Essays on Risk Preferences, Time Preferences, and Credit Risk Contagion

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Abstract

This cumulative dissertation comprises two contributions on behavioral finance and one contribution on credit risk management.

The first contribution examines the impact of investors' probability distortion on the stock market and future economic growth. The empirical challenge is to quantify the optimality of today's decisions in order to study its impact on future economic growth. Risk preferences can be estimated using stock prices. We use a time series of monthly aggregated stock prices from 1926 to 2015 and estimate risk preferences via an asset pricing model using cumulative prospect theory agents and compute a recently proposed probability distortion index. This index negatively forecasts future GDP growth, both in-sample and out-of-sample, with stronger and more reliable predictability as the time increases. Our research results suggest that distorted stock prices can lead to significant welfare losses.

The second contribution establishes empirical relationships of risk and time preferences on academic success. Subjects of our experiment are fourth-semester undergraduate economics students at Leibniz University Hannover. We measure academic success via the points achieved in a business exam in the 4th semester as well as the grade point average of the academic progress so far. Our methodology is based on Tanaka et al. (2010), who use a multiple price list to estimate time preferences and lotteries for the preference parameters of cumulative prospect theory. We find empirical evidence for quasi-hyperbolic discounting and a relationship between higher academic success and lower time discounting. No empirical evidence is observed for a link between risk preferences and academic performance.

In the final contribution, we examine contagion effects in credit default risk defined as co-movement in the distances-to-default of U.S. firms, which we estimate from the model of Campbell et al. (2008). We quantify financial, inter-industry, and intra-industry contagion effects based on Fama and French's 12 sectors and document significant co-movement across sectors during times of crises. We also find that a firm's size and average share of total sales in each sector are significantly related to intra-industry contagion. Our results are robust to different crisis definitions and index weighting methodologies. Moreover, our results suggest that the probability of default increases in times of crisis due to contagion effects, which may lead to an underestimation of the risk measures of individual loans or portfolios and ultimately of economic capital.

Keywords: Economic growth, probability distortion, suboptimal decision making, risk preferences, time preferences, quasi-hyperbolic discounting, academic success, contagion, credit risk, sector-specific contagion, financial crisis, intra-industry contagion, inter-industry contagion
JEL Classification: C19, C69, D83, D90, G01, G02, G12, G14, G18, G20, P36

Zusammenfassung

Die vorliegende kumulative Dissertation umfasst zwei Aufsätze zu Behavioral Finance und einen Aufsatz zum Kreditrisikomanagement.

Der erste Beitrag untersucht den Einfluss der Wahrscheinlichkeitsverzerrung von Investoren auf dem Aktienmarkt und dem künftigen Wirtschaftswachstum, wobei die empirische Herausforderung darin besteht, die Optimalität der heutigen Entscheidungen zu quantifizieren, um ihre Auswirkungen auf das künftige Wirtschaftswachstum zu untersuchen. Allerdings können die Risikopräferenzen anhand von Aktienpreisen geschätzt werden. Wir verwenden eine Zeitreihe von monatlichen aggregierten Aktienkursen von 1926 bis 2015 und schätzen die Risikopräferenzen über ein Modell zur Preisbildung von Wertpapieren anhand von Agenten der kumulativen Prospekt-Theorie und berechnen einen kürzlich vorgeschlagenen Wahrscheinlichkeitsverzerrungsindex. Dieser Index prognostiziert das zukünftige Wachstum des Bruttoinlandsprodukts sowohl In-Sample als auch Out-Of-Sample, wobei die Prognose mit steigendem Zeitraum stärker und zuverlässiger ist. Unsere Untersuchungsergebnisse lassen darauf schließen, dass verzerrte Aktienkurse zu signifikanten Wohlfahrtseinbußen führen können.

Der zweite Beitrag stellt empirische Zusammenhänge von Risiko- und Zeitpräferenzen zum akademischen Erfolg her. Probanden unseres Experiments sind Bachelorstudenten der Wirtschaftswissenschaften im vierten Semester an der Leibniz Universität Hannover. Akademischen Erfolg messen wir über die erreichten Punkte in einer betriebswirtschaftlichen Klausur im 4. Semester sowie der Durchschnittsnote des bisherigen Studienverlaufs. Die verwendete Methodik basiert auf Tanaka et al. (2010), die zur Schätzung der Zeitpräferenzen eine Mehrfachpreisliste verwenden und Lotterien für die Präferenzparamter der kumulativen Prospekt-Theorie. Wir finden empirische Evidenz für eine quasi-hyperbolische Diskontierung und einen Zusammenhang zwischen höherem akademischen Erfolg und geringerer Zeitdiskontierung. Ein Zusammenhang zwischen Risikopräferenzen und akademischer Leistung ist empirisch nicht belegbar.

Im letzten Beitrag untersuchen wir Ansteckungseffekte in Kreditausfallrisiken, die wir als Co-movement der Distances-to-Default von US-Unternehmen definieren, welche wir aus dem Modell von Campbell et al. (2008) schätzen. Wir quantifizieren finanzielle, branchenübergreifende und brancheninterne Ansteckungseffekte auf Basis der 12 Sektoren von Fama und French und dokumentieren ein signifikantes Co-movement zwischen den Sektoren während Krisen. Wir stellen zudem fest, dass die Unternehmensgröße und der durchschnittliche Anteil des Unternehmens am Gesamtumsatz im jeweiligen Sektor mit der Ansteckung innerhalb einer Branche signifikant zusammenhängen. Unsere Ergebnisse sind gegenüber verschiedenen Krisendefinitionen und Indexgewichtungen robust. Zudem deuten unsere Ergebnisse darauf hin, dass die Ausfallwahrscheinlichkeit in Krisenzeiten aufgrund von Ansteckungseffekten steigt, was zu einer Unterschätzung der Risikomaße von Einzelkrediten oder Portfolios und letztlich des ökonomischen Kapitals führen kann.

Schlagwörter: Wirtschaftswachstum, Wahrscheinlichkeitsgewichtung, suboptimale Entscheidungen, Risikopräferenzen, Zeitpräferenzen, quasi-hyperbolisches Diskontieren, akademischer Erfolg, Ansteckungseffekte, Kreditrisiko, sektorspezifische Ansteckung, Finanzkrise, Intra-Industrie-Ansteckung, Inter-Industrie-Ansteckung
JEL Klassifikationen: C19, C69, D83, D90, G01, G02, G12, G14, G18, G20, P36

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Chapter 1

Preface

This cumulative dissertation focuses on empirical studies in two research areas: the first two essays cover topics in the field of behavioral finance, while the third essay shifts focus to credit risk management. Each essay in this dissertation contains a comprehensive introduction to the research problem and conclusion. The mathematical notation in each essay is independent from each other.

Expected utility theory (Bernoulli, 1954) of decision-making under risk is widely applied in finance. This normative theory fails to capture observed behavioral patterns such as loss aversion, diminishing value sensitivity, probability weighting and reference dependence in experiments (i.e., Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). The descriptive cumulative prospect theory (CPT) of Tversky and Kahneman (1992) addresses these phenomena and is a central component of current research in the field of behavioral finance. Chapter 2 *"Probability Distortion, Asset Prices, and Economic Growth"* (joint work with Maik Dierkes and Vulnet Sejdiu) investigates the effect of cumulative prospect theory preferences estimated via aggregate stock prices on future economic growth measured by the GDP. We start by assuming that all agents are CPT investors and behave as described in the equilibrium model of Barberis and Huang (2008) to determine stock prices. We derive that in equilibrium the Sharpe Ratio is solely determined by the agents' CPT preference parameters. Therefore, we can estimate the market's Sharpe Ratio to infer the CPT preference parameters. We conduct a sensitivity analysis and find that changes in the probability weighting parameter has the largest impact on the Sharpe Ratio, while value sensitivity and loss aversion have a second order effect. An implicit assumption of our estimation technique is that risk preferences can vary over time which has been documented in the lab by Birnbaum (1999), Glöckner and Pachur (2012), and Zeisberger et al. (2012), as well as outside the lab by Guiso et al. (2018). To facilitate our predictive regressions, we propose a new index of probability distortion that is able to appropriately quantify deviations from additive probabilities (like in expected utility theory). It turns out that likelihood insensitivity is a better concept than Tversky and Kahneman's (1992) probability weighting parameter. Hence, we shall use deviations of likelihood sensitivity from additive probabilities in our predictive regressions and focus on CPT's probability distortion when estimating preference parameters from the financial market. Even when including control variables, our likelihood sensitivity based measure of probability distortion still significantly predicts future GDP growth. Put differently, our probability distortion index is not tantamount to macroeconomic uncertainty measures, systemic risk, or other financial market factors. We find that stronger probability distortion negatively forecasts future GDP growth, both in-sample and out-of-sample, with stronger and more reliable predictability as the time increases. Our results are robust to in-sample and out-of-sample analyses, different estimation procedures of the asset pricing model (i.e. simple average vs. moving average estimators; GARCH vs. EGARCH), different measures for probability distortion (likelihood insensitivity and Prelec's (1998) probability weighting function), and sample splits (1953–1984 and 1985–2015).

Time preference is a further subject of research in behavioral finance and concerned with how individuals behave in intertemporal decisions. While some experimental designs simply opt to detect which subjects are able to delay immediate rewards, others use intertemporal financial choices in matching or choice tasks (see Frederick et al., 2002) to estimate discount functions (see Benhabib et al., 2010). Time preferences and related decisions impose potentially far reaching impacts on personal finances and consumer behavior (i.e., Warner and Pleeter, 2001; Ashraf et al., 2006; Meier and Sprenger, 2010), pension plans (i.e., Bernheim et al., 2001; Cagetti, 2003), health choices (i.e., Kirby et al., 1999; DellaVigna and Malmendier, 2006; Johnson et al., 2015), but also on academic success. In chapter 3 "*Time Preferences, Risk Preferences and Academic Success: Evidence from the Classroom*" (joint work with Maik Dierkes) we change methodology and conduct experiments to evaluate time and risk preferences of 4th semester students to gauge a potential link on the academic success. The early study of Mischel et al. (1989) shows preschool students who were able to delay the immediate consumption of one marshmallow by 15 minutes in order to get an additional one later significantly scored higher in verbal and quantitative Scholastic Assessment Test scores, which were assessed when they were adolescents. Reimers et al. (2009), Bauer and Chytilová (2010), Perez-Arce (2017) among others document a link between delay discounting and the level of education, where higher educated individuals tend to be more patient. De Wit et al. (2007) find more patient subjects feature a higher IQ in addition to a higher level of education, even after controlling for socioeconomic variables. This result is closely related to the higher cognitive ability of more patient subjects (i.e. Borghans et al., 2008; Oechssler et al., 2009). Duckworth and Seligman (2005), however, find self-control has a higher impact on the variance of final grades than cognitive ability as measured by the IQ among students of the 8th grade. Kirby et al. (2005) document a negative correlation between the grade point average (GPA) and discount rates of undergraduate students. Silva and Gross (2004) find college students who are able to delay immediate rewards obtain higher study scores and choose to engage in work to gain extra credits as compared to more impatient students. Lee et al. (2012) ascertain that lower time discounting breeds higher academic motivation and better academic performance among Dutch secondary school students. They suggest a feedback loop where more patient students earn better grades and develop a higher level of academic motivation, resulting in increased performance. Non and Tempelaar (2016) study the impact of time discounting on first-year business and economics students and find that impatient students, who always prefer the immediate reward, earn lower scores and have a higher rate at failing exams. We study a potential link of time preferences on the academic success of business and economics students at the Leibniz University Hannover. The hypothesis is that students who delay immediate gratification in favor of dedicating more time to their academic progress during the semester, perform better than students whose ability to delay gratification is less pronounced. Additionally, we explore the relationship between academic success and a subject's CPT preferences. The hypothesis is that more risky behavior, as measured by CPT, will lead to lower academic success, e.g., students gambling that not all class topics will be covered in an exam and thus limit topics to learn. Borghans et al. (2008), Benjamin et al. (2013), and Beauchamp et al. (2017) find a lower risk aversion among subjects with a high cognitive ability, whereas Booth and Katic (2013) do not find a link between cognitive ability and risk preference. In a study Dohmen et al. (2010) find subjects with higher risk aversion and higher impatience to score lower in cognitive ability tests. Frederick (2005) and Oechssler et al. (2009) compare low vs. high scores of subjects in the cognitive reflection test. Low scores are associated with lower patience and higher risk aversion. Participants of our experiments are bachelor students of economics and management at the Leibniz University Hanover. We contribute to the literature in several ways. We consider a wide range of potential discounting functions (exponential, hyperbolic, quasi-hyperbolic discounting, and the enhanced model of Benhabib et al. (2010)), and find the best fitting function to our sample. We include explanatory variables directly in the discounting function to investigate the impact of time discounting on academic performance using the methodology of Tanaka et al. (2010). To the best of our knowledge, we are the first to apply the methodology of

Tanaka et al. (2010) to investigate the relationship between risk and time preferences on academic success. While we find evidence for a link between time preferences and academic performance, we do not find a link for risk preferences as measured by CPT.

