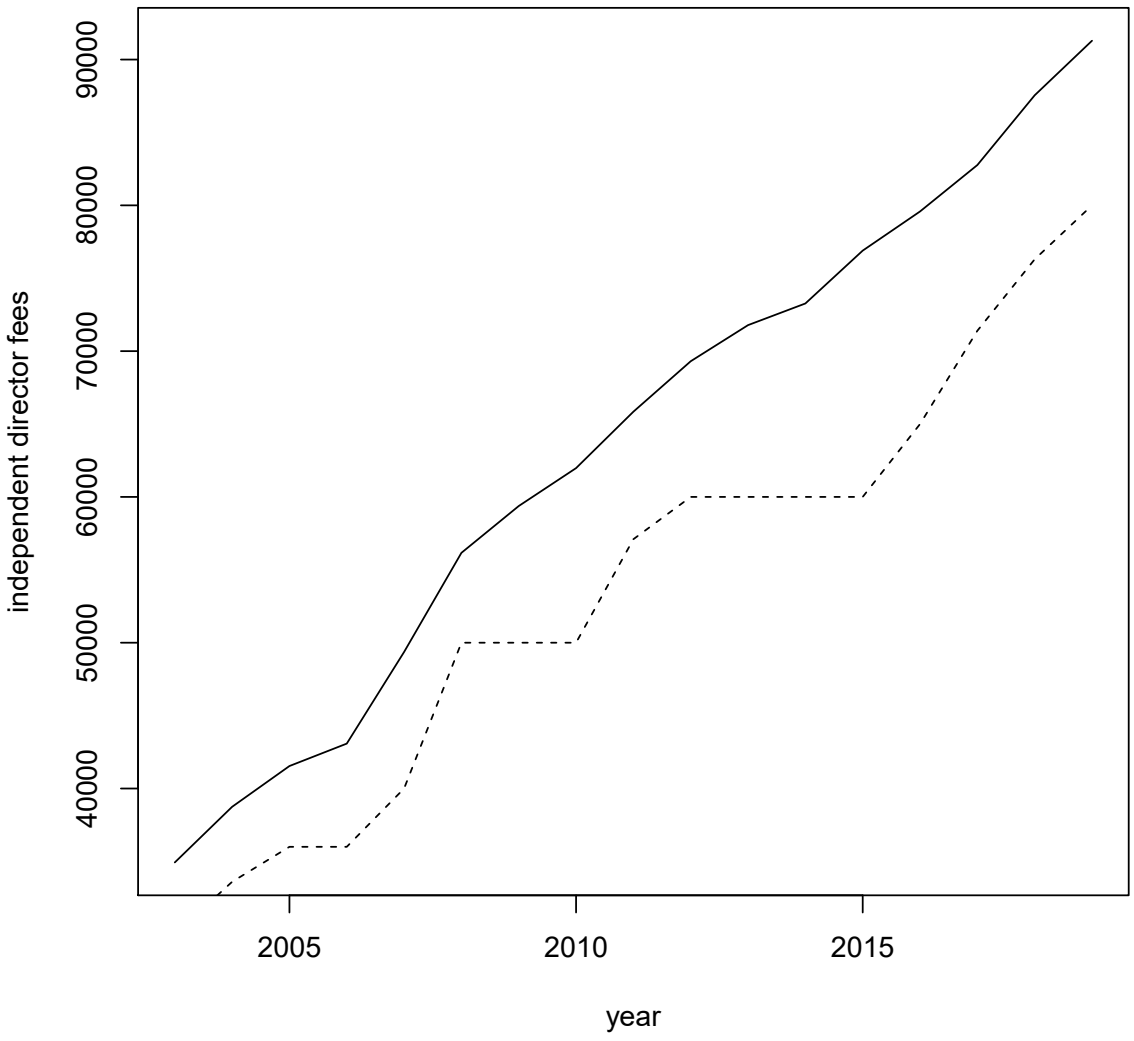


Figure 6: Time series plots: independent director fees among mainland firms

The figure presents the time series plots of the mean and median independent director fees in solid and dashed lines, respectively.



