Essays in Financial and Monetary Economics

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Symbols and Abbreviations

Chapter 1

bs	Balance statistic
c	Constant
d	Proportion of statements indicating a negative deviation from trend
fiscal	Assessment indicator for fiscal activity
$\hat{m}$	Deviation of money growth from target
M3	Monetary aggregate
money	Assessment indicator for monetary activity
price	Assessment indicator for price activity
R-squared	Coefficient of determination
real	Assessment indicator for real economic activity
t	Index for the time dimension
trade	Assessment indicator for foreign trade activity
u	Proportion of statements indicating a positive deviation from trend
$\hat{y}$	Output gap
Δi	First differenced monthly average of the German day-to-day money market rate
$\boldsymbol{\beta}$	Coefficient vector of independent variables
ϵ	Random error term
$\hat{\pi}$	Deviation of inflation from target

Chapter 2

$\mathbf{1}$	Indicator function
c	Chebyshev polynomial
d^*	Latent endogeneous variable, loan-quota ratio
d	Loan-quota ratio

E	Expectation operator
e	Error term
$\boldsymbol{g}$	Vector of Mundlak variables
$\boldsymbol{I}$	Identity matrix
i	Index for the cross-section dimension
index	Index of institutional quality
$\boldsymbol{q}$	Vector of Mundlak variables
R-squared	Coefficient of determination
r	Error term
t	Index for the time dimension
u	Error term
$\tilde{u}$	Error term
Var	Variance
v	Error term
w	Conditioning variable
$\boldsymbol{x}$	Vector of control variables
y^*	Latent endogeneous variable, real GDP per capita growth rate
y	Real GDP per capita growth rate
$\boldsymbol{z}$	Vector of explanatory variables
α	Country-specific effect
$\boldsymbol{\beta}$	Vector of coefficients of explanatory variables
$\boldsymbol{\gamma}$	Vector of coefficients of explanatory variables
δ	Partial derivative
ϵ	Error term
$\tilde{\epsilon}$	Error term
χ	Error term
ϕ	Standard normal probability density function
Φ	Standard normal cumulative density function
η	Coefficients in Chebyshev polynomial
ι	Vector of ones
$\boldsymbol{\kappa}$	Coefficient vector of the Mundlak variables
μ	Country-specific effect
θ	Coefficient of the loan-quota ratio

σ	Standard deviation
$\tilde{\tau}$	Coefficient of correction terms
τ	Coefficient of correction terms
$\boldsymbol{\xi}$	Coefficient vector of Mundlak variables
ψ	Constant
ζ	Constant

Chapter 3

$\mathbf{1}$	Indicator function
A	Banks' initial endowment with capital
a	Interbank lending
b	Non-liquid asset
c	Liquid asset
Cov	Covariance
$\boldsymbol{D}$	Diagonal matrix scaling the stepsize of changes in control variables
$\bar{d}$	Average stepsize
d	Deposits
exp	Exponential function operator
f	Index for different banks
H	Systemic risk charge
i	Index for different banks
j	Index for different banks
l	Interbank liabilities
ln	Logarithmic function operator
max	Maximum operator
min	Minimum operator
p	Market price of the non-liquid asset
prob	Probability
q	Number of parallel processes in the optimization procedure
$\boldsymbol{R}$	Diagonal matrix containing the absolute value of successfully implemented steps

s	Amount of non-liquid assets sold on the market
T	Temperature
$\boldsymbol{u}$	Vector of uniformly distributed numbers
v(k)	Value obtained by coalition k
w	Index for scenarios exceeding the SVaR
α	Parameter controlling amounts lent between banks
β	Parameter controlling amounts invested in liquid and non-liquid assets
γ	Capital requirement ratio
δf^+	Increase in the loss function at the updated vector of control variables
$\delta \bar{f}^+$	Average positive change in the loss function
ϵ	Loss function value
Φ^E	Expected systemic risk
ϕ	Shapley Value
ϕ^E	Expected Shapley Value
ι	Scaling parameter in the temperature adjustment
o	Systemic risk in a given scenario
π	Scaling parameter for step adjustment
θ^d	Amount a bank desires to net
θ^s	Amount a bank is willing to net
θ_{ji}	Amount netted between banks i and j
$\boldsymbol{\rho}$	Vector of control variables
σ	Standard deviation
τ	Additional amount of capital injected into a bank
ξ	Parameter to scale price sensitivity
ω	Scaling parameter for step adjustment
Ψ	Capital collected for the systemic risk fund
ς	Highest conceivable shock to the banking system