Chapter 4 *"A Study of Inter- and Intra-Industry Credit Risk Contagion of U.S. Companies"* shifts focus to credit risk management. A vital part of credit risk management in financial institutions is the allocation of an adequate risk capital; for example the economic capital which is the difference between the value-at-risk and the expected loss. This allocation requires the measurement of credit risk. Data on corporate defaults show clusters which typically occur around times of economic turmoil, like recessions or stock market crashes, and are accompanied by a higher number of corporate defaults than during normal times (see i.e. Azizpour et al., 2018). For example, a high number of corporate failures were observed across all sectors of the U.S. economy during the global financial crisis. Identifying the source of the clustered default events is of great importance for accurate risk analysis of financial institutions' credit portfolios and the stability of the financial system. Systematic factors alone, like the gross domestic product or interest rates, cannot explain the emergence of default clusters with increased default rates (Das et al. (2007)). Duffie et al. (2007) and Duffie et al. (2009) introduce the concept of frailty, an unobservable systematic factor that triggers higher default rates during crisis periods. Koopman et al. (2011) find that frailty is a significant factor driving default clustering in addition to macroeconomic factors. Contagion is a further concept to explain default clusters and the main focus of this contribution.

Dornbusch et al. (2000) define contagion as "a significant increase in cross-market linkages after a shock [...], as measured by the degree to which asset prices or financial flows move together across markets relative to this co-movement in tranquil times" (p. 178). We adopt the definition of Azizpour et al. (2018) who describe the impact of a corporate default on the default of other companies as credit default contagion, and define credit risk contagion as the increase in co-movement of credit quality changes. Azizpour et al. (2018) gauge the importance of the systematic factors, frailty, and contagion by using a parameterized moving average of the face value of defaulted companies to fit an intensity model to CDX data and find that the contagion factor has the highest fraction in intensity rate decomposition. Therefore, we focus on contagion as explanation for the default clusters. We infer monthly estimates for the annual probability of default from the Campbell et al. (2008) model for U.S. companies. This approach uses stock market information (i.e. excess returns, market capitalization), as well as accounting data (i.e. long-term liabilities, net income) and default events to estimate the probability of default on the firm level. Then we adopt model of Baur (2012) to changes in distances-to-default which we obtain from the probability of default estimates using monthly stock market information and quarterly accounting data assigned to monthly observations. This allows us to study inter- and intra-industry contagion effects with a sufficient number of observations. To the best of our knowledge, we are the first to explore inter- and intra-industry contagion based on probabilities of defaults which are not directly inferred from market prices. Our paper contributes to the existing literature in the following ways. First, we show that in the context of logit models, that are fitted based on default events, contagion effects are identifiable at the inter-industry level, including financial contagion. The results are robust to the choice of crisis definition and index weighting methodology. Second, we explore intra-industry contagion by analyzing a firm's impact on its respective sector index and identify drivers associated with enhanced co-movement during times of crisis. We find evidence for inter-industry contagion independent of the crisis definition, suggesting co-movement during times of crisis is associated with negative changes in the distances-to-default that yield an increase in the probability of default. The results are robust to the choice of crisis definition and weighting methodology. The Basel II framework states that,"[i]n order to avoid over-optimism, a bank must add to its estimates a margin of conservatism" (Basel Committee on Banking Supervision, 2006, § 425, p. 100). Opting for point-in-time estimates for the probability of default based on macroeconomic variables as proposed by Rösch (2005) might not be sufficient to capture the enhanced co-movement causing increased probability of default during crisis periods. It can be argued that an "over-optimism" can arise if financial institutions neglect the influence of credit risk contagion. Finally, we find small (large) companies and companies with a high (low) share of sales in their sector to have a lower (higher) probability to be subject to intra-industry contagion.

Chapter 2

Probability Distortion, Asset Prices, and Economic Growth

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Abstract

In this paper, we link stock market investors' probability distortion to future economic growth. The empirical challenge is to quantify the optimality of today's decision making to test for its impact on future economic growth. Fortunately, risk preferences can be estimated from stock markets. Using monthly aggregate stock prices from 1926 to 2015, we estimate risk preferences via an asset pricing model with Cumulative Prospect Theory (CPT) agents and distill a recently proposed probability distortion index. This index negatively predicts GDP growth in-sample and out-of-sample. Predictability is stronger and more reliable over longer horizons. Our results suggest that distorted asset prices may lead to significant welfare losses.

Keywords: Economic growth, probability distortion, suboptimal decision making

JEL Classification: G02, G12

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Chapter 3

Time Preferences, Risk Preferences and Academic Success: Evidence from the Classroom

The content of this chapter refers to the working paper:

Dierkes, M. and Germer, S. (2022). Time Preferences, Risk Preferences and Academic Success: Evidence from the Classroom. *Working Paper, Leibniz University Hannover.*

Abstract

In this paper, we conduct experiments to explore the effect of risk and time preferences on academic success. Subjects are business and economics students at Leibniz University Hannover who enrolled in 4th-semester courses. We investigate the preferences relationship to academic success as measured by the points achieved in a business administration exam written in the 4th semester and overall GPA. We adopt the methodology of Tanaka et al. (2010) who use a multiple price list to elucidate time preferences and estimate cumulative prospect theory preferences. We find evidence for quasi-hyperbolic discounting and a link between high academic success and lower time discounting, we do not find a link between risk preferences and academic performance.

Keywords: Risk preferences, time preferences, quasi-hyperbolic discounting, academic success

JEL Classification: D83, D90, P36

3.1 Introduction

Intertemporal choices are omnipresent in daily life, for example, the decision to save money now in order to consume later as in pension plans (i.e., Bernheim et al., 2001; Cagetti, 2003). Such decisions do not only impose potentially far reaching impacts on personal finances and consumer behavior (i.e.,l Warner and Pleeter, 2001; Ashraf et al., 2006; Meier and Sprenger, 2010), and health (i.e., Kirby et al., 1999; DellaVigna and Malmendier, 2006; Johnson et al., 2015), but also on academic success.

A striving example for the importance of time preferences on academic success has been documented by Mischel et al. (1989) who presented 4-year-old Stanford pre-school students one marshmallow and promised them another one if the student could successfully wait for 15 minutes without eating the first marshmallow. Students who were able to delay the immediate consumption of the marshmallow as a child for a longer time showed a significant positive correlation in verbal and quantitative Scholastic Assessment Test scores, which were assessed more than ten years later. In addition to the empirical findings, their parents also described the more patient students as "better in self-control, more able to resist temptation, to tolerate frustration, and to cope maturely with stress" (Mischel et al., 1989, p. 936). This early study provides empirical evidence for a link between time preferences and academic performance measured via the SAT scores as an entry requirement for many universities. In the present paper, we study a potential link of time preferences on the academic success of business and economics students at the Leibniz University Hannover. The hypothesis is that students who delay immediate gratification, like meeting friends or binge-watching a series, in favor of dedicating more time to their academic progress during the semester, academically perform better than students whose ability to delay gratification is less pronounced.

Reimers et al. (2009), Bauer and Chytilová (2010), Perez-Arce (2017) among others document a link between delay discounting and the level of education, where higher educated individuals tend to be more patient. De Wit et al. (2007) find more patient subjects feature a higher IQ in addition to a higher level of education, even after controlling for socioeconomic variables. This result is closely related to the higher cognitive ability of more patient subjects (i.e. Borghans et al., 2008; Oechssler et al., 2009). Duckworth and Seligman (2005), however, find self-control has a higher impact on the variance of final grades than cognitive ability as measured by the IQ among students of the 8th grade. Kirby et al. (2005) document a negative correlation between the grade point average (GPA) and discount rates of undergraduate students. Silva and Gross (2004) find college students who delay immediate rewards less obtain higher study scores and choose to engage in work to gain extra credits as compared to more impatient students. Lee et al. (2012) ascertain that lower time discounting breeds higher academic motivation and better academic performance among Dutch secondary school students. They suggest a feedback loop where more patient students earn better grades and develop a higher level of academic motivation, resulting in even better grades. Non and Tempelaar (2016) study the impact of time discounting on first-year business and economics students and find that impatient students, who always prefer the immediate reward, score lower grades and have a higher rate at failing exams. They do not estimate the students discount function but identify impatient students by creating a dummy variable for students who always prefer the immediate reward. There is no payout provided to the participants of their study.

Additionally, we explore the relationship between academic success and a subject's cumulative prospect theory's (CPT) risk preferences. The hypothesis is that more risky behavior, as measured by CPT, will lead to lower academic success, e.g., students gambling that not all class topics will be covered in an exam and thus focusing on a limited set of topics to study for the exam. Borghans et al. (2008), Benjamin et al. (2013), and Beauchamp et al. (2017) find a lower risk aversion among subjects with a high cognitive ability. Booth and Katic (2013) do not find a link between cognitive ability and risk preference. Dohmen et al. (2010) study adults with a higher risk aversion and higher impatience and find them to achieve lower grades in cognitive ability tests. Frederick (2005) and Oechssler et al. (2009) compare low to high scores of subjects in the cognitive reflection test.

Where low scores are associated with lower patience and higher risk aversion. While Frederick (2005) documents a higher loss aversion for lower CRT scores, Oechssler et al. (2009) find a muted effect.

Participants of our experiments are bachelor students of economics and management at the Leibniz University Hanover, who have enrolled in the 4th semester mandatory module in business administration 5 consisting of two courses, (1) investments and finance and (2) controlling. Both courses are tested in one combined exam at the end of the summer semester 2017. All students are automatically registered for the mandatory courses and the corresponding exams, according to the examination regulations. Up to the 6th semester, there are only mandatory courses. A student can only withdraw from a mandatory exam due to illness, which has to be documented by medical certificate. In case of medically induced withdrawal or failure of the exam, a student is automatically re-registered for the respective exam in the middle of the following semester. Note that these examination regulations prevent students who tend to procrastinate from extending their duration of study beyond regular study time of eight semesters.

Our paper contributes to the literature in several ways. We consider a wide range of potential discounting functions (exponential, hyperbolic, quasi-hyperbolic discounting, and the enhanced model of Benhabib et al. (2010)), and identify the best fitting function to our sample. We include explanatory variables directly in the discounting function to investigate the impact of time discounting on academic performance using the methodology of Tanaka et al. (2010). To the best of our knowledge, we are the first ones to apply the methodology of Tanaka et al. (2010) to investigate the relationship between risk and time preferences on academic success.

While we find evidence for a link between time preferences and academic performance, we do not find a link for risk preferences as measured by CPT.

The remainder of this paper is structured as follows. Section 3.2 explains the research design and trail description. Section 3.3 presents the methodology and empirical results of the risk preferences. Section 3.4 describes the methodology of the time preference assessment and the empirical findings. The mathematical notation in sections 3.3 and 3.4 is independent from each other. Section 3.5 concludes the analysis.

3.2 General Methodology

We structure the experiments analogously to Tanaka et al. (2010). The structure of the questionnaires on the risk and time preferences is explained to all participants including the division of each questionnaire into sets and the requirement to make one decision for each lottery or time decision pair without switching more than once per set. The students were informed that we randomly select one participant in each assessment for a payoff based on the choices he or she made. To do this, we randomly select a questionnaire and draw a random number according to the number of decisions to be made in each questionnaire. Lotteries that would provide a potentially negative payout to the students were specifically excluded. We guarantee that the payout will be made in cash immediately after the experiment using a random number generator based on the

Table 3.1 Summary statistics for the explanatory variables. This table reports the summary statistics of the explanatory variables. N denotes the number of observations.

	N	Mean	Std. Dev.	Min	Max
Sex (Male=1)	322	0.61	0.49	0.00	1.00
Age	322	22.28	2.07	19.00	32.00
Rural	322	0.28	0.45	0.00	1.00
Extra Attempts	322	3.07	4.03	0.00	32.00
GPA	321	2.85	0.54	1.28	4.00
Exam Points	246	346.19	172.83	8.00	826.50
VAT	322	0.20	0.40	0.00	1.00

randomly chosen question and their decision. A random number generator is used to simulate the lottery outcome for the risk preference assessment. For the time preference assessment, we assure the students that the payout will occur at the exact time chosen in case of a selected delayed payout. To determine the payout, we divide the possible amounts of the risk assessment by 20 and those of the time preference assessment by 25. This payout scheme, where we randomly pick to pay one participant per experiment, is as effective as providing all participants payouts (Charness et al., 2016).

We exclude inconsistent answers from our analysis. Bauer and Chytilová (2010) find that this procedure does not impose a bias as inconsistent responses are uncorrelated with explanatory variables. Time preferences were assessed on April 17, 2017 and risk preferences on June 20, 2017. Table 3.1 presents the summary statistics of the explanatory variables. Sex is a dummy variable taking the value one if the student is male and zero if the student is female. Age is the student's age at the end of the semester. Rural is a dummy variable indicating one if the ZIP code of the student's permanent address is in a rural area with less than 300 inhabitants per square kilometer and zero otherwise. Data on inhabitants per square kilometer are provided by the Federal Statistical Office.[1] Extra attempts are the number of additional attempts to pass exams after the first attempt. Students who have passed an exam cannot re-register to improve their grades. GPA is the grade point average achieved by each student at the end of the semester, where 1.0 is very good, and 4.0 is the worst score possible. The business administration 5 exam consists of two parts, each comprising 50% of the total points. The first part covers topics from the class investments and finance and the second part from the class controlling. In order to pass the exam, 50% of the total points must be achieved regardless in with part. Exam points are the product of achieved points in each exam part. In one exercise in the first part of the exam, the value-added tax had to be deducted from a given gross price to obtain the amount to be financed. VAT is a dummy variable that takes the value one if the student correctly calculated the net price and zero if not.

Other studies include variables for education and income in their analysis (i.e. Meier and Sprenger, 2010; Harrison et al., 2002) which are not provided in our data. Since our data consists of students only, all of them passed the A-levels as an entry requirement to study in Germany. Thus, we have a homogeneous sample regarding the level of education. We assume the same for the students' personal income in our sample.

[1] The data is available at https://www.destatis.de/DE/Themen/Laender-Regionen/Regionales/Gemeindeverzeichnis/Administrativ/04-kreise.html.