References

Arping, S. and Sautner, Z. (2013). Did SOX section 404 make firms less opaque? evidence from cross-listed firms. *Contemporary Accounting Research*, **30** (3), 1133–1165.

Banerjee, A., Nordqvist, M. and Hellerstedt, K. (2020). The role of the board chair—a literature review and suggestions for future research. *Corporate Governance: An International Review*, **28** (6), 372–405.

Berkman, H., Cole, R. A. and Fu, L. J. (2009). Expropriation through loan guarantees to related parties: Evidence from china. *Journal of Banking & Finance*, **33** (1), 141–156.

Boone, A. L., Field, L. C., Karpoff, J. M. and Raheja, C. G. (2007). The determinants of corporate board size and composition: An empirical analysis. *Journal of Financial Economics*, **85** (1), 66–101.

Boutchkova, M., Gonzalez, A., Main, B. G. and Sila, V. (2020). Gender diversity and the spillover effects of women on boards. *Corporate Governance: An International Review*, **29** (1), 2–21.

Calomiris, C. W., Fisman, R. and Wang, Y. (2010). Profiting from government stakes in a command economy: Evidence from chinese asset sales. *Journal of Financial Economics*, **96** (3), 399–412.

Cotugno, M., D'Amato, A., Gallo, A. and Stefanelli, V. (2020). Do supervisory enforcement actions affect board composition? *Corporate Governance: An International Review*, **29** (1), 22–44.

Crossland, C., Zyung, J., Hiller, N. J. and Hambrick, D. C. (2014). CEO career variety: Effects on firm-level strategic and social novelty. *Academy of Management Journal*, **57** (3), 652–674.

Djankov, S., Hart, O., McLiesh, C. and Shleifer, A. (2008). Debt enforcement around the world. *Journal of Political Economy*, **116** (6), 1105–1149.

Eisenhardt, K. M. (1989). Agency theory: An assessment and review. *Academy of Management Review*, **14** (1), 57–74.

Fama, E. F. and Jensen, M. C. (1983). Separation of ownership and control. *The Journal of Law and Economics*, **26** (2), 301–325.

Feng, H. and Xiao, J. Z. (2021). Board change and firm risk: Do new directors mean unstable corporate policies? *Corporate Governance: An International Review*, **30** (2), 212–231.

Firth, M., Wong, S., Xin, Q. and Yick, H. Y. (2016). Regulatory sanctions on independent directors and their consequences to the director labor market: Evidence from china. *Journal of Business Ethics*, **134** (4), 693–708.

Fracassi, C. and Tate, G. (2012). External networking and internal firm governance. *The Journal of Finance*, **67** (1), 153–194.

Hauser, R. (2018). Busy directors and firm performance: Evidence from mergers. *Journal of Financial Economics*, **128** (1), 16–37.

He, Q. and Rui, O. M. (2016). Ownership structure and insider trading: Evidence from china. *Journal of Business Ethics*, **134** (4), 553–574.

Hermalin, B. E. and Weisbach, M. S. (2012). Information disclosure and corporate governance. *The Journal of Finance*, **67** (1), 195–233.

Hou, W. and Moore, G. (2010). Player and referee roles held jointly: The effect of state ownership on china's regulatory enforcement against fraud. *Journal of Business Ethics*, **95** (S2), 317–335.

Huyghebaert, N. and Wang, L. (2012). Expropriation of minority investors in chinese listed firms: The role of internal and external corporate governance mechanisms. *Corporate Governance: An International Review*, **20** (3), 308–332.

Jensen, M. C. and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, **3** (4), 305–360.

Jiang, G., Lee, C. M. and Yue, H. (2010). Tunneling through intercorporate loans: The china experience. *Journal of Financial Economics*, **98** (1), 1–20.

Krause, R., Li, W., Ma, X. and Bruton, G. D. (2019). The board chair effect across countries: An institutional view. *Strategic Management Journal*, **40** (10), 1570–1592.

La Porta, R., de Silanes, F. L., Shleifer, A. and Vishny, R. W. (1998). Law and finance. *Journal of Political Economy*, **106** (6), 1113–1155.