Acronyms

AIC Akaike Information Criterion

AIG American International Group

CDS Credit Default Swaps

CoCos Contingent Convertible Bonds

CDO Collateralized Debt Obligations

CPI Consumer Price Index

EFF Extended Fund Facility

ESAF Enhanced Structural Adjustment Facility

GDP Gross Domestic Product

IMF International Monetary Fund

IWF Internationaler Währungsfonds

PRGF Poverty Reduction and Growth Facility

ROW Rest of the World

SAF Structural Adjustment Facility

SBA Stand-by Arrangement

SVaR System Value at Risk

VaR Value at Risk

Deutsche Zusammenfassung

Die vorliegende Dissertation umfasst drei Kapitel, die sich mit drei verschiedenen Themengebieten aus der Finanzökonomie und Volkswirtschaft befassen. Im ersten Kapitel wird eine neue Methode entwickelt, mit Hilfe derer sich öffentliche Aussagen einer Zentralbank in quantitative Einschätzungsindikatoren umwandeln lassen, die zur Analyse der Geldpolitik dieser Zentralbank herangezogen werden können. Im zweiten Kapitel[1] wird der Einfluss von an die Umsetzung von Reformen geknüpften Kreditprogrammen des Internationalen Währungsfonds (IWF) auf das Wirtschaftswachstum der an den Programmen teilnehmenden Länder untersucht. Im dritten Kapitel[2] werden die Entstehung systemischen Risikos in einem Netzwerkmodell von Banken, die über ihre Bilanzen miteinander verbunden sind, sowie die Möglichkeit, systemisches Risiko über einen Systemrisikowert-Ansatz und eine systemische Risikogebühr zu senken, analysiert. Alle drei Kapitel eröffnen wichtige Einblicke in die Politikgestaltung bedeutender volkswirtschaftlicher Institutionen wie Zentralbanken, IWF und makroprudenzieller Aufsicht.

Die im ersten Kapitel der Dissertation entwickelten Einschätzungsindikatoren bilden Erwartungen und Einschätzungen einer Zentralbank über die für ihre Geldpolitik relevanten Variablen, wie zum Beispiel die reale Wirtschaftsaktivität oder Inflation ab und können zur Analyse der geldpolitischen Strategie von Zentralbanken, beispielsweise durch Schätzung einer Taylor-Regel verwendet werden.

Der Informationsgehalt von Einschätzungen einer Zentralbank über die für ihre Geldpolitik relevanten Variablen kann sich vom Informationsgehalt dieser Variablen selbst unterscheiden. Zum Beispiel kann eine Zentralbank davon ausgehen, dass ein auftretender Inflationsschock nur temporärer Natur ist. In diesem Fall wird sie dem Schock wahrscheinlich nicht viel Gewicht

[1] Das zweite Kapitel wurde zusammen mit Professor Michael Binder, Goethe-Universität Frankfurt am Main, verfasst.

[2] Das dritte Kapitel wurde zusammen mit Professor Jan Pieter Krahnen, Goethe-Universität Frankfurt am Main, verfasst.

für ihre geldpolitischen Entscheidungen beimessen. Falls sie aber davon ausgeht, dass der Inflationsschock von Dauer ist, dann ist es wahrscheinlich, dass ihre geldpolitischen Entscheidungen davon stärker beeinflusst werden. Die Einschätzung der Zentralbank über den Inflationsschock und dessen Auswirkungen sind jedoch nicht in der Inflationsrate selbst enthalten. Da die geldpolitischen Entscheidungen in der Zentralbank stark von ihren Einschätzungen abhängen, bietet es sich an, diese für eine Analyse der Geldpolitik dieser Zentralbank heranzuziehen.

Zentralbanken erreichen in der Öffentlichkeit durch Transparenz und Kommunikation über ihre geldpolitischen Entscheidungen ein Verständnis ihres geldpolitischen Entscheidungsprozesses und erhöhen damit nicht zuletzt die Wirksamkeit ihrer Geldpolitik. Da die meisten Zentralbanken aus diesem Grunde ihre geldpolitischen Entscheidungen in regelmäßig erscheinenden Berichten erklären und kommunizieren, bietet es sich an, diese Informationsquelle zur Analyse ihrer Geldpolitik heranzuziehen. Um die von den Zentralbanken kommunizierten Einschätzungen für eine statistische Analyse verwertbar zu machen, wird im ersten Kapitel gezeigt, wie sich Erwartungsindikatoren erstellen lassen. Die vorgeschlagene Herangehensweise besteht darin, in einem ersten Schritt Aussagen der Zentralbank in ihrem Monatsberichtsheft mit ordinalen Kennzahlen zu bewerten, die anzeigen, ob die Aussage darauf hindeutet, dass die bewertete Größe (i) positiv, (ii) negativ oder (iii) nicht von ihrem Trend abweicht. In einem zweiten Schritt werden diese ordinalen Kennzahlen dann mit Hilfe des Gleichgewichtsstatistik-Ansatzes in quantitative Einschätzungsindikatoren der Zentralbank über für ihre Geldpolitik relevante Richtgrößen, wie zum Beispiel Inflation oder die reale Wirtschaftsaktivität umgewandelt. Diese können dann für die statistische Analyse der Geldpolitik im Rahmen einer Taylor-Regel verwendet werden.

Nachdem diese neue Analysemethode erläutert wurde, wird sie verwendet, um einen neuen Datensatz zu erstellen, der die Einschätzungen der Deutschen Bundesbank über die für sie politikrelevanten Variablen aus ihren Aussagen in den Monatsberichtsheften über den Zeitraum Januar 1970 bis Dezember 1998 herausfiltert. Dieser Datensatz wird dann zur Schätzung einer Taylor-Regel für die Deutsche Bundesbank über den betrachteten Zeitraum herangezogen.