3.3 Risk Preferences

We apply the methodology of Tanaka et al. (2010) and model risk preferences using the cumulative prospect theory of Tversky and Kahneman (1992).

Given a lottery L, all possible outcomes x_i are sorted in ascending order

$$L = \{(x_{-m}, p_{-m}), \ldots, (x_{-1}, p_{-1}), (x_0, p_0), (x_1, p_1), \ldots, (x_n, p_n)\} \tag{3.1}$$

satisfying $x_{i-1} < x_i$, where x_0 is the reference point. p_i is the corresponding probability of outcome x_i. Losses and gains are defined based on the reference point x_0 resulting in m losses and n gains as possible outcomes of the lottery. Following Tanaka et al. (2010), we set $x_0 = 0$ as the reference point. The outcomes x are valued using the value function of Tversky and Kahneman (1992)

$$v(x) = \begin{cases} x^{\alpha} & \text{if } x \geq 0 \\ -\lambda(-x)^{\alpha} & \text{if } x < 0, \end{cases} \tag{3.2}$$

where α is the value sensitivity parameter for gains and losses, and λ is the loss aversion parameter. Following Tanaka et al. (2010), we use the probability weighting function of Prelec (1998)

$$w(p) = \exp\left(-(-\ln p)^{\delta}\right), \tag{3.3}$$

where δ is the probability weighting parameter determining the shape of the weighting function. For $\delta < 1$ it is inverse-S shaped resulting in small probabilities to be overweighted and higher ones to be underweighted. In the special case of $\delta = 1$ the probability weighting function is linear and the probabilities are processed as they occur. We can thus model expected utility theory (EUT) preferences in the special case of $\delta = 1$. The probability weighting function is used to determine the (de-)cumulative decision weights

$$\pi^-(p_i) = w\left(\sum_{j=-m}^{i} p_j\right) - w\left(\sum_{j=-m}^{i-1} p_j\right) \qquad \text{if } -m \leq i < 0 \tag{3.4}$$

$$\pi^+(p_i) = w\left(\sum_{j=i}^{n} p_j\right) - w\left(\sum_{j=i+1}^{n} p_j\right) \qquad \text{if } 0 \leq i \leq n, \tag{3.5}$$

$\pi^-(p_i)$ for losses and $\pi^+(p_i)$ for gains. The CPT value of lottery L is then calculated as

$$\mathrm{CPT}(L) = \sum_{i=-m}^{-1} \pi^-(p_i) \cdot v(x_i) + \sum_{i=0}^{n} \pi^+(p_i) \cdot v(x_i). \tag{3.6}$$

Table 3.2 shows the structure of the lotteries which is based on Tanaka et al. (2010). Since all lotteries feature exactly two possible outcomes, they derive under the assumptions above that the CPT value of a lottery $\tilde{L} = \{(x_1, p_1), (x_2, p_2)\}$ with only two possible outcomes x_1 and x_2 is

$$\mathrm{CPT}(\tilde{L}) = \begin{cases} v(x_2) + \pi(p_1)(v(x_1) - v(x_2)) & \text{if } x_1 x_2 > 0 \text{ and } |x_1| > |x_2| \\ v(x_2) + \pi(p_1)v(x_1) + \pi(p_2)v(x_2) & \text{otherwise.} \end{cases} \tag{3.7}$$

The lotteries are divided into three sets where the subject chooses between lottery A or B. In the first two sets lottery A is fixed, and only one possible outcome of lottery B is altered. All potential payouts in these sets are positive, so loss aversion can be neglected. After we determine the switching point in each set where a subject switches from lottery A to lottery B, we use Eq. (3.7) to estimate α and δ. Note that it is possible that a subject never switches from A to B, or directly

Table 3.2 Design of the risk preference assessment. We follow Tanaka et al. (2010) and divide the questionnaire to assess CPT preferences into three sets. This table lists the lotteries in each set and shows the expected payout difference. All values are in Euros. We use the number of balls in an urn out of which one is randomly drawn to represent probability values, e.g., lottery A in set 1 pays 80 Euros with a probability of 30% and 20 Euros with a probability of 70%. A subject is expected to switch no more than once between the lotteries in each set. E(Lottery A) – E(Lottery B) is the expected difference in payouts between lottery A and B, which indicates the switching point of an individual under expected utility theory with $\alpha = 1$.

Lottery A		Lottery B		E(Lottery A) – E(Lottery B)
		Set 1		
Ball 1–3	Ball 4–10	Ball 1	Ball 2–10	
80	20	136	10	15.4
80	20	150	10	14
80	20	166	10	12.4
80	20	186	10	10.4
80	20	212	10	7.8
80	20	250	10	4
80	20	300	10	−1
80	20	370	10	−8
80	20	440	10	−15
80	20	600	10	−31
80	20	800	10	−51
80	20	1200	10	−91
80	20	2000	10	−171
80	20	3400	10	−311
		Set 2		
Ball 1–9	Ball 10	Ball 1–7	Ball 8–10	
80	60	108	10	−0.6
80	60	112	10	−3.4
80	60	116	10	−6.2
80	60	120	10	−9
80	60	124	10	−11.8
80	60	130	10	−16
80	60	136	10	−20.2
80	60	144	10	−25.8
80	60	154	10	−32.8
80	60	166	10	−41.2
80	60	180	10	−51
80	60	200	10	−65
80	60	220	10	−79
80	60	260	10	−107
		Set 3		
Ball 1–5	Ball 6–10	Ball 1–5	Ball 6–10	
50	−8	60	−42	12
8	−8	60	−42	−9
2	−8	60	−42	−12
2	−8	60	−32	−17
2	−16	60	−32	−21
2	−16	60	−28	−23
2	−16	60	−22	−26

Table 3.3 Summary statistics of the estimated CPT parameters.

	N	Mean	Median	Std. Dev.	Min	Max
α	227	0.84	0.85	0.32	0.05	1.50
δ	227	0.69	0.65	0.23	0.05	1.20
λ_{lower}	213	0.95	0.29	1.09	0.14	5.43
λ_{upper}	159	2.27	1.53	1.35	1.26	9.78

switches to B. The lotteries in the last set provide potential losses, which allows us to estimate the loss aversion parameter λ , given the estimates for α and δ, using Eq. (3.7). Tanaka et al. (2010) point out that this approach results in lower and upper-bound estimates for the loss aversion parameter, which we denote λ_{lower} and λ_{upper}.

Summary statistics of the estimated preference parameters are shown in Table 3.3. The median estimate for the value sensitivity parameter α is 0.85 and models diminishing value sensitivity for $\alpha < 1$. The median estimated probability weighting parameter δ is 0.65 resulting in an inverse-S shape where small probabilities are overweighted and high probabilities are underweighted. Median estimates for the lower bound of the loss aversion parameter is 0.29, and the upper bound is 1.53. A subject features loss aversion if $\lambda > 1$, which is fulfilled by all upper bound estimates. None of the estimated parameters are EUT preferences.

Next, we regress the CPT parameters on explanatory variables. We use Sex, Age, and Rural as control variables and include Extra Attempts, VAT, and Exam Points as exam-related and GPA as study-related variables. Results for the value sensitivity and probability weighting parameter are presented in Table 3.4.

The coefficients for Age, Rural, Extra Attempts, Exam Points, and GPA are insignificant in all models. The intercept of the model for the curvature parameter is 0.82671 and significant at the 10%

Table 3.4 Explaining present bias and discount rate with explanatory variable for quasi-hyperbolic discounting. We regress the estimated CPT parameters α and δ on explanatory variables. Standard errors are reported in parentheses. Significance levels are denoted as follows: * $p < 0.1$ ** $p < 0.05$, *** $p < 0.01$.

	α	δ
Intercept	0.82671*	0.59856**
	(0.47702)	(0.29898)
Sex (Male=1)	0.13455**	−0.03524
	(0.05826)	(0.04082)
Age	−0.00968	−0.00456
	(0.01612)	(0.01078)
Rural	0.02284	0.00124
	(0.05668)	(0.03933)
Extra Attempts	−0.00355	0.01010
	(0.01762)	(0.01535)
VAT	−0.04284	0.12228***
	(0.06391)	(0.04350)
Exam Points	0.00004	0.00019
	(0.00024)	(0.00017)
GPA	0.03340	0.02329
	(0.07709)	(0.06003)
Adj. R^2	0.052	0.066
N	169	169

level. Additionally, we find a significant positive impact of sex at the 5% level, resulting in a higher value sensitivity parameter for males. Females thus show more diminishing value sensitivity. In the regression for probability weighting parameter, the intercept (0.59856) is positive significant at the 5% level, and VAT (0.12228) has a significant positive influence at the 1% level. Students who correctly answered the VAT question are, on average, associated with a higher probability weighting parameter, indicating that they tend to overweight small probabilities to a lesser extent than those who answered the question incorrectly. Note that in both regressions the intercept estimates are comparable to the median estimates Tversky and Kahneman (1992). The interval regression for the loss aversion is not significant (p-value 0.333 for the $\mathcal{X}^2$-test), and thus results are not reported. Except for the influence of VAT on the probability weighting parameter, we do not find a significant relationship between academic performance and the estimated CPT parameters. Our results are supported by the findings of Booth and Katic (2013) who document an influence of gender on risk aversion but no effect of cognitive ability among students aged 20, which is similar to our sample.

3.4 Time Preferences

To estimate the subjects' time preferences, we apply the multiple price list (MPL) methodology of Coller and Williams (1999) and Harrison et al. (2002). We follow the design of Tanaka et al. (2010) where the subjects answer 15 sets of questions, each with 5 choices between a delayed and an immediate reward, totaling 75 choices. Option A is an immediate payout of x at time $t = 0$ and option B is a delayed payout of y_t at time t. The immediate rewards vary from 40 to 590 Euros, and delayed rewards vary between 60 to 600 Euros. The time t for the delayed payout varies from 2 days to 3 months. Green et al. (1997) find the amount of rewards influences the estimated discount function, so we choose rewards that are suited to students in our sample. Students in Germany can earn a tax-free salary of up to 450 Euros per month, which is reasonably close to the upper bound of the rewards of 600 Euros. An overview of the general structure is given in Table 3.5 and an excerpt of the questionnaire is depicted in Figure 3.5 in Appendix. Within each set, we determine the switching point when the subject switches between the delayed and the immediate payout and exclude a subject's responses if he or she switched more than once in a set. To model the time preferences,

Table 3.5 Design of the time preference assessment. We follow Tanaka et al. (2010) and divide the questionnaire to estimate time preferences into 15 sets. In each set, the delayed award and the time of its payout are fixed, and only the amount of the potential immediate reward varies.

Set	Delayed reward in EUR	Delay	Choice of immediate rewards in EUR
1	240	1 week	{150, 200, 220, 235, 238}
2	240	1 month	{150, 200, 220, 235, 238}
3	240	3 months	{150, 200, 220, 235, 238}
4	600	1 week	{400, 500, 550, 570, 590}
5	600	1 month	{400, 500, 550, 570, 590}
6	600	3 months	{400, 500, 550, 570, 590}
7	60	1 week	{40, 50, 54, 56, 58}
8	60	1 month	{40, 50, 54, 56, 58}
9	60	3 months	{40, 50, 54, 56, 58}
10	480	3 days	{300, 380, 420, 460, 475}
11	480	2 weeks	{300, 380, 420, 460, 475}
12	480	2 months	{300, 380, 420, 460, 475}
13	120	3 days	{70, 90, 105, 115, 118}
14	120	2 weeks	{70, 90, 105, 115, 118}
15	120	2 months	{70, 90, 105, 115, 118}

we consider exponential, quasi-exponential discounting, and the model of Benhabib et al. (2010). An overview of time discounting functions is given by Benhabib et al. (2010). In the case of exponential discounting the delayed reward y_t is discounted using

$$d_E(t;r) = \exp(-rt) \tag{3.8}$$

the exponential function, were r is the discount rate and $t > 0$ is the amount of time between the immediate and the delayed payout. In the case of hyperbolic discounting y_t is discounted using

$$d_H(t;r) = \frac{1}{1+rt}. \tag{3.9}$$

While exponential discounting yields a constant subjective interest rate, it is non-constant for the hyperbolic discounting. The quasi-hyperbolic discounting function of Laibson (1997)

$$d_Q(t;\beta,r) = \begin{cases} 1 & \text{if } t = 0 \\ \beta \exp(-rt) & \text{if } t > 0 \end{cases} \tag{3.10}$$

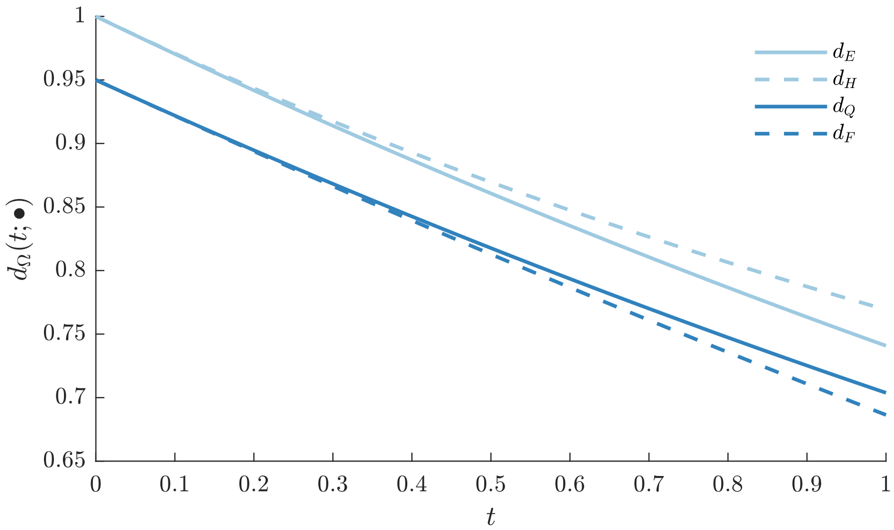


Figure 3.1 Exponential, hyperbolic, quasi-hyperbolic and Benhabib et al. (2010) discount factors. We use $r = 0.3$, $\beta = 0.95$ and $\theta = 0.5$ to calculate the discounting factors. d_E denotes the exponential, d_H the hyperbolic, d_Q the quasi-hyperbolic discount factors, and discounting factor d_F of the enhanced model by Benhabib et al. (2010).

features a present bias β for $t > 0$ which represents a discontinuous discounting for all future payouts. Benhabib et al. (2010) develop an enhanced model

$$d_F(t;\beta,r,\theta) = \beta\,(1-(1-\theta)\,rt)^{1/(1-\theta)}, \qquad (3.11)$$

where r denotes conventional time discounting, β the present bias and θ the hyperbolicity. In general, a subject is more patient if the discount rate $r \geq 0$ or the hyperbolicity $\theta \geq 0$ is lower or the present bias β is higher. Following Tanaka et al. (2010), we test for all four discounting models. Figure 3.1 depicts the four different discount functions. A subject is indifferent between the two options A or B, that is between the future reward y_t at time t and the immediate reward x, if

$$x = y_t \cdot d_\Omega(t;\bullet), \qquad (3.12)$$

Table 3.6 Parameter estimates for discounting models. We use Eq. (3.13) to estimate the parameters of the exponential, hyperbolic, quasi-hyperbolic discounting models and the full model of Benhabib et al. (2010). Standard errors are adjusted for within-subject correlations and reported in parentheses. BIC is the bayesian information criterion by Schwarz (1978). Significance levels are denoted as follows: * $p < 0.1$ ** $p < 0.05$, *** $p < 0.01$.