—, Lopez-De-Silanes, F. and Shleifer, A. (1999). Corporate ownership around the world. *The Journal of Finance*, **54** (2), 471–517.

—, —, — and Vishny, R. (2000). Investor protection and corporate governance. *Journal of Financial Economics*, **58** (1-2), 3–27.

—, —, — and — (2002). Investor protection and corporate valuation. *The Journal of Finance*, **57** (3), 1147–1170.

—, —, — and Vishny, R. W. (1997). Legal determinants of external finance. *The Journal of Finance*, **52** (3), 1131–1150.

Li, Y., Liu, J., Tian, G. G. and Wang, X. (2021). Courtesy calls for reciprocity: Appointment of uncertificated independent directors in china. *Corporate Governance: An International Review*.

Lin, C.-P. and Chuang, C.-M. (2011). Principal-principal conflicts and IPO pricing in an emerging economy. *Corporate Governance: An International Review*, **19** (6), 585–600.

Linck, J. S., Netter, J. M. and Yang, T. (2009). The effects and unintended consequences of the sarbanes-oxley act on the supply and demand for directors. *Review of Financial Studies*, **22** (8), 3287–3328.

Melis, A. and Rombi, L. (2021). Country-, firm-, and director-level risk and responsibilities and independent director compensation. *Corporate Governance: An International Review*, **29** (3), 222–251.

Moore, C. B., Bell, R. G., Filatotchev, I. and Rasheed, A. A. (2012). Foreign ipo capital market choice: Understanding the institutional fit of corporate governance. *Strategic Management Journal*, **33** (8), 914–937.

Moursli, R. M. (2019). The effects of board independence on busy directors and firm value: Evidence from regulatory changes in sweden. *Corporate Governance: An International Review*, **28** (1), 23–46.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies*, **22** (1), 435–480.

Ryan, A. M., Kontopantelis, E., Linden, A. and Burgess, J. F. (2018). Now trending: Coping with non-parallel trends in difference-in-differences analysis. *Statistical Methods in Medical Research*, **28** (12), 3697–3711.

Shan, Y. G. (2013). Can internal governance mechanisms prevent asset appropriation? examination of type i tunneling in china. *Corporate Governance: An International Review*, **21** (3), 225–241.

Shleifer, A. and Vishny, R. W. (1997). A survey of corporate governance. *The Journal of Finance*, **52** (2), 737–783.

Sun, J., Yuan, R., Cao, F. and Wang, B. (2017). Principal-principal agency problems and stock price crash risk: Evidence from the split-share structure reform in china. *Corporate Governance: An International Review*, **25** (3), 186–199.

Vallelado, E. and García-Olalla, M. (2021). Bank board changes in size and composition: Do they matter for investors? *Corporate Governance: An International Review*, **30** (2), 161–188.

Westphal, J. D. and Zajac, E. J. (2013). A behavioral theory of corporate governance: Explicating the mechanisms of socially situated and socially constituted agency. *Academy of Management Annals*, **7** (1), 607–661.

Wowak, A. J., Mannor, M. J., Arrfelt, M. and McNamara, G. (2016). Earthquake or glacier? how ceo charisma manifests in firm strategy over time. *Strategic Management Journal*, **37** (3), 586–603.

Xu, W., Zeng, Y. and Zhang, J. (201). Tax enforcement as a corporate governance mechanism: Empirical evidence from china. *Corporate Governance: An International Review*, **19** (1), 25–40.

Young, M. N., Peng, M. W., Ahlstrom, D., Bruton, G. D. and Jiang, Y. (2008). Corporate governance in emerging economies: A review of the principal-principal perspective. *Journal of Management Studies*, **45** (1), 196–220.

Zattoni, A., Dedoulis, E., Leventis, S. and Ees, H. V. (2020). Corporate governance and institutions—a review and research agenda. *Corporate Governance: An International Review*, **28** (6), 465–487.

Zhang, M., Gao, S., Guan, X. and Jiang, F. (2014). Controlling shareholder-manager collusion and tunneling: Evidence from china. *Corporate Governance: An International Review*, **22** (6), 440–459.