Der geldpolitische Erfolg der Deutschen Bundesbank wird nach wie vor als eine Referenz für das Erreichen von Geldwertstabilität betrachtet. Ein herausragendes Merkmal der geldpolitischen Strategie der Deutschen Bundesbank war der Ansatz flexibler Geldmengensteuerung. Diesem Ansatz folgend versuchte die Deutsche Bundesbank, Geldwertstabilität zu erreichen, indem sie geldpolitische Entscheidungen auf das Erreichen von Wachstumszielen für Geldmengenaggregate ausrichtete. Die Deutsche Bundesbank ist hierbei jedoch flexibel und pragmatisch vorgegangen und hat ihre Geldpolitik nicht mechanisch vom Erreichen dieser Wachstumsziele beeinflussen lassen, sondern auch andere Richtgrößen berücksichtigt, wie zum Beispiel die reale Wirtschaftsaktivität oder Inflation. Sowohl Clarida, Gali und Gertler (1998) als auch Bernanke und Mihov (1997) haben jedoch in Frage gestellt, dass die Deutsche Bundesbank tatsächlich Wachstumsziele für Geldmengenaggregate in ihren geldpolitischen Entscheidungen berücksichtigt hat. Bei einer Analyse der Geldpolitik der Deutschen Bundesbank mittels einer Taylor-Regel finden die Autoren keine statistische Signifikanz von Geldmengenaggregaten als erklärende Variablen.

Im Gegensatz dazu führt die im ersten Kapitel vorgestellte Analysemethode zu einem anderen Ergebnis. Verwendet man die Einschätzungsindikatoren als erklärende Variablen in einer Taylor-Regel, dann zeigt die Analyse, dass die realwirtschaftliche Aktivität, Inflation und die Entwicklung von Geldmengenaggregaten die geldpolitischen Entscheidungen der Deutschen Bundesbank signifikant erklären können. Strukturbruchtests nach Bai and Perron (1998) zeigen an, dass die Deutsche Bundesbank dieser Geldpolitik flexibler Geldmengensteuerung von April 1975 bis Dezember 1998 gefolgt ist. Dieses Ergebnis deutet darauf hin, dass die Verwendung von Geldmengenaggregaten, wie beispielsweise auch von der Europäischen Zentralbank praktiziert, Teil einer erfolgreichen geldpolitischen Strategie sein kann.

Im zweiten Kapitel der Dissertation wird der Einfluss von an Reformen geknüpften Kreditprogrammen des IWF auf das Wirtschaftswachstum von teilnehmenden Ländern untersucht.

Als der IWF im Jahre 1945 seine Tätigkeit aufnahm, sollte er als unabhängige internationale Organisation sowohl zu makroökonomischer und finanzieller Stabilität beitragen als auch das Wachstum der Weltwirtschaft befördern. Nach dem Scheitern des Bretton-Woods Systems in den 1970er Jahren erweiterte der IWF seine Aktivitäten in den Bereich von an Bedingungen geknüpfter Entwicklungshilfe. Um sich für derartige Kreditprogramme des IWF zu qualifizieren, muss sich ein Land im Gegenzug zur Durchführung wirtschaftlicher und struktureller Reformen verpflichten. Diese Konditionalität soll sicherstellen, dass die wirtschaftliche Entwicklung in dem entsprechenden Land eine spätere Rückzahlung der Hilfszahlungen ermöglicht.

Bisherige Analysen der Auswirkungen von IWF-Kreditprogrammen auf das Wirtschaftswachstum von teilnehmenden Ländern führen zu unterschiedlichen Ergebnissen. So kommen Barro und Lee (2005), die politökonomische Variablen benutzen, um mögliche Endogenität der IWF-Programmteilnahme zu berücksichtigen, zu dem Schluss, dass die Teilnahme an Kreditprogrammen des IWF einen negativen Effekt auf das Wirtschaftswachstum hat. In einer kontrafaktischen Analyse findet auch Vreeland (2003) Hinweise darauf, dass die Teilnahme an IWF-Kreditprogrammen zu einer Verringerung des Wirtschaftswachstums führt. Im Gegensatz dazu zeigen Dicks-Mireaux, Mecagni und Schadler (2000) ebenfalls anhand einer kontrafaktischen Analyse, dass sich IWF-Kreditprogramme positiv auf das Wirtschaftswachstum von teilnehmenden Ländern auswirken. Diese unterschiedlichen Ergebnisse deuten darauf hin, dass bei der Untersuchung von IWF-Kreditprogrammen auf das Wirtschaftswachstum Zustandsabhängigkeit der Teilnahmeeffekte eine wichtige Rolle spielt.