	Exponential	Hyperbolic	Quasi-hyperbolic	Full Model
μ	0.018***	0.019***	0.023***	0.023***
	(0.001)	(0.001)	(0.001)	(0.001)
r	0.002***	0.002***	0.001***	0.005***
	(0.000)	(0.000)	(0.000)	(0.001)
β			0.948***	0.970***
			(0.003)	(0.004)
θ				23.112***
				(2.257)
Adj. R^2	0.540	0.540	0.547	0.547
Obs.	9660	9660	9660	9660
BIC	13208.65	13197.6	13071.91	13073.4

where $d_\Omega(t;\bullet)$ is one of the four discount functions of Eq. (3.8)–(3.11) denoted with $\Omega \in \{E,H,Q,F\}$. Eq. (3.12) is used in a logistic function to model the probability of a subject selecting the immediate payout x at time $t = 0$ over the delayed reward y_t at time t

$$P(x > y_t) = \frac{1}{1 + \exp[-\mu(x - y_t \cdot d_\Omega(t;\bullet))]} \tag{3.13}$$

to estimate the parameter(s) of the respective discount function and the noise parameter μ via non-linear least squares. Table 3.6 reports the results for the exponential, hyperbolic, and quasi-hyperbolic discounting, as well as the enhanced model of Benhabib et al. (2010). We exclude observations from two subjects because they contain multiple switching points and calculate cluster-robust standard errors. For all four discounting models, all parameters are significant at the 1%-level, and the adjusted R^2s range from 54% to 54.7%. We choose the quasi-hyperbolic model to include explanatory variables because it has the lowest BIC of all models, and the enhanced model does not feature a higher goodness of fit as measured by the adjusted R^2. We include the explanatory variables X_i for subject i by decomposing the parameters of the quasi-hyperbolic discount function into a linear combination of the variables plus a constant. We estimate

$$P(x > y_t) = \frac{1}{1 + \exp\left[-\mu\left(x - y_t \beta(X_i) \exp\left(-r(X_i)t\right)\right)\right]} \tag{3.14}$$

with $\beta(X_i) = \beta_0 + \sum_i \beta_i X_i$ and $r(X_i) = r_0 + \sum_i r_i X_i$. Table 3.7 presents the results; the upper panel reports the coefficients for the present bias and the lower panel for the discount rate. We use the variables Sex, Age, and Rural as control variables for the discount rate and the present bias and include the exam-specific variables Extra Attempts, VAT, and Exam Points in Model 1. We find that students with higher Exam Points are more patient (higher present bias), as well as students who correctly answered the VAT question (lower discount rate). There is a negative impact between patience and the number of extra attempts (higher discount rate). One possible explanation for these effects is that patient students invest more time preparing for an exam and therefore achieve a higher overall score. Furthermore, early learning enables them to retain the learned content in their long-term memory, so the correct solution of the subtask with the VAT is easier to recall. More impatient students spend less time preparing for the exam and therefore have to pass extra attempts.

In Model 2, we replace Exam Points with GPA which we interacted with a dummy variable which indicates if the student is in delay (GPA delayed) with his study. A student's study is not delayed (GPA non-delayed) if he or she is in the 4th semester at the time of the exam. Note that it is impossible to re-register for an exam to improve the grade once passed. A student with many extra attempts is less patient (lower interest rate). However, this effect is reduced by the negative

Table 3.7 Explaining present bias and discount rate with explanatory variables for quasi-hyperbolic discounting. We use Eq. (3.14) to estimate quasi-hyperbolic discounting by linearly decomposing the present bias and discount rate using explanatory variables. Standard errors are adjusted for within-subject correlations and reported in parentheses. Significance levels are denoted as follows: * $p < 0.1$ ** $p < 0.05$, *** $p < 0.01$.

	Model 1	Model 2
μ	0.02470***	0.02493***
	(0.00174)	(0.00176)
Present Bias		
β_0	0.60693***	0.95309***
	(0.04844)	(0.04065)
Sex (Male = 1)	0.00889	0.01024
	(0.00678)	(0.00666)
Age	0.00128	0.00085
	(0.00169)	(0.00170)
Rural	−0.00285	−0.00264
	(0.00646)	(0.00646)
Extra Attempts	0.00140	0.00154
	(0.00139)	(0.00136)
VAT	−0.01218	−0.00994
	(0.00809)	(0.00790)
Exam Points	0.00004*	
	(0.00002)	
GPA delayed		−0.00969
		(0.00669)
GPA non-delayed		−0.06551***
		(0.00705)
Discount Rate		
r_0	0.01512***	0.00289***
	(0.00128)	(0.00096)
Sex (Male = 1)	−0.00488	−0.00826
	(0.01545)	(0.01455)
Age	−0.00016	−0.00131
	(0.00412)	(0.00364)
Rural	0.00034	0.00316
	(0.01474)	(0.01455)
Extra Attempts	0.00974*	0.01790***
	(0.00435)	(0.00548)
VAT	−0.02854*	−0.02236
	(0.01622)	(0.01657)
Exam Points	0.00005	
	(0.00005)	
GPA delayed		−0.06033***
		(0.01762)
GPA non-delayed		0.18345***
		(0.02141)
Adj. R^2	0.547	0.546
Obs.	6810	6810

impact of the GPA for delayed students. Students with a low GPA and non-delayed studies tend to be more impatient (lower present bias and higher discount rate).

We do not find a significant impact of age, which we expect due to the homogeneous distribution in our sample, or sex which is in line with the finding of Allen et al. (1998) and Tanaka et al. (2010). Furthermore, we do not find empirical evidence for our hypothesis that students from rural areas tend to be more patient, confirming the results of Harrison et al. (2002).

3.5 Conclusion

This paper establishes a link between students' time preferences and academic performance. We do not find a significant relationship between the subjects' risk preferences and academic performance. At the time we conducted the experiments, the study regulations for bachelor students of Business and Economics at the Leibniz University Hannover hindered students from postponing graduation well beyond the standard study time of eight semesters by automatically enrolling them for all courses up to the 4th semester with no option to withdraw, other than for health reasons or studies abroad. Even in this regime, which works against our results, we conclude that academically more successful students, as measured by the grade point average and exam points, tend to show higher patience as modeled via the quasi-hyperbolic discounting than students with less academic success.

3.A Appendix

Alternative 1	Wahl		Alternative 2
Erhalte 240 Euro in 1 Woche.			Erhalte 150 Euro heute.
Erhalte 240 Euro in 1 Woche.			Erhalte 200 Euro heute.
Erhalte 240 Euro in 1 Woche.			Erhalte 220 Euro heute.
Erhalte 240 Euro in 1 Woche.			Erhalte 235 Euro heute.
Erhalte 240 Euro in 1 Woche.			Erhalte 238 Euro heute.
Erhalte 240 Euro in 1 Monat.			Erhalte 150 Euro heute.
Erhalte 240 Euro in 1 Monat.			Erhalte 200 Euro heute.
Erhalte 240 Euro in 1 Monat.			Erhalte 220 Euro heute.
Erhalte 240 Euro in 1 Monat.			Erhalte 235 Euro heute.
Erhalte 240 Euro in 1 Monat.			Erhalte 238 Euro heute.

Figure 3.2 Excerpt from the time preference questionnaire demonstrating the MPL design. The design of the questionnaire follows Tanaka et al. (2010); only the first two sets of questions are depicted.

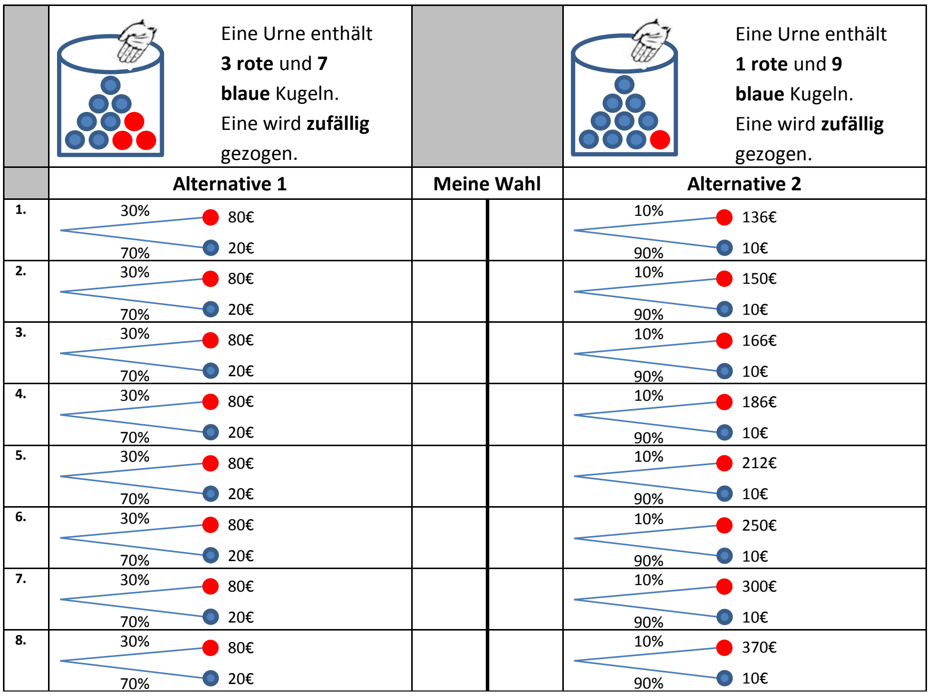


Figure 3.3 Excerpt from the risk preference assessment. The design of the questionnaire follows Tanaka et al. (2010), we represent the probabilities using red and blue stylized balls in a bucket; one of the balls is randomly drawn. Additionally, we print the probabilities for each branch of a tree representing a lottery. The first eight lottery pairs are shown.

Chapter 4

A Study of Inter- and Intra-Industry Credit Risk Contagion of U.S. Companies

The content of this chapter refers to the working paper:

Germer, S. (2021). A Study of Inter- and Intra-Industry Credit Risk Contagion of U.S. Companies. *Working Paper, Leibniz University Hannover.*

Abstract

In this paper, we explore contagion effects, which we define as co-movement in the distance-to-defaults of U.S. companies which we infer from the Campbell et al. (2008) model. We gauge financial, inter-industry, and intra-industry contagion effects based on the specification of the 12 sectors of Fama and French and find substantial co-movement across sectors if a crisis is present. We observe that the firm size and the firm's average share of total sales in the respective sector are characteristics linked to intra-industry contagion. Our findings are robust to various crisis definitions and index weighting methodology. Our results suggest an increase of the probability of default during times of crisis due to contagion which may lead to an underestimation of risk measures of single name credits or portfolios, and ultimately, the economic capital.

Keywords: Contagion, credit risk, sector-specific contagion, financial crisis, intra-industry contagion, inter-industry contagion

JEL Classification: C19, C69, G01, G14, G18, G20

4.1 Introduction

During the global financial crisis (GFC) a high number of corporate failures were observed across all sectors of the U.S. economy. Such default clusters typically occur around times of economic turmoil, like recessions or stock market crashes, and are accompanied by a higher number of corporate defaults than during normal times (see i.e. Azizpour et al., 2018). The source for the occurrence of these clusters is of great importance for accurate risk analysis of financial institutions' credit portfolios and the stability of the financial system.

Nickell et al. (2000), Shumway (2001), Rösch (2003), Lando and Nielsen (2010) and Giesecke and Kim (2011), among others, document empirical evidence for correlation between macroeconomic variables (i.e., gross domestic product, interest rates) and clusters in default rates. Das et al. (2007), however, find that systematic factors alone cannot explain the emergence of default clusters with increased default rates.

Duffie et al. (2007) and Duffie et al. (2009) introduce the concept of frailty, which is an unobservable systematic factor that triggers higher default rates during crisis periods. Koopman et al. (2011) find that frailty is a significant factor driving default clustering in addition to macroeconomic factors. In their model the frailty factor also includes contagion effects.