Curriculum Vitae

Wei LIN

Email: wei.lin@unisg.ch

Nationality: Chinese

Date of Birth: 10/10/1991

Education

02/2018 – 09/2022 **University of St. Gallen (HSG), St. Gallen, Switzerland**
- PhD in Finance
- Dissertation topics: Essays on Corporate Governance and Asset Pricing
- Thesis Committee: Roland Füss, Paul Söderlind, Karl Frauendorfer

09/2014 – 03/2018 **University of St. Gallen (HSG), St. Gallen, Switzerland**
- Master of Arts in Banking and Finance
- Thesis: The Performance of Private Commercial Real Estate5

09/2010 - 07/2014 **Beijing Foreign Studies University (BFSU), Beijing, China**
- Bachelor of Arts in English Literature
- Bachelor of Economics, Finance major
- Exchange semester at FHNW, Switzerland
- Thesis: Short Selling Mechanism of US Hedge Funds targeting Chinese Stocks

Employment

02/2020 – 07/2020 **Bachelor Programme in Business Administration (BBA), University of St. Gallen (HSG), St. Gallen, Switzerland**
Tutor of Statistics

11/2017 – 08/2020 **Swiss Institute of Banking and Finance (SBF), University of St. Gallen (HSG), St. Gallen, Switzerland**
Graduate Research and Teaching Assistant

11/2015 – 09/2016 **Project Firefly, St. Gallen, Switzerland**
Finance Community Specialist

10/2013 - 04/2014 **Commando Capital Management Ltd., Beijing, China**
Intern, Equity Research Analyst Assistant

Research Papers

Working Paper **Do Investor Protection Laws Benefit Investors? Evidence from a Natural Experiment on Cross-listed Firms**
We examine the effects on corporate governance where the Chinese legislators revise the Securities Law aiming at improved minority shareholder protection. We find significantly higher independent director turnover amongst the treated

firms that we attribute to increased responsibility of the independent directors following the law revision.

Working Paper **Pricing the Location of Commercial Properties**– joint with Roland Füss
The study aims to identify and break down the priced factors of private commercial property returns. We are especially interested in the influence of location on the returns of real estate investments. Our preliminary estimates suggest mixed results from an all-encompassing location factor.

Working Paper **Corporate Transparency and Bond Liquidity** – joint with Falko Fecht, Roland Füss, Philipp Rindler
We investigate the impact of accounting transparency on liquidity and liquidity risk of corporate bonds. Our findings buttress the common belief that higher transparency contributes to higher liquidity. On top of the main effect, we find that such positive correlation strengthens when firms are closer to default, and that transparency reduces liquidity risk during the 07-09 crisis.

Presentations at Academic Conferences

07/2022 **Academy of International Business (AIB) 2022, Miami, USA**
Presentation on *Do Investor Protection Laws Benefit Investors? Evidence from a Natural Experiment on Cross-listed Firms*

10/2021 **7th Annual International Corporate Governance Society (ICGS) Conference, Groningen, the Netherlands**
Presented a former version of *Do Investor Protection Laws Benefit Investors? Evidence from a Natural Experiment on Cross-listed Firms*

09/2021 **Financial Management & Accounting Research Conference (FMARC), Paphos, Cyprus**
Cancelled due to COVID-19

10/2020 **1st International Real Estate Society (IRES) (virtual) Symposium for Doctoral Students**
Top 9 finalists – presentation and discussions on *Pricing the Location of Commercial Properties*

10/2019 **10th NTNU Business School Conference, Trondheim, Norway**
Presentation on *Corporate Transparency and Bond Liquidity*

06/2018 **25th European Real Estate Society (ERES) Conference, Reading, UK**
Presentation on *Risk Factors in Private Commercial Real Estate*

Languages

Computer		Human	
R, Python, Excel VBA	*Advanced*	English	*Fluent*
Matlab, Stata SQL, LaTex	*Good knowledge*	German	*Working Proficiency (B2)*
		Mandarin, Cantonese, Hakka	*Native*