Für die Analyse der Wachstumseffekte von an Reformen geknüpften Kreditprogrammen verwenden wir ein zustandsabhängiges Paneldatenmodell mit festen Effekten. Um Selektionsverzerrung und Endogenität zu berücksichtigen, benutzen wir ein Gleichungssystem, das aus zwei Gleichungen besteht. Die erste Gleichung modelliert die Effekte der Programmteilnahme auf das Wirtschaftswachstum („Wachstumsgleichung“) und die zweite Gleichung modelliert die Wahrscheinlichkeit der Teilnahme an IWF Kreditprogrammen („Teilnahmegleichung“). Die Schätzung der Gleichungskoeffizienten findet in zwei Schritten statt. In einem ersten Schritt wird die Teilnehmegleichung mit dem Kredit-Quote-Verhältnis als abhängiger Variable geschätzt.[3] Aus dem Fehlerterm dieser Schätzung lassen sich Korrekturterme erstellen, die als zusätzliche erklärende Variablen in die Wachstumsgleichung mit aufgenommen werden. Durch die Berücksichtigung dieser Korrekturterme kann der Effekt des Kredit-Quote-Verhältnis auf das reale pro Kopf Wirtschaftswachstum von an IWF-Kreditprogrammen teilnehmenden Ländern unverzerrt geschätzt werden.

Die Heterogenität der Effekte von IWF-Kreditprogrammen auf das Wirtschaftswachstum wird mit Hilfe eines semiparametrischen zustandsabhängigen Pooling Ansatzes berücksichtigt, bei dem die Effekte der IWF-Kreditprogrammteilnahme auf das Wirtschaftswachstum selbst Funktion einer bedingenden Variable sind. Um möglicher Zustandsabhängigkeit der Teilnahmeeffekte Rechnung zu tragen, werden in der Analyse zwei bedingende Variablen verwendet, einerseits der Grad, zu dem vereinbarte Reformen tatsächlich umgesetzt werden, und andererseits institutionelle Faktoren, die die Effektivität der Hilfsprogramme beeinflussen können. Da die von einem am IWF-Kreditprogramm teilnehmenden Land zugesagten Reformen meist nur schrittweise umgesetzt werden, zahlt der IWF vereinbarte Kreditbeträge auch nur schrittweise aus, und zwar zu jeweils vorher festgelegten Terminen, wenn das Land die vereinbarten Reformen tatsächlich umgesetzt hat. Aus diesem Grunde kann das Verhältnis von tatsächlich ausgezahlten Geldern zu in dem Hilfsprogramm insgesamt vereinbarten Geldern als Proxyvariable für den Grad, zu dem ein Land die vereinbarten Reformschritte tatsächlich umgesetzt hat, verwendet werden. Als zweite Proxyvariable für die Zustandsabhängigkeit der Effekte von IWF-Kreditprogrammteilnahme auf das Wirtschaftswachstum wird die institutionelle Qualität des teilnehmenden Landes verwendet, da (i) diese einen direkten Einfluss auf die Effektivität von verwendeten Hilfsgeldern hat und (ii) der IWF seit den 1980er Jahren strukturelle Reformbedingungen, die vor allem auf Fortschritte im politischen, legislati-

[3] Das Kredit-Quote-Verhältnis ist das Verhältnis der Summe aller an Bedingungen geknüpften Kredite des IWF, die für ein Land bewilligt wurden, zu dessen Quote beim IWF.

ven und institutionellen Umfeld abzielen, in seinen Kreditprogrammen verwendet. Um ein möglichst breites Spektrum von Merkmalen institutioneller Qualität abzubilden, verwenden wir einen Index, in den länderspezifische Informationen über die Qualität des Beamtenapparates, Korruption, Recht und Ordnung, Stabilität der Regierung, ethnische Spannungen, interne Konflikte, Lebenserwartung und Schulbildung einfließen.

Die Analyse, in der jährliche Daten für 86 Länder über den Zeitraum von 1975 bis 2005 verwendet werden, zeigt, dass die Teilnahmeeffekte von IWF-Kreditprogrammen auf das Wirtschaftswachstum systematisch mit dem Grad der Umsetzung vereinbarter Reformschritte sowie dem Index institutioneller Faktoren variieren. IWF-Kreditprogramme führen zu positiven Teilnahmeeffekten, wenn die vereinbarten Reformen zu einem ausreichenden Grad umgesetzt werden oder wenn die Teilnahme am Kreditprogramm mit ausreichenden Fortschritten bei der institutionellen Qualität verbunden ist. Im Hinblick auf die Stärke der Effekte zeigt sich in einer Analyse der Wachstumsbeiträge, dass die Teilnahme an IWF-Kreditprogrammen im Durchschnitt über alle Länder und Zeitpunkte beträchtlich zum Wirtschaftswachstum eines Landes beiträgt. Der durchschnittliche Beitrag von bedingten IWF-Kreditprogrammen zum Wirtschaftswachstum ist durchschnittlich größer als der von Inflation, aber weitaus kleiner als der von Investitionen. Ferner deutet eine intertemporale Analyse darauf hin, dass IWF-Kreditprogramme bis zu einem Zeitraum von drei Jahren nach Programmteilnahme einen signifikant positiven Einfluss auf das Wirtschaftswachstum haben, wenn ein teilnehmendes Land die vereinbarten Reformen zu einem ausreichenden Grad umsetzt oder wenn die Programmteilnahme mit ausreichenden Fortschritten bei der institutionellen Qualität verbunden ist. Insgesamt zeigen die Analyseergebnisse des zweiten Kapitels, dass Länder, die an bedingten IWF-Kreditprogrammen teilnehmen, versuchen sollten, die damit verbundene Konditionalität weitestgehend zu erfüllen sowie größtmögliche Fortschritte in ihrer institutionellen Qualität zu erreichen.