Contagion is a further concept to explain default clusters and the main focus of this work. Dornbusch et al. (2000) define contagion as "a significant increase in cross-market linkages after a shock [...], as measured by the degree to which asset prices or financial flows move together across markets relative to this comovement in tranquil times" (p. 178). We adopt the definition of Azizpour et al. (2018) who describe the impact of a corporate default on the default of other companies as credit default contagion and define credit risk contagion as the increase in co-movement of credit quality changes. Azizpour et al. (2018) gauge the importance of the systematic factors, frailty and contagion and use a parameterized moving average of the face value of defaulted companies to fit an intensity model to CDX data. The intensity rate is decomposed into a systematic, frailty, and contagion factor. They find that the contagion factor has the highest fraction in intensity rate decomposition. Therefore, we focus on contagion as explanation for the default clusters. Our work is closely related to research on contagion in the stock and CDS market. Baur (2012) examines financial contagion in the stock market across various countries and industries during the period of the GFC and find evidence of an increase in the co-movement of stock market returns across countries and sectors. Bekaert et al. (2014) use a factor model, which includes both global and national factors, and find evidence of contagion during the financial crisis in the analysis of 55 countries across 10 sectors. Countries with weaker macroeconomic indicators are more vulnerable to contagion effects than countries with more robust macroeconomic indicators. During the financial crisis of 1997 and 1998 Chiang et al. (2007) document contagion in the Asian stock market. Jorion and Zhang (2007) investigate CDS spreads for the effects of a business failure on other companies to gauge potential benefits resulting from the bankruptcy. Most interestingly, in the case of a default caused by the reorganization of liabilities, the contagion effects predominate. But if the market participant disappears after being liquidated, the competitive effects outweigh the negative contagion effects. Broto and Pérez-Quirós (2015) examine CDS data from 10 OECD countries as part of the 2010 European debt crisis and use a dynamic three-factor model that consists of a general factor for all countries, a factor for peripheral European countries, and an idiosyncratic factor. They document evidence for credit contagion, which differs from country to country in the strength of its expression. Kalbaska and Gątkowski (2012) show that contagion does not only affect the market segments and companies, but can also spread to entire countries. They examine contagion effects using the interbank and state-owned CDS market. They reveal contagion effects of bank bailouts and state aid in the Euro-area on the PIIGS states (Portugal, Ireland, Italy, Greece, and Spain) and core states (France, Germany, and the UK). Sabkha et al. (2019) examine the sovereign CDS data of 35 countries from five different economic regions (Eastern Europe, South, and Central America, Asia, and Western Europe) and their economic developments during the period of the GFC and the European debt crisis. The results show that all countries in both crises are affected by contagion. The effect is more measurable in economies with lower growth than in industrialized and emerging countries. Furthermore, regionally independent markets are vulnerable to the spread of credit risk and portfolio diversification thus loses effectiveness. Various transmission channels have been proposed to explain the mechanism behind contagion. Our study focuses on the counter-party risk channel that a company's default will negatively affect the probability of default of affiliated companies as argued by Shahzad et al. (2017). Other channels are the information (i.e Chakrabarty and Zhang, 2012; Bekaert et al., 2014) and liquidity channel (i.e. Goldstein and Pauzner, 2004; Shahzad et al., 2017).

Schmukler (2004) finds that "sound macroeconomic and financial fundamentals are key in lowering the probability of crises and contagion" (p. 60) in settings where contagious effects spread from one country to an other. In this paper, we also aim to find determinants for intra-industry contagion and use determinants proposed by Lang and Stulz (1992) and Jorion and Zhang (2007).

While empirical studies based on CDS, CDO, bonds etc. feature a sufficient number of observations, they do underlie market expectations. Probabilities of default which are inferred from CDS spreads, for example, are sensitive to changes in the stock market (Naifar, 2011). Alternatively, one could use the correlation of default events to study the impact of contagion. This approach does not depend on market expectations, but the number of default events per month, or even per quarter, is too low to study them in a context where the co-movement is assessed in an inter- or intra-industry framework. Therefore, we opt to infer monthly estimates for the annual probability of default from the Campbell et al. (2008) model for U.S. companies. This approach uses stock market information (i.e., excess returns, market capitalization), as well as accounting data (i.e., long-term liabilities, net income) and default times to estimate probability of default estimates on the firm level. By estimating the probability of default based on actual default events, the effect of market expectations is muted and and the inferred probability of default is a close proxy of the physical probability of default (Anginer and Yıldızhan, 2018). Chava and Jarrow (2004) enhance the model of Shumway (2001) by industry interactions. Campbell et al. (2008), however, find limited evidence for industry effects in their model. Baur (2012) develops an empirical framework to study contagion effects using stock returns. We adopt their model to changes in distances-to-default which we obtain from the probability of default estimates using monthly stock market information and quarterly accounting data assigned to monthly observations. This allows us to study inter- and intra-industry contagion effects with a sufficient number of observations.

Our paper contributes to the existing literature in the following ways. First, we show that in the context of logit models, that are fitted based on default events, contagion effects are identifiable at the inter-industry level, including financial contagion. The results are robust to the choice of crisis definition. Second, we explore intra-industry contagion by analyzing a firm's impact on its respective sector index and identify drivers associated with enhanced co-movement during times of crisis. To the best of our knowledge, we are the first to explore inter- and intra-industry contagion based on probabilities of default.

We find evidence for inter-industry contagion independent of the crisis definition, suggesting co-movement during times of crisis is associated with negative changes in the distances-to-default that yield an increase in the probability of default. The Basel II framework states that,"[i]n order to avoid over-optimism, a bank must add to its estimates a margin of conservatism" (Basel Committee on Banking Supervision, 2006, § 425, p. 100). Opting for point-in-time estimates for the probability of default based on macroeconomic variables as proposed by Rösch (2005) might not be sufficient to capture the enhanced co-movement causing increased probability of default during crisis periods. It can be argued that an "over-optimism" can arise if financial institutions neglect the influence of credit risk contagion. Finally, we find small (large) companies and companies with a high (low) share of sales in their sector to have a lower (higher) probability to be subject to intra-industry contagion.

The paper is organized as follows. Section 4.2 introduces our empirical model and section 4.3 describes the data. Section 4.4 presents the preliminary results for the probability of default estimates, which are transformed to distance-to-defaults underlying the main results of inter- and intra-industry contagion presented in the remainder of the section. Section 4.5 concludes the analysis.

4.2 Econometric Model of Credit Risk Contagion

We adopt the methodology of Baur (2012) to model credit risk contagion with a linear regression. This model is related to the model proposed by Bekaert et al. (2005) who introduce a crisis dummy indicator in the GARCH decomposition. Here, the crisis indicator is introduced in the mean equation.[1] As probabilities are real numbers between zero and one, we transform the probabilities of default to distances-to-defaults, which can take values in the positive domain of the real numbers. As the distance-to-default is non-stationary, we use monthly changes in the distance-to-defaults between time $t-1$ and t denoted $\Delta DD_{i,t}$

$$\begin{aligned} \Delta DD_{i,t} &= b_0 + b_1 \cdot \Delta DD_{j,t} + b_2 \cdot \Delta DD_{j,t} \cdot C_t + \varepsilon_{i,t} && (4.1) \\ \sigma^2_{i,t} &= \omega + \sum_{k=1}^{K} \left(\alpha_k + \beta_k \mathbb{1}_{\varepsilon_{i,t-k}<0} \right) \varepsilon^2_{i,t-k} + \sum_{l=1}^{L} \gamma_l \sigma^2_{i,t-l} && (4.2) \\ \varepsilon_{i,t} &= \sigma_{i,t} z_{i,t}, \qquad z_{i,t} \sim \mathbb{N}(0,1), && (4.3) \end{aligned}$$

where i denotes the company or sector that is subject to contagion and j is the initiating company or sector of the contagious effect. C_t is a dummy variable that is equal to 1 if a crisis is present at time t and equal to 0 in normal times. Eq. (4.2) describes the conditional variance $\sigma^2_{i,t}$ as an asymmetric TGARCH(K,L)-model (see Glosten et al., 1993). Applying the restriction $\beta_k = 0 \forall k$ enables us to consider GARCH(K,L) specifications. This allows us to estimate possible GARCH and TGARCH specifications for $1 \leq K, L \leq 2$ and choose the best fit based on the Schwartz Criterion.

[1] See Dungey et al. (2005) for an overview of methodologies to study contagion.

The coefficient b_1 measures the co-movement between i and j during all times. Additionally, b_2 captures the additional co-movement if a crisis is present. If b_2 is positive, there is additional co-movement during a crisis between i and j, which we define as contagion. Therefore, a test for contagion is performed using a one-sided t-test with the null hypothesis $H_0 : b_2 \leq 0$.

Dungey et al. (2005) argue among others that tests for contagion are crucially dependent on the definition of crisis periods. To address this issue, we use a battery of alternate crisis definitions to check for robustness. A simplistic definition is to use the U.S. National Bureau of Economic Research's (NBER) recession times. Following Baur (2012), we will consider quantiles of the conditional volatility extracted from the financial sector index. While Baur (2012) uses a combination of pre-crisis quantiles of the conditional volatility of the financial sector and NBER recession dummies, we opt to solely use the quantiles in order to allow crisis times to lay outside of U.S. recession times.

To address specific effects of the global financial crisis, we use a dummy variable, that assumes the value 1 between the beginning of July 2007 and the end of March 2009 and 0 otherwise. Finally, we follow the approach of Boyer et al. (2006) and Rodriguez (2007) and use regime switching models to identify volatile and stable regimes. We employ a two state $s \in \{1, 2\}$ model

$$\Delta DD_{\text{Money},t} = \mu^{(s)} + \epsilon_t^{(s)}, \tag{4.4}$$

where Money denotes the index of the financial sector and ϵ_t is normally distributed with zero-mean and a state-specific variance. States 1 and 2 are identified by the maximum probability of the corresponding probability of being in that state. That is, if the probability for state 1 (2) is higher than 50%, then we infer the economy is in state 1 (2). We define the state with the higher volatility and higher correlation to the NBER recession times as the crisis regime.

Additionally, our results depend on the weighting methodology of the calculated indices. For our analysis we consider weights by market value of equity and total liabilities.

4.3 Data

We employ the Refinitiv (formerly Thomson Reuters) Eikon and Datastream databases to form a comprehensive data set to estimate the Campbell et al. (2008) model by filtering all available active and delisted U.S. companies traded on NYSE, NYSE AMEX, NYSE Arca and NASDAQ that have pricing information as well as balance sheet and income statement data available for the period from January 1990 to December 2016. Eikon provides accounting data for listed companies which are acquired from the SEC Edgar database and directly linked to the respective 10-Q as well as 10-K filings. We use the CRSP database for stock market data and filter for share codes 10 and 11, and hand match the KYPERMNO to the RIC to ensure the integrity of the final data set. We attribute each company to one sector for each month by using the SIC and the Fama and French 12 industry specifications, and we thereby allow a company to change sectors each month over our sample period. We adjust fiscal to calendar quarters and lag all accounting data by one quarter. We use the following data items denoted in millions of U.S. Dollars to construct the accounting-based variables for the regressions: net income (TR.NetIncome), the book value of equity (TR.TotalEquity), total liabilities (TR.TotalLiabilities) and cash and short-term investments (TR.CashAndSTInvestments). We handle missing data, outlier treatment, and variable definition as described in Campbell et al. (2008): the weighted 12-month average of net income divided by the market-valued total assets (NIMTAAVG), total liabilities divided by the market valued total assets (TLMTA), cash and short-term investments divided by the sum of market-valued total assets (CASHMTA), the weighted 12-month moving average of the log-returns in excess of the S&P 500 (EXRETAVG), the annualized standard deviation of daily stock returns over the past three months (SIGMA), the natural logarithm of the market capitalization divided by the market capitalization of the S&P 500 index (RSIZE), the natural logarithm of the share price capped at 15 USD (PRICE), market-to-book ratio (MB). The market-valued total assets are defined as the sum of the market value of equity and the book value of total liabilities and adjusted by adding 10% of the difference between the market value and the book value of equity. Chava et al. (2011) and Chava (2014) collect data on defaulted companies from various sources, including the SEC, the Wall Street Journal Index, SDC, and Capital Changes Reporter. A bankruptcy is indicated in our data with the value 1 if a company filed for Chapter 7 or 11 in the respective month and 0 otherwise. Default data ends in December 2016. We allow companies to enter the final data set if there are fewer than or equal to 12 months of missing values between the stock market or accounting data and the (future) default event. For crisis dummies, we use the recession times provided by the U.S. National Bureau of Economic Research's

(NBER).[2]

Finally, we compute market value of equity and total liabilities weighted indices for the probability of default and the distance-to-default. We refer to the indices containing all companies as the market indices. Further, we calculate indices for the sectors based on the Fama and French 12 industry classification:[3] business equipment (BusEq), chemicals (Chems), durables (Durbl), energy (Enrgy), finance (Money), health (Hlth), manufacturing (Manuf), non-durables (NoDur), shops, telecommunication (Telcm), utilities (Utils) and other.

4.4 Results

4.4.1 Preliminary Results for the Probability of Default Estimates

The panel data used spans from March 1990 to December 2016 and contains 8,891 companies. The summary statistics for the explanatory variables entering the logistic regressions are shown in Table 4.1. We estimate monthly probabilities of default and calculate equally and value-weighted indices for all companies, which we call the market index, and the 12 sectors following the sector definition of Fama and French. We estimate the logit model of Campbell et al. (2008)

$$\mathbb{P}(D_{i,t+1} = 1 \mid D_{i,t} = 0, x_{i,t}) = \frac{1}{1 + e^{-\kappa - \lambda' x_{i,t}}}, \tag{4.5}$$

[2] Dates of the U.S. recessions are provided at `https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions`

[3] See `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_12_ind_port.html` for detailed information about the mapping of SIC codes to the 12 sector definitions.