Im dritten Kapitel der Dissertation werden die Entstehung systemischen Risikos in einem Netzwerkmodell von Finanzinstituten sowie die Möglichkeit, systemisches Risiko über einen Systemrisikowert-Ansatz und eine systemische Risikogebühr zu senken, analysiert.

Die globale Finanzkrise, die im Jahre 2007 ihren Anfang nahm, hat deutlich gemacht, dass ein System vernetzter Finanzinstitute systemischem Risiko ausgesetzt ist und durch Insolvenzen die Realwirtschaft in Mitleidenschaft ziehen kann. Systemisches Risiko ist die Gefahr, dass durch Ausfälle im Finanzsystem eine ausreichende Bereitstellung von Krediten und Finanzdienstleistungen nicht mehr gewährleistet ist, so dass sich negative realwirtschaftliche Effekte ergeben. Finanzinstitute können ein Interesse daran haben, zu groß oder zu vernetzt um zu fallieren zu werden, damit sie von den daraus resultierenden günstigen Refinanzierungsbedingungen profitieren können. Im Falle eines drohenden Systemzusammenbruchs gehen dieselben Finanzinstitute jedoch davon aus, dass sie von der Regierung „gerettet“ werden, um Schaden von der Realwirtschaft abzuwenden. Systemisches Risiko ist demnach eine negative Externalität, die von Finanzinstituten ausgelöst wird und das gesamte Finanzsystem betrifft. Eines der zentralen Anliegen gegenwärtiger Reformbemühungen ist, Finanzinstitute angemessen an den durch systemisches Risiko entstehenden Kosten zu beteiligen.

Systemisches Risiko wird vor allem durch die Vernetzung der Finanzinstitute untereinander sowie durch Korrelationen zwischen den Bilanzen der Finanzinstitute hervorgerufen. Zum einen besteht zwischen Banken über gegenseitig eingegangene Verpflichtungen (z.B. Interbankenkredite) ein Kontrahentenrisiko. Gerät eine Bank in Schieflage und kann den eingegangenen Verpflichtungen nicht mehr nachkommen, überträgt sie einen Schock auf ihre Gegenparteien. Zum anderen sind die Bilanzen von Banken, die dieselben Finanzinvestitionen getätigt haben, indirekt über Marktpreisbewertung dieser Investitionen miteinander verbunden. Ausfälle im Portfolio einiger Finanzinstitute können diese in Schieflage bringen. Um regulatorische Kapitalanforderungen zu erfüllen, können sich diese Banken dann zu Notverkäufen ihrer Vermögenswerte gezwungen sehen. Dies kann jedoch zu einem Absinken der Preise dieser Vermögenswerte führen und durch Marktpreisbewertung die Bilanzen anderer Banken, die ebenfalls in diese Vermögenswerte investiert haben, unter Druck setzen. Schocks können dementsprechend direkt (Kreditrisiko) oder indirekt (Marktrisiko) über das Finanzsystem übertragen werden.

Das im dritten Kapitel entwickelte Modell soll diese Zusamenhänge erfassen. Es besteht aus drei Banken, die über ihre Bilanzen direkt und indirekt miteinander verbunden sind und ihr Portfolio automatisch anpassen, um regulatorische Eigenkapitalanforderungen zu erfüllen. Die Banken sind untereinander direkt über gegenseitig eingegangene Verbindlichkeiten und indirekt über einen modellendogenen Vermögensmarkt miteinander verbunden. Erfüllt eine Bank nicht die regulatorisch vorgeschriebene Eigenkapitalquote, hat sie die Möglichkeit, ihre Eigenkapitalposition zu verbessern, indem sie mit anderen Banken eingegangene Verbindlichkeiten auflöst oder Vermögenswerte verkauft. Letzteres hat jedoch einen negativen Effekt auf die Preise dieser Vermögenswerte. Da Banken in dem Modell ihre Vermögenswerte zu Marktpreisen bewerten, hat der Verkauf von Vermögenswerten einer Bank Auswirkungen auf die Bilanzen aller Banken, die diese Vermögenswerte auch halten und sich vielleicht gezwungen sehen, auch entsprechende Portfolioanpassungen vorzunehmen. Im Modell ist systemisches Risiko als der anteilige Ausfall der Vermögenswerte von insolventen Finanzinstituten relativ zur Summe aller systemweit gehaltenen Vermögenswerte definiert. Der Beitrag einzelner Institute zum systemischen Risiko wird mit Hilfe des Shapleywertes ermittelt, eines Konzeptes aus der Spieltheorie.[4]

Um das Risiko tiefgehender Systemkrisen zukünftig zu verringern, besteht mittlerweile Einigkeit, dass die Finanzaufsicht die „traditionelle“ mikroprudentielle Überwachung um eine makroprudentielle, das heißt systemumfassende Dimension erweitern muss. Diese erweiterte Aufsicht soll es ermöglichen, die Auslöser systemischen Risikos zu identifizieren, sie zu überwachen und angemessen darauf zu reagieren. Das entwickelte Modell repliziert empirisch beobachtbare Phänomäne, die durch systemisches Risiko im Finanzsystem während der Finanzkrise aufgetreten sind, und wird dazu verwendet, die Eigenschaften eines systemischen Risikowerts („Systemic Value at Risk“) zu analysieren.

Bei dem systemischen Risikowertansatz soll eine Systemrisikogebühr Fi-

[4] Siehe Shapley (1953).

nanzinstituten einen Anreiz geben, ihren Beitrag zum systemischen Risiko - und damit das gesamte systemische Risiko - zu senken. Diese Gebühr kann gleichzeitig zur Kapitalisierung eines systemischen Risikofonds herangezogen werden. Im Modell hängt der Umfang des Systemrisikofonds vom Zustand des Finanzsystems, einer Anzahl möglicher Stressszenarien in Bezug auf die Bilanzen der Finanzinstitute und dem systemischen Risikowert ab. Der systemische Risikowert wird hierbei als der erwartete prozentuale Ausfall des Finanzsystems in einem festgelegten Quantil der Verteilung von Stressszenarien definiert. Die Gebühr einzelner Finanzinstitute zum Systemrisikofonds bemisst sich nach dem Beitrag der einzelnen Institute zum erwarteten systemischen Risiko. Um das Finanzsystem robuster gegenüber systemischem Risiko zu machen, werden die Gelder des Systemrisikofonds als zusätzliche Kapitalpuffer in die Finanzinstitute injiziert und zwar so, dass der gewünschte systemische Risikowert erfüllt wird. Die optimale Lösung, in der das notwendige Gesamtaufkommen, das zur Erfüllung des vorgegebenen systemischen Risikowertes benötigt wird, minimiert wird, kann mit Hilfe eines für das Modell angepassten parallelisierten simulierten Abkühlungsverfahrens gefunden werden.

Die Analyse des dritten Kapitels zeigt, dass der Beitrag eines Finanzinstituts zum systemischen Risiko nicht unbedingt mit dem Wert der optimalen Kapitalinjektion zur Erfüllung des systemischen Risikowertes übereinstimmen muss. Unserem Ansatz folgend ist es deshalb wichtig, zwischen der Beitragszahlung, die sich aus dem Beitrag zum systemischen Risiko und dem notwendigen Gesamtaufkommen des systemischen Risikofonds ergibt und von einer Vielzahl verschiedener Risikofaktoren ausgelöst wird, und der den Systemrisikowert erfüllenden optimalen Kapitalinjektion zu unterscheiden, wenn letztere die Risikofaktoren unterschiedlich beeinflusst. Die Untersuchungsergebnisse deuten auch darauf hin, dass ein Systemrisikofonds, dessen Gelder in den Banken als zusätzliche Kapitalpuffer angelegt werden, geringere Gebühren verursacht als ein Fonds, dessen Aufkommen zentral aufbewahrt wird und nach Auftreten eines Schocks zur Rettung von Banken aufgewendet wird.

Abstract

This thesis consist of three chapters of which each investigates a topic from financial and monetary economics. In the first chapter a novel method to analyze the monetary policy of central banks is presented. In the second chapter the effects of conditional loan programs of the International Monetary Fund (IMF) on participating countries' output growth are investigated. In the third chapter a network model of interconnected bank balance sheets which gives rise to systemic risk is developed and used to analyze the implications of a bank levy related to banks' contribution to systemic risk. All three chapters give important insights to the policy design of macroeconomic institutions such as central banks, the IMF, and agencies charged with macroprudential supervision.

The first chapter outlines a method for using qualitative information to analyze the monetary policy strategy of central banks. Quantitative assessment indicators that are extracted from a central bank's public statements via the balance statistic approach are employed to estimate a Taylor-type rule. This procedure allows to directly capture a policymaker's assessments of macroeconomic variables that are relevant for its decision making process. As an application of the proposed method the monetary policy of the Deutsche Bundesbank is re-investigated with a new dataset. One distinctive feature of the Deutsche Bundesbank's strategy consisted of targeting growth in monetary aggregates. The analysis using the proposed method provides evidence that the Deutsche Bundesbank indeed took into consideration monetary aggregates but also real economic activity and inflation developments in its monetary policy strategy since 1975.

In the second chapter[5] the effect of conditional loan programs of the IMF on participating countries' output growth is re-investigated with a state-dependent panel data model. The model accounts in particular for program participation selection and the potential conditionality of the output growth

[5]The second chapter is joint work with Professor Michael Binder, Goethe-Universität Frankfurt am Main.

effects of program participation on a country's degree of program implementation and institutional factors such as quality of governance, internal stability, health, and educational attainment. It is shown that the effects of IMF program participation on output growth vary systematically with the degree of program implementation as well as an index of institutional factors, and that these effects are positive only if the IMF program is implemented to a sufficient degree or if program participation is coupled with sufficient progress in improving institutional quality.