Table 4.1 Summary statistics for the explanatory variables. Panel data featuring 1,038,499 firm-months for the period from March 1990 to December 2016, 8,891 companies. Data sources: Refinitiv Eikon, Datastream and CRSP.

	NIMTAAVG	TLMTA	EXRETAVG	RSIZE	SIGMA	CASHMTA	MB	PRICE
Mean	−0.00	0.44	−0.01	−10.31	0.57	0.09	2.35	2.17
Q1	−0.01	0.19	−0.03	−11.83	0.32	0.01	1.05	1.85
Median	0.03	0.40	−0.00	−10.40	0.47	0.04	1.71	2.71
Q3	0.07	0.68	0.02	−8.89	0.74	0.12	2.93	2.71
Std	0.13	0.28	0.04	1.93	0.34	0.10	1.92	0.85
Min	−0.38	0.05	−0.10	−13.52	0.20	0.00	0.37	−4.16
Max	0.14	0.91	0.07	−6.65	1.42	0.37	7.82	2.71

where $\mathbb{P}(D_{i,t+1} = 1 \mid D_{i,t} = 0, x_{i,t})$ is the marginal probability of default of company i at time t for one time step ahead $t+1$, conditional on company i's survival in period t. $D_{i,t} = 1$ is a binary variable indicating a default, and taking the values 0 or 1. The value 1 denotes a default of company i at time t. $x_{i,t}$ is a vector of explanatory variables for company i at time t, λ is a vector of corresponding estimates. To estimate the annual probability of default, we estimate 12 models with monthly leads $m \in \{1, \dots, 12\}$

$$\mathbb{P}(D_{i,t-1+m} = 1 \mid D_{i,t-2+m} = 0) = \frac{1}{1 + e^{-\kappa - \lambda_m' x_{i,t-1}}}. \tag{4.6}$$

Table 4.2 reports the estimated coefficients of the logit model (4.6) for leads 1 to 12. With the exception of the market-to-book ratio, the coefficients are significant at the 5% level for all leads in all models. The maximum rescaled R^2 of Nagelkerke (1991) is decreasing with increasing monthly leads from 0.3567 to 0.1367, and the AUC decreases from 0.9603 to 0.8695. We find a similar term structure to coefficients of the variables reported in Campbell et al. (2008) and use their approach to capture this dynamic when calculating the

Table 4.2 Estimated coefficients of the logit model. We use panel data featuring 1,038,499 monthly observations of 8,891 companies to estimate Eq. (4.6) for monthly leads $m \in \{1,\ldots,12\}$. Data sources: Refinitiv Eikon & Datastream, CRSP, default data are provided by Chava et al. (2011) and Chava (2014). Standard errors are reported in parenthesis. AUC denotes the area under the curve. The maximum rescaled R^2 is computed as described in Nagelkerke (1991).

	Monthly Leads											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Intercept	−9.4863	−8.5562	−8.4977	−7.7779	−7.3856	−8.0111	−8.3566	−8.2725	−8.1573	−7.7728	−7.4861	−8.1192
	(0.7611)	(0.7251)	(0.7074)	(0.6857)	(0.6646)	(0.661)	(0.656)	(0.6523)	(0.6469)	(0.6404)	(0.6349)	(0.6357)
NIMTAAVG	−4.4474	−5.1454	−5.4562	−5.5246	−5.4741	−5.4482	−5.3588	−5.131	−4.737	−4.3538	−4.3536	−4.3285
	(0.3731)	(0.378)	(0.379)	(0.3767)	(0.3752)	(0.3749)	(0.3754)	(0.3765)	(0.3748)	(0.3739)	(0.3766)	(0.3792)
TLMTA	4.6101	4.194	3.7406	3.4846	3.355	3.2169	3.1755	2.957	2.7773	2.627	2.4767	2.4603
	(0.3079)	(0.2885)	(0.2744)	(0.266)	(0.2567)	(0.2519)	(0.249)	(0.2473)	(0.2449)	(0.243)	(0.2414)	(0.2415)
EXRETAVG	−15.8578	−11.7375	−11.3218	−10.2781	−9.6331	−9.3891	−8.8239	−9.1731	−8.8196	−9.0095	−8.8102	−8.0455
	(1.4835)	(1.2827)	(1.2426)	(1.2034)	(1.1808)	(1.1628)	(1.1476)	(1.1645)	(1.1581)	(1.1655)	(1.1657)	(1.149)
SIGMA	1.4521	1.0604	1.0609	0.8256	0.6499	0.7888	0.8192	0.7459	0.7972	0.7884	0.7399	0.8972
	(0.2266)	(0.2108)	(0.206)	(0.2004)	(0.1968)	(0.1966)	(0.1963)	(0.1964)	(0.1962)	(0.1962)	(0.1965)	(0.1967)
RSIZE	0.184	0.1793	0.1645	0.1747	0.1798	0.1454	0.122	0.1086	0.1045	0.118	0.1276	0.0998
	(0.0468)	(0.0453)	(0.0443)	(0.0432)	(0.0421)	(0.0419)	(0.0417)	(0.0416)	(0.0415)	(0.0411)	(0.0408)	(0.0408)
CASHMTA	−1.7644	−2.5792	−3.417	−3.7831	−4.0509	−3.8322	−3.6304	−3.5761	−3.4407	−3.2759	−3.4319	−2.7861
	(0.5859)	(0.6055)	(0.6336)	(0.6436)	(0.6571)	(0.6495)	(0.6474)	(0.6478)	(0.6453)	(0.6403)	(0.6488)	(0.6272)
MB	−0.00774	−0.00973	−0.0131	−0.00937	0.0362	0.0473	0.0656	0.0556	0.0535	0.0482	0.0495	0.0445
	(0.0357)	(0.0345)	(0.0339)	(0.0331)	(0.0301)	(0.0298)	(0.0291)	(0.0298)	(0.0301)	(0.0305)	(0.0303)	(0.031)
PRICE	−1.154	−1.0641	−0.8454	−0.884	−0.891	−0.6983	−0.6061	−0.5743	−0.5647	−0.6023	−0.6019	−0.4527
	(0.1413)	(0.1284)	(0.1216)	(0.1178)	(0.1142)	(0.1119)	(0.1105)	(0.1099)	(0.1092)	(0.1087)	(0.1085)	(0.1081)
N	900,751	892,815	884905	877,031	869,216	861,455	853,740	846,076	838,464	830,905	823,395	815,944
AUC	0.9603	0.9522	0.9444	0.9377	0.931	0.9239	0.9144	0.9045	0.8957	0.8857	0.882	0.8695
Max. rescaled R^2	0.3567	0.3172	0.2899	0.2684	0.2453	0.2229	0.2047	0.1877	0.1717	0.1608	0.151	0.1367

Table 4.3 Summary statistics of probability of default indices. This table reports summary statistics for the probability of default market index and 12 indices based on the sector definitions of the Fama and French 12 industry portfolios. Data spans from March 1990 to December 2016, the number of observations is 320 months.

Index	Mean	Std	Min	Max	Mean	Std	Min	Max
	weight: market value of equity				*weight: total liabilities*			
Market	0.0012	0.0006	0.0007	0.0063	0.0039	0.0038	0.0017	0.0358
Business Equipment	0.0009	0.0006	0.0004	0.0035	0.0022	0.0021	0.0006	0.0123
Chemicals	0.0008	0.0002	0.0005	0.0022	0.0013	0.0012	0.0006	0.0133
Durables	0.0007	0.0010	0.0003	0.0102	0.0028	0.0050	0.0006	0.0461
Energy	0.0010	0.0007	0.0003	0.0052	0.0022	0.0030	0.0004	0.0237
Money	0.0023	0.0021	0.0009	0.0234	0.0048	0.0060	0.0019	0.0552
Health	0.0006	0.0001	0.0004	0.0011	0.0015	0.0011	0.0005	0.0091
Manufacturing	0.0011	0.0004	0.0005	0.0041	0.0026	0.0018	0.0008	0.0153
Non Durables	0.0010	0.0005	0.0005	0.0051	0.0022	0.0019	0.0007	0.0162
Shops	0.0009	0.0003	0.0005	0.0026	0.0038	0.0043	0.0008	0.0419
Telecommunication	0.0019	0.0017	0.0006	0.0161	0.0051	0.0068	0.0010	0.0501
Utilities	0.0019	0.0010	0.0011	0.0097	0.0027	0.0032	0.0012	0.0283
Other	0.0014	0.0008	0.0006	0.0066	0.0045	0.0052	0.0011	0.0409

annual cumulative probability of default (CPD)

$$CPD_{i,t-1} = 1 - \prod_{m=1}^{12} \frac{\exp(-\kappa_m - \lambda_m' x_{i,t-1})}{1 + \exp(-\kappa_m - \lambda_m' x_{i,t-1})}, \tag{4.7}$$

which we transform into distance-to-defaults and use monthly changes thereof for all further analysis. For the analysis of contagious effects, we calculate indices of the probability of defaults for all companies, which we refer to as the market index, and indices following the sector definitions of Fama and French. We consider two weighting schemes: the market value of equity and the total liabilities. Table 4.3 provides the summary statistics of the probability of default indices. The data set features 320 monthly observations. The left panel shows the indices weighted by the market value of equity, the right panel shows of those weighted by the total liabilities. It is crucial to note the higher probability of default estimates for indices weighted by the total liabilities, which highlights the importance of the debt-to-equity ratio. Additionally, it can be seen that the financial sector has the largest mean PD (0.0023) when considering market value of equity weights, and the second highest mean PD estimate (0.0048) for the total liabilities weighted indices.

The ratio of the mean market PD to the financial sector mean PD is substantially different: for the total liability weights it is 81.25% vs. 52.17% for the market value of equity weights. This, again, can be attributed to the high average debt-to-equity ratio of the financial sector in relation to the remaining sectors.

Using the total liabilities as weights gauges the magnitude of the exposure default in case of a credit event, as opposed to market capitalization. Consider two identical companies with identical firm values and default probabilities, but substantially different debt-to-equity ratios. If firm A – with a low debt-to-equity ratio – defaults, its effect is highest for the shareholders who would potentially lose their invested capital. If firm B – with a high debt-to-equity – ratio defaults, it could trigger a cascade of events attributed to the higher value of debt that would negatively effect financial institutions.

Figure 4.1 compares the probability of default indices for the market and financial indices for the two weighting methodologies. For comparison, NBER recessions times are shaded in gray. The first increase corresponds to the July 1990 recession, followed by a moderate increase during the late 1990s, the Dotcom bubble, and the global financial crisis. During the financial crisis the probability of default for the market index increases from 0.11% to a maximum of 0.63% (weight: market value of equity), and from 0.37% to 3.58% (weight: total liabilities). During the same period, the financial index increases from 0.19% to a maximum of 1.98% (weight: market value

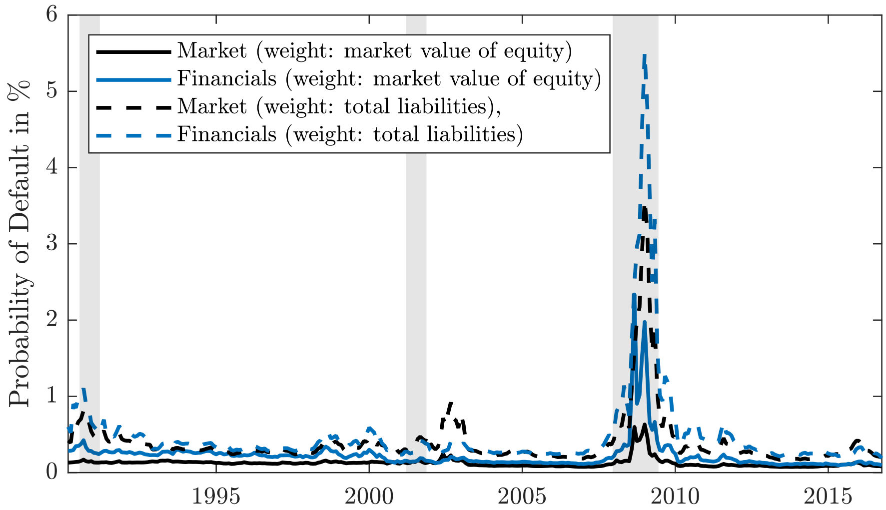


Figure 4.1 Estimated probability of default indices. Indices are value-weighted based on the estimates of the Campbell et al. (2008) model reported in Table 4.2. The market indices are depicted as black lines, the financial indices as blue lines; solid lines denote market value of equity weights, dashed lines denote weighting by total liabilities. Data spans from March 1990 to December 2016. Gray bars indicate the U.S. National Bureau of Economic Research's (NBER) recession times.

of equity), and from 0.47% to 5.52% (weight: total liabilities). Two features can be gauged. First, the calculated probabilities are higher if weighted by the total liabilities as opposed to those weighted by the market value of equity. Second, during the majority of points in time, the probability for the market index is lower than for the financial sector. From March 1992 to December 2016, the sample covers three recessions. The increase in the probabilities of default is highest for the global financial crisis.