In the third chapter[6] the emergence of systemic risk in a network model of interconnected bank balance sheets is analyzed. Given a shock to assets of one or several banks, systemic risk in the form of multiple bank defaults depends on the strength of balance sheets and asset market liquidity. The price of assets on the secondary market is endogenous in the model, thereby relating funding liquidity to bank solvency – an important stylized fact of banking crises. A systemic risk charge which relies on the Shapley Value in a system value at risk model is then introduced. Using a parallelized simulated annealing algorithm the properties of an optimal charge are derived. Among other things we find that there is not necessarily a correspondence between a bank's contribution to systemic risk – which determines its risk charge – and the capital that is optimally injected into it to make the financial system more resilient to systemic risk. The analysis has policy implications for the design of optimal bank levies.

[6]The third chapter is joint work with Professor Jan Pieter Krahnen, Goethe-Universität Frankfurt am Main.

Chapter 1

Investigating the Monetary Policy of Central Banks with Assessment Indicators

Empirical analyses of monetary policy are usually characterized by estimating interest rate rules which express the central bank's policy rate as a function of data on macroeconomic variables.[1] One strand of literature in this field uses qualitative information to capture a policymaker's assessments of macroeconomic variables that are important for its decision making process. The analysis in this chapter extends that literature and outlines how quantitative assessment indicators that are generated from a central bank's statements about economic and monetary developments can be used to estimate a monetary policy rule. As an application of the proposed method the monetary policy of the Deutsche Bundesbank is re-investigated.

The information content of a policymaker's *assessment* of a variable which is important for its decision making process can differ from the numerical value of the same variable. For example, a policymaker might think that a shock to a variable that plays an important role for its monetary policy, such as the inflation rate, is of temporary nature only. In this case the shock will not be attributed much weight in the central bank's monetary policy

[1] For a general review of Taylor-type rules see Orphanides (1998).

decisions. In contrast, if a policymaker judges the shock to be of permanent nature its actions are likely to be shaped (partly) in response to the shock. When the monetary policy stance of a central bank is to be investigated, incorporating the decision maker's assessment of key-variables can thus add important information going beyond the numerical value of these variables.

Central banks achieve an understanding of their monetary policy decisions in the public through transparency and communication.[2] On the one hand, they are accountable to the public because of their relatively high degree of independence and, on the other hand, it improves the efficiency of their monetary policy. Since most central banks thus regularly explain and communicate their monetary policy decisions to the public it offers the possibility to use this information for an analysis of their monetary policy. The information about variables that are important for a central bank's decision making process, such as, for example, real economic activity, can be captured via collecting its public statements from its regular economic statistical bulletins. To render the information contained in the statements accessible for statistical analysis this chapter proposes an approach which consists of two steps. In a first step the statements are assigned ordinal index marks which depend on whether the statement is indicative (i) of an upward, (ii) of a downward or (iii) of no deviation of the variables of interest from trend. In a second step these ordinally indexed statements are then transformed with the balance statistic approach into quantitative assessment indicators which can be used for statistical analysis.

As an application of the proposed method a new dataset that allows to re-examine the monetary policy strategy of the Deutsche Bundesbank is set up. The Deutsche Bundesbank's monetary policy continues to be considered as a benchmark for many central banks in light of the Deutsche Bundesbank's success in maintaining price stability. One distinctive feature of its strategy was the targeting of growth in monetary aggregates. However, this notion has been challenged by Clarida, Gali, and Gertler (1998) as well as Bernanke

[2]For an overview on the importance of transparency and accountability for central banks see, for example, Eijffinger and Hoeberichts (2002) or Hahn (2002). For a theoretical and empirical analysis on transparency see, for example, Faust and Svensson (2001) and Eijffinger and Geraats (2006), respectively.

and Mihov (1997) who find monetary aggregates to be statistically insignificant when estimating Taylor-type rules for the Deutsche Bundesbank. By contrast, using the proposed assessment indicator approach to analyze the monetary policy of the Deutsche Bundesbank provides evidence that the Deutsche Bundesbank indeed took into consideration monetary aggregates but also real economic activity and inflation developments in its monetary policy strategy from 1975 to 1998.

The remainder of the chapter is organized as follows: Section 1.1 reviews the existing literature. Section 1.2 describes the construction of assessment indicators, and Section 1.3 provides an analysis of the Deutsche Bundesbank's monetary policy using the proposed method. Section 1.4 concludes. Further details regarding the dataset, results, and econometric modelling framework are described in several appendices at the end of the chapter.

1.1 Review of Previous Literature

The usefulness of qualitative information to investigate central banks' monetary policy has become evident in numerous analyses. In a related article Gerlach (2007) constructs quantitative indicators of the ECB Governing Council's assessments of economic conditions to analyze its interest rate decisions. Among other things he finds that the ECB did not react to temporary inflation shocks but to economic activity because it influences the outlook for inflation. Furthermore, the Konjunkturforschungsstelle der Eidgenössischen Technischen Hochschule Zürich (2005) regularly publishes an indicator that captures the ECB president's statements concerning risks to price stability. The index contains information about the future path of monetary policy of the ECB. Using the index, Lamla and Rupprecht (2006) find that the ECB communication affects the term structure in the medium term. They provide evidence that the ECB's forecasts of price developments and its interpretations are important news for the markets. Sturm and de Haan (2009), also using the index and four additional qualitative information indicators,[3] analyze whether communication by the ECB offers additional information as compared to the information content in standard Taylor rules. They show that the indicators indeed contain additional information that helps to predict future policy decisions of the ECB.