Figure 4.2 shows the conditional volatility of changes in the distance-to-default index for the financial sector. Each conditional volatility is estimated using Eq. (4.2) with a mean equation that includes only a constant. The specification of the volatility model is then selected based on the Schwartz criterion. To create Figure 4.2, a GARCH(1,1) specification is chosen. The volatility index weighted

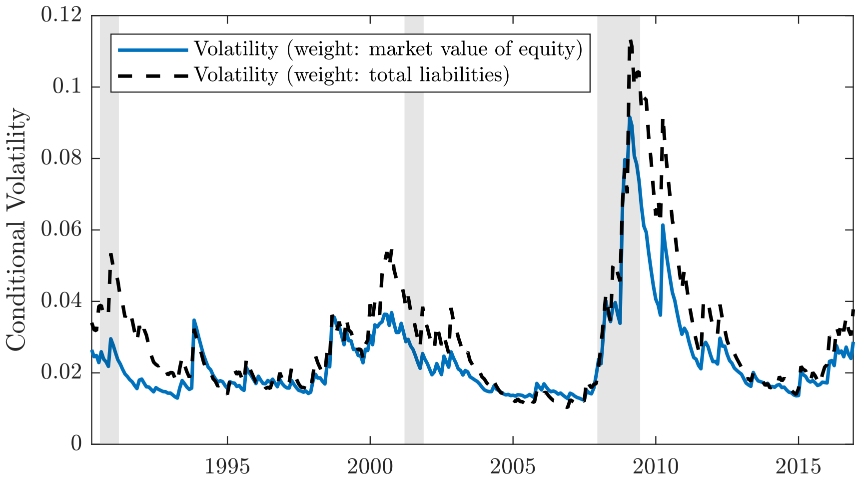
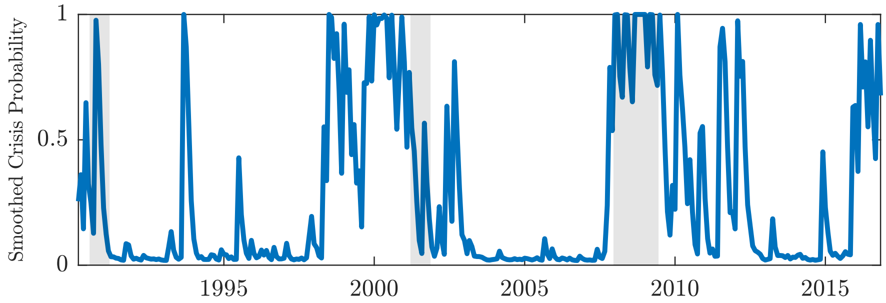
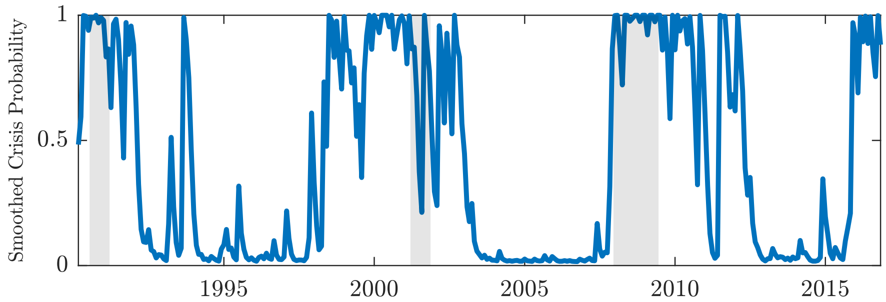


Figure 4.2 Conditional volatility of changes in distance to default index for the financial sector. The conditional volatility is estimated using Eq. (4.2) with a mean equation that only includes a constant. Based on the Schwartz criterion a GARCH(1,1) specification is chosen. The blue solid line denotes market value of equity weights, the black dashed line denotes weighting by total liabilities. Data spans from March 1990 to December 2016. Gray bars indicate the U.S. National Bureau of Economic Research's (NBER) recession times.

by total liabilities is greater than the volatility index weighted by market value of equity. Again, it can be seen that the largest increase in conditional volatility occurs during the global financial crisis. The increase beginning 2015 can be linked to the sell-off in the stock market and the "mini-recession" of the years 2015 and 2016. Note that the recession times are of short duration compared to more persistent high volatility phases around severe recessions. Additionally, the volatility peak of the Dotcom bubble does not occur during a recession as defined by the NBER. To address this issue, we consider econometrics-based approaches like in Boyer et al. (2006), Dimitriou et al. (2013), Sabkha et al. (2019). Specifically, we use these financial time series to compute the quantile-based crisis definition by calculating the 95% percentile for the pre-GFC period. If the conditional volatility time series exceeds its 95% percentile, we identify



(a) Smoothed crisis probabilities, weight: market value of equity



(b) Smoothed crisis probabilities, weight: total liabilities

Figure 4.3 Extracted smoothed state probabilities for crisis regimes from Markov switching models using the differences of the distance-to-defaults of the financial sector. Following Boyer et al. (2006) and Rodriguez (2007), we use regime switching models to identify crisis and stable regimes in the differences of the distance-to-defaults of the financial sector. Indices are weighted by (a) the market value of equity and (b) the total liabilities. For estimation, we opt to use a two-state simple mean model with a state-specific normal distribution of the residuals. We identify a regime as a "crisis" period if the corresponding smoothed state probabilities are higher than 50% and are highly correlated with the U.S. National Bureau of Economic Research's (NBER) recession times (indicated by the gray bars).

the period as a crisis. As another crisis definition, we follow Boyer et al. (2006) as well as Rodriguez (2007) and fit a two-state regime-switching model with a state varying simple mean model for the differences in the distance-to-defaults of the financial sector. Figure 4.3 shows the corresponding smoothed crisis state probabilities for the index of the financial sector (a) weighted by the total liabilities and (b) the market value of equity. The expected duration of the stable regime equals 24.72 months and is linked to a variance of 0.0019, whereas the crisis regime features an expected duration of

10.43 months and a variance of 0.0018. The smoothed crisis probabilities for the total liabilities weighted index capture the recession, which is followed by the Dotcom bubble better than the smoothed crisis probabilities of equity market value-weighted index. The expected duration of the crisis regime is almost twice as long (21.73 months) compared to the model of the index weighted by the market value of equity. The associated variance equals 0.00233 compared to 0.000207 for the stable regime, which has an expected duration of 27.54 months. In our further analysis, we identify a period as crises period if the smoothed crises probabilities are greater than or equal to 50%. Note that both models capture the July 1990 recession, the Dotcom bubble (for an extended period), the GFC, and the sell-off in the stock market of the years 2015 and 2016. Due to the nature of this pure econometric approach, the resulting crisis dummies will feature some noise, i.e., during the recession following the Dotcom bubble, or between the years 2012 and 2014.

4.4.2 Empirical Results of the Contagion Framework

Inter-Industry Contagion

We start our analysis by investigating inter-industry contagion for the market index and the 12 sectors. We conduct our analysis by applying equations (4.1) to (4.3), and follow the logic of Baur (2012) that the financial sector is the initiator of contagious effects. Table 4.4 reports the results for the financial contagion for the two weighting methodologies (upper panel: market value of equity, lower panel: total liabilities). For robustness we consider the four different models of crisis definition. The first two models use economic events-based

Table 4.4 Inter-industry financial contagion. We use Eq. (4.1)–(4.3) to estimate inter-industry contagious effects caused by the financial sector. The upper panel reports the results for market value of equity weighted and the lower for total liabilities weighted indices. We consider four different crisis definitions: (1) the U.S. recession times (USREC) by the NBER, (2) the period of the global financial crisis (GFC) from July 2007 to March 2009, (3) if the pre-GFC conditional volatility of the financial sector's index is greater than its 95%-percentile (QVOL), and (4) if the smoothed crisis state probabilities of a two-regime switching model for the financial sector index are greater than 50% (RS). The column Contagion reports the t-statistic for coefficient b_2 in Eq. (4.1).

Crisis Definition	(1) USREC		(2) GFC		(3) QVOL		(4) RS	
	weight: market value of equity							
	Contagion	Adj. R^2	Contagion	Adj. R^2	Contagion	Adj. R^2	Contagion	Adj. R^2
Market	3.7146	0.4619	3.9101	0.4625	3.6983	0.4567	2.2041	0.4410
Business Equipment	0.9037	−0.0132	1.9027	−0.0039	1.1591	−0.0115	2.0205	−0.0215
Chemicals	1.8301	0.0414	1.1417	0.0424	1.7075	0.0495	2.4394	0.0578
Durables	5.4289	0.1151	5.7836	0.1172	3.5393	0.1100	1.2124	0.0852
Energy	0.7417	0.0404	−1.4390	0.0356	0.4035	0.0424	1.0315	0.0455
Health	−0.0954	−0.0030	−0.1932	−0.0028	−0.9296	0.0008	0.4458	−0.0017
Manufacturing	3.6066	0.1724	3.3165	0.1719	4.4791	0.1926	3.1319	0.1892
Non Durables	4.9909	0.0657	3.6942	0.0560	2.1684	0.0560	1.1041	0.0488
Shops	0.3186	0.0308	0.8271	0.0303	1.2666	0.0311	0.1636	0.0310
Telecomunication	1.9401	0.0065	2.0199	0.0097	1.2888	−0.0016	−0.6177	−0.0043
Utilities	1.2454	−0.0258	1.0466	−0.0250	1.1384	−0.0231	0.6947	−0.0154
Other	1.9223	0.1400	2.1822	0.1421	2.2190	0.1424	1.8765	0.1328
	weight: total liabilities							
	Contagion	Adj. R^2	Contagion	Adj. R^2	Contagion	Adj. R^2	Contagion	Adj. R^2
Market	4.0220	0.8826	4.0612	0.8831	1.2148	0.8817	1.8144	0.8825
Business Equipment	1.0204	−0.0125	0.5203	−0.0172	−0.9192	−0.0244	−2.1227	−0.0213
Chemicals	1.0372	0.1713	5.7698	0.2097	4.2511	0.2126	1.4899	0.1791
Durables	3.7315	0.2036	3.8058	0.1983	0.3616	0.1947	1.2061	0.1932
Energy	−0.1130	0.0626	−1.1258	0.0601	0.2082	0.0632	3.8672	0.0844
Health	0.0206	0.0152	−0.4068	0.0160	−1.0515	0.0183	−0.7214	0.0151
Manufacturing	3.7157	0.2731	2.9514	0.2692	0.4589	0.2513	2.3537	0.2610
Non Durables	8.4692	0.1582	7.6996	0.1422	3.9961	0.1308	−0.4676	0.1089
Shops	2.4088	0.1528	2.5458	0.1521	0.9688	0.1448	0.4515	0.1478
Telecommunication	3.2429	0.0449	4.8053	0.0551	1.1244	0.0309	0.9565	0.0289
Utilities	1.1463	−0.0402	1.5078	−0.0428	1.0410	−0.0331	−0.1477	−0.0289
Other	4.3476	0.3272	5.0854	0.3366	3.2017	0.3151	0.9243	0.3083

crisis definitions, that are (1) the US recession times (USREC) reported by the NBER, and (2) the period of the global financial crisis (GFC) which spans from July 2007 to March 2009. Model (3) is a mixture of the economic events based approach and the econometric approach suggested by Baur (2012). If the 95%-percentile of the pre-GFC conditional volatility extracted by a GARCH(1,1) model for the financial sector's changes in distance-to-default is exceeded, a crisis is identified. By applying this approach, the GFC is identified as crisis, as well as volatile periods that are not captured by economic events based approaches, that occur outside of NBER recessions. Model (4) uses an econometric approach by employing the smoothed crisis probabilities extracted from a two-regime switching model for the changes in distances-to-default. We identify a crisis, if the corresponding smoothed state probability is greater than 50% of the regime with higher volatility and correlation to the NBER recession times. For the remainder of this paper, we identify contagion if the t-statistic of the contagion test is greater than 1.6497 (p-value of 5%), and the adjusted R^2 is greater than 5%.

First, we evaluate the results for the market value of equity weighted indices. The market index shows contagion with the financial sector for all models with an adjusted R^2 of at least 44%. Manufacturing and Other also exhibit financial contagion for models (1)–(4), although the R^2s are much lower at about 14%. The sectors Durables, Non Durables, and Manufacturing show financial contagion for the models (1)–(3).

For the models using the total liabilities as weights, with the exception of the market index for the QVOL crisis definition, all models provide evidence for contagion with an R^2 of over 88%. Models (3) and (4) reveal only five sectors with contagion that are not common for both crisis definitions. Models (1) and (2) show a battery of common sectors with financial contagion: Others, Manufacturing, Durables, Shops, Non Durables (in decreasing order of R^2s).

Comparing all crisis definitions and the two weighting methodologies, we conclude that for each weighting methodology the market and manufacturing index provide robust evidence for financial contagion. Results of the econometrics-based crisis definitions for models

(3) and (4) are mixed.

Next, we relax the assumption of contagion originating from the financial sector and consider each sector as potential source of contagious transmission between all other sectors. Table 4.5 reports the results of the U.S. recession times as crisis definition and Table 4.6 depicts the findings for the period of the global financial crisis. In Table 4.7, a crisis is present if the financial volatility exceeds its pre-GFC 95% quantile. Table 4.8 identifies a crisis if the smoothed crisis state probabilities of a two-state Markov switching model are greater or equal to 50%.

We find fewer contagion relationships for all models using the market value of equity weights compared to the weights by total liabilities. In line with Shahzad et al. (2017), we find no financial contagion of the utility sector. Also, in the inter-industry results, we document very few contagious transmissions to this sector, which can be attributed to a monopolistic structure and high regulations (Shahzad et al., 2017). This finding is robust to the choice of crisis definition and weighting methodology. Additionally, the sectors Health and Telecommunication show only few co-movement relationships with other industries. We confirm the results of Azizpour et al. (2018), who show that the financial sector is not necessarily the initiator of contagious effects and receives contagious transmissions from other sectors. Various contagious relationships are found in our sample for all weighting methodologies – independently of the choice of crisis definition.

Table 4.5 Inter-industry contagion with U.S. recession times as crisis definition. We use Eq. (4.1)–(4.3) to estimate inter-industry contagious effects by regressing each industry on another industry. All results in this table use the U.S. recession times by the NBER as crisis definition. The upper panel reports the results for market value of equity weighted and the lower for total liabilities weighted indices. The t-statistics for the contagion tests are reported in this table if the value is greater than 1.6497, which corresponds to a p-value of 5%, and the adjusted R^2 is greater than 5%.

	Contagious transmission from											
	Money	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Other
to	*weight: market value of equity*											
Money		2.53	3.87			3.77				3.08		
NoDur	4.87		5.17			4.62					5.64	
Durbl	4.53											3.67
Manuf	3.83		6.57			2.03						4.73
Enrgy		2.49				2.47			4.46			
Chems												
BusEq									1.88			
Telcm												
Utils											2.13	
Shops												
Hlth												
Other	2.32		5.27	2.95		5.18	4.95			5.62		
to	*weight: total liabilities*											
Money		4.09	2.53	1.77		2.74		3.45		3.65		
NoDur	7.54		13.15	6.69	10.05	8.49		11.44		9.07	4.24	6.08
Durbl	4.45	9.47		2.90	4.74	5.94	7.71	9.22		4.97		5.86
Manuf	3.77	4.89	4.58		3.58	5.78	7.04	9.30		5.96		5.61
Enrgy		3.76							2.97			
Chems		4.69	8.41	1.98								
BusEq			2.25	3.29				2.32		4.02		1.88
Telcm			5.77	5.97			3.02			3.34		2.81
Utils												
Shops	1.79	5.64	4.32	3.03		3.97	6.14	5.66				2.51
Hlth		2.77							2.42			
Other	3.61	9.52	8.45	5.95		10.10	9.02	8.06		8.24		

Table 4.6 Inter-industry contagion with the period of the global financial crisis as crisis definition. We use Eq. (4.1)–(4.3) to estimate inter-industry contagious effects by regressing each industry on another industry. We identify the period of the global financial crisis from July 2007 to March 2009 as the crisis period. The upper panel reports the results for market value of equity weighted and the lower for total liabilities weighted indices. The t-statistics for the contagion tests are reported in this table if the value is greater than 1.6497, which corresponds to a p-value of 5%, and the adjusted R^2 is greater than 5%.

	Contagious transmission from											
	Money	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Other
to	*weight: market value of equity*											
Money		3.87	5.80	4.14	2.71	3.58		3.86		5.28		6.41
NoDur	3.59				4.64	5.17	5.05		1.70		6.33	
Durbl	4.93			1.76			7.73	9.87		7.08		5.45
Manuf	3.65		5.05			2.25		5.05				6.61
Enrgy						3.14			2.95			
Chems		2.22		1.78								
BusEq									4.22			
Telcm												
Utils							2.72					
Shops												
Hlth		2.23				2.60						
Other	2.54		3.19			3.62	5.04			4.94		
to	*weight: total liabilities*											
Money		2.37	2.35	10.70				2.06		12.52		13.77
NoDur	7.11		12.81	7.38	10.94	9.44	16.86	11.81		9.52	4.00	6.96
Durbl	4.80	9.86		3.34	5.88	6.93	10.37	9.05		6.82		5.46
Manuf	3.06	4.44	5.49			6.16	8.52	7.76		3.41	3.44	2.98
Enrgy		2.89				2.00	3.92		2.75			
Chems		6.96	8.28	3.55								
BusEq			1.96	2.56				2.02		2.73	5.50	
Telcm	3.48	5.65	4.89	7.48		4.16	7.55			6.21		4.19
Utils												
Shops	2.82	5.79	6.99	2.82		5.14	6.63	6.47				2.82
Hlth		4.04					6.30		2.55			
Other	4.93	5.11	5.72	3.46		4.31	4.31	4.92		5.10	1.97	

Table 4.7 Inter-industry contagion with QVOL as crisis definition. We use Eq. (4.1)–(4.3) to estimate inter-industry contagious effects by regressing each industry on another industry. We identify a crisis if the pre-GFC conditional volatility of the financial sector's index is greater than its 95%-percentile (QVOL). The upper panel reports the results for market value of equity weighted and the lower for total liabilities weighted indices. The t-statistics for the contagion tests are reported in this table if the value is greater than 1.6497, which corresponds to a p-value of 5%, and the adjusted R^2 is greater than 5%.

	Contagious transmission from											
	Money	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Other
to	*weight: market value of equity*											
Money		3.55	3.36	4.92	3.57	1.81				3.30		5.66
NoDur	2.15				3.45	4.40					2.30	
Durbl	3.53			8.14						8.00		6.78
Manuf	4.32		4.70			2.90						7.01
Enrgy		3.16							2.25			
Chems		2.74		2.42								
BusEq									1.84			
Telcm												
Utils							1.86					
Shops												1.73
Hlth												
Other	2.53		4.38	1.89			2.65			4.40		
Other	2.54		3.19			3.62	5.04			4.94		
to	*weight: total liabilities*											
Money		5.69	3.05	3.64	2.41	3.53		1.93		2.27		4.19
NoDur	3.78		4.12	5.97	4.13	5.67				3.73	4.35	4.71
Durbl		4.59		2.84	3.55	3.18	3.35	3.82				
Manuf		3.60	1.74			1.74	2.81	3.41				1.67
Enrgy		2.30										
Chems	3.70	6.30	5.77	4.69	3.41			2.69				2.51
BusEq												
Telcm			2.45				2.46					2.15
Utils												
Shops		3.22	2.67	2.37		2.94	7.13	4.45				
Hlth												
Other	2.72	6.62	5.52	5.27		4.40	5.26	5.52		3.12	5.26	

Table 4.8 Inter-industry contagion with Markov switching model-based crisis definition. We use Eq. (4.1)–(4.3) to estimate inter-industry contagious effects by regressing each industry on another industry. We identify a crisis if the smoothed crisis state probabilities of a two-regime switching model for the financial sector index are greater than 50%. The t-statistics for the contagion tests are reported in this table if the value is greater than 1.6497, which corresponds to a p-value of 5%, and the adjusted R^2 is greater than 5%.

	Contagious transmission from											
	Money	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Other
to	*weight: market value of equity*											
Money				7.60	7.27	4.19				3.98		7.59
NoDur					4.20	4.11					5.16	
Durbl	2.02			5.98								10.80
Manuf	3.05		4.02		1.97	3.61						5.14
Enrgy						1.67						
Chems	2.01	3.23		2.99	2.66				3.39		3.23	
BusEq												
Telcm												
Utils		1.72			2.08	2.72					2.87	
Shops												
Hlth		3.67				2.98			1.89			
Other	1.99		3.96									
to	*weight: total liabilities*											
Money		1.74	4.29	4.66	6.83	5.97				5.08		12.70
NoDur				2.30	2.00	5.24			3.13		1.73	
Durbl		3.39		3.88	2.16	4.91	5.12	2.27		2.52		6.84
Manuf	2.37	4.85	4.58		4.52	5.79	7.25	3.49		2.53		3.66
Enrgy	3.77	4.11	2.12	2.02		3.07			2.81			1.77
Chems	2.22	4.66	5.91	4.04	2.25							2.49
BusEq			2.51	2.85				2.93		3.97		1.83
Telcm				1.96			3.16			3.40		2.32
Utils					1.86						2.38	
Shops		3.32	4.08	2.33		2.50	3.64	4.85				
Hlth		2.36										
Other		2.00	2.84	3.03		4.35						

Intra-Industry Contagion

Next, we explore intra-industry contagion effects, which we define as a co-movement between an individual company and its sector index. We run Eq. (4.1)–(4.3) for each company i and its respective sector index j, and require each company to feature at least 50 consecutive observations for the whole sample, of which at least 5 observations occur during crisis times. We define a contagious relationship as significant if the t-statistic for the contagion test is greater than 1.6497, which corresponds to a p-value of 5%, and if the adjusted R^2 is greater than 5%. For the all companies satisfying these conditions, we set the dummy indicator $I_{i,j}$ equal to 1 if company i and its corresponding sector index j feature a significant contagion relationship and 0 otherwise. To gauge the drivers of intra-industry contagion, we use a logarithmic regression in the cross section

$$\mathbb{P}(I_{i,j} = 1) = (1 + \exp(-\delta' x_i))^{-1}, \tag{4.8}$$

where x_i is a vector of company-specific explanatory variables and δ of corresponding estimates. We follow Lang and Stulz (1992) and Jorion and Zhang (2007) who propose determinants for contagion effects which we adopt to our intra-industry setting. We use the natural logarithm of the firm's average total liabilities plus shareholders equity (SIZE), the firm's average leverage ratio divided by the average leverage ratio of the sector (LEV), and the firm's average sales divided by the sum of all firms average sales in the sector (SALES) as a measure of concentration.

Table 4.9 reports the results of the logistic regression model (4.8). We consider the four crisis definitions: (1) the U.S. recession times,

Table 4.9 Determinants of intra-industry contagion. We use Eq. (4.8) to gauge determinants for intra-industry contagious effects. SIZE is the natural logarithm of the firm's average total liabilities plus shareholders equity, LEV the firm's average leverage ratio divided by the average leverage ratio of the sector, SALES the firm's average sales divided by the sum of all firms average sales in the sector. Data sources: Refinitiv Eikon & Datastream, CRSP. The upper panel reports the results for market value of equity weighted and the lower for total liabilities weighted sector indices. We consider four different crisis definitions: (1) the U.S. recession times (USREC) by the NBER, (2) the period of the global financial crisis (GFC) from July 2007 to March 2009, (3) if the pre-GFC conditional volatility of the financial sector's index is greater than its 95%-percentile (QVOL), and (4) if the smoothed crisis state probabilities of a two-regime switching model for the financial sector index are greater than 50% (RS). AUC denotes the area under the curve. The maximum rescaled R^2 is computed as described in Nagelkerke (1991). *, ** and *** denote statistical significance at the 5%, 1% and 0.1% level.

	(1)	(2)	(3)	(4)
Crisis Definition	USREC	GFC	QVOL	RS
	weight: market value of equity			
Intercept	−3.2231***	−2.9606***	−4.3540***	−3.9433***
SIZE	0.2755***	0.2628***	0.4090***	0.4209***
LEV	−0.0977	−0.0329	−0.0884	−0.1204*
SALES	−9.8604**	−1.8666	−2.2901	−7.2587*
N	4951	2646	4362	5870
AUC	0.6469	0.6317	0.6999	0.6963
Max. rescaled R^2	0.0586	0.0554	0.1031	0.1245
	weight: total liabilities			
Intercept	−3.0177***	−2.1611***	−4.7535***	−4.5124***
SIZE	0.3073***	0.1868***	0.4841***	0.4906***
LEV	−0.0254	0.0961	−0.0999	−0.0630
SALES	−13.6505***	−4.5353	−15.5234***	−9.3185**
N	4951	2646	4258	6238
AUC	0.6625	0.6164	0.7152	0.7275
Max. rescaled R^2	0.0841	0.0470	0.1247	0.1554

(2) the time span of the global financial crisis, (3) if the pre-GFC conditional volatility exceeds its 95%-percentile and (4) if the smoothed crisis state probabilities are greater or equal to 50%. We calculate the sector indices weighted by the market value of equity and total liabilities. We report the maximum rescaled R^2 of Nagelkerke (1991) and the area under the curve (AUC). Note that the number of observations differ for all models and weighting methodologies of the sector index as we require at least 50 consecutive observations with at least 5 observations during crisis times for each firm in order to be included

in the regression. We find that the predictability of the models is higher for the econometrics-based approaches of models (3) and (4) (max. rescaled R^2 ranges from 0.1031 to 0.1247 and the AUC from 0.6963 to 0.7275) than for the event-based definitions of models (1) and (2) (max. rescaled R^2 ranges from 0.047 to 0.0841 and the AUC from 0.6164 to 0.6625). We observe a positive significant effect of SIZE, i.e., the larger the firm's balance sheet, the higher is the probability of a contagious transmission to its sector index. This effect is independent of the weighting methodology and crisis definition and has been documented for bankruptcy announcements (Lang and Stulz, 1992), contagion in loan spreads (Hertzel and Officer, 2012), and CDS spreads (Jorion and Zhang, 2007). Contrary to Jorion and Zhang (2007), we find no significant effect of LEV, except for model (4) when is the sector index is weighted by the market value of equity. The significant negative coefficient of SALES hints to competitive advantages of firms which concentrate a large share of total sector sales which lowers their probability of co-movement to the sector. This effect is in line with the findings for the previously mentioned studies. For models (2) and (3) for the market value of equity, as well as model (2) of the total liability weighted sector indices, we do find this effect to be insignificant.

We thus find evidence for intra-industry contagion and identify SIZE as a proxy for co-movement independent of crisis definition and weighting methodology of the sector index. At the same time, the impact of SALES is mixed.

4.5 Conclusion

In this paper, we examine the influence in changes of credit quality measured by the changes in the distances-to-default inferred by the Campbell et al. (2008) model. We identify contagion effects within an inter-industry setting suggesting co-movement during times of crisis which are associated with a negative change in the distances-to-default, and thus an increase in the probability of default. Additionally, we identify large companies as well as companies that account for minor sales in their industry to be more likely to transfer shocks among their sector peers in an intra-industry study. Our results suggest that a financial institution which uses the Campbell et al. (2008) or a similar model based on default events to calculate risk measures and capital reserves – for single loans or a portfolio – is prone to an under-capitalization during times of crisis.

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