Heinemann and Ullrich (2007) analyze the information content of ECB statements during monthly press conferences and show that the inclusion of an indicator for signal words can improve a model's fit when added to standard explanatory variables in a Taylor rule. Berger, de Haan, and Sturm (2006) analyze the role of money in the ECB monetary policy using qualitative information from the introductory statements of the ECB monthly press conferences. The authors find that the indicator of the monetary policy only plays a minor role in the ECB's interest rate decisions. Rosa and Verga (2005) analyze to what extent markets react to the information of the ECB released during its press conferences. Translating the qualitative infor-

[3] The four additional communication indicators are (i) an updated version of the Rosa and Verga (2007) index, (ii) the index of Heinemann and Ullrich (2007), (iii) the aggregate index of Berger, de Haan, and Sturm (2006), and (iv) the indicator of Ullrich (2008).

mation of the press conferences into an ordinal scale they find that the public understands and believes in the signals sent by the ECB.

Hansen and De Haan (2009) examine whether ECB statements on the main refinancing rate and future inflation are significantly related to interest rate decisions. In an out-of-sample evaluation they show that communication based models do not outperform models based on macroeconomic data in predicting policy rate decisions. Hayo, Kutan, and Neuenkirch (2008) study the effect of Federal Open Market Commitee (FOMC) communication on U.S. financial markets. The authors find that more formal communication channels such as monetary policy reports have higher impact on financial markets' return and volatility.

Hayo and Neuenkirch (2009) use a Taylor rule augmented with Federal Reserve communication indicators and find that including the communication indicators significantly improves explanatory power for interest rate decisions in and out of sample. Pakko (2005) analyzes the predictive content of U.S. FOMC statements which contain information about a subsequent tightening or easing of monetary policy. Using a Taylor rule framework he provides evidence that these statements are usefull for forecasting changes in the federal funds target.

In a broader sense this chapter is also related to the so-called 'narrative approach', that is, the identification of monetary shocks through non-statistical procedures. This literature involves historical records that contain information about the motives that led to decisions by monetary authorities. For example, Romer and Romer (2004) use quantitative and narrative records to infer the Federal Reserve's intention for its target rate and find that monetary policy decisions by the Federal Reserve had large and rapid effects on output and inflation.

In the next section the proposed method of constructing assessment indicators to capture qualitative information from a central bank's statements is outlined.

1.2 Construction of Assessment Indicators

Transparency and accountability have become central elements in the statute of most central banks.[4] Not at least to counterbalance their independence, they have to justify their policy decisions vis-à-vis the public and outline to which extent they achieve the assigned policy objectives. Central banks communicate this information, *inter alia*, via giving press conferences, organizing research conferences, publicizing minutes of internal meetings, and issuing economic statistical bulletins. At the same time these communication channels offer central banks the opportunity to influence expectations and thereby the opportunity of more efficiently implementing their monetary policy.[5] The information captured in a central bank's communication hence offers an important point of departure for analyzing its monetary policy.

Among the outlined communication channels, economic statistical bulletins have an outstanding position. For example, the ECB's monthly bulletin is described to be its "communication flagship".[6] To enhance the public understanding of monetary policy, economic statistical bulletins contain "some descriptive commentary and analysis that go beyond data dissemination".[7] Most central bank's bulletins consist of a statistical section with economic key figures and a section in which these key figures are interpreted with respect to the overall economic situation, and in light of the monetary policy decisions taken by the central bank. In addition they usually contain articles covering a broad range of topics related to economic questions that help fostering a deeper understanding of the economy and contribute to the aca-

[4]See, for example, Eijffinger and Hoeberichts (2002).

[5]Blinder, Ehrmann, Fratzscher, de Haan, and Jansen (2008) give a survey on the communication channel and show that it has become increasingly important for the conduct of monetary policy. In particular, they find that central bank communication can move financial markets and makes monetary policy decisions more predictable. Amato, Morris, and Shin (2002) explore the economic effects of public information in monetary policy and find that it is very effective in influencing agents, however, that there is also a danger if agents only rely on that channel to coordinate actions away from fundamentals. On the importance of expectation formation for the conduct of monetary policy, see, for example, Demertzis (2006).

[6]Issing (2008), p. 74.

[7]Dyiobek and Jin (2002), p. 2.

demic debate.[8] The proposed method in this chapter uses the information conveyed by a central bank's assessment of macroeconomic variables based on the statements given in its periodic economic statistical bulletins.[9]

The following sub-section outlines how statements are selected from economic statistical bulletins and assigned to prespecified categories that are relevant for a central bank's monetary policy decisions.

1.2.1 The Statement Data

Prior to capturing information from a central bank's public statements, different *categories* that will serve to group the statements have to be specified. One possibility to determine potential categories for grouping the statements is to use the structure of the analyzed central bank's economic statistical bulletin because it gives important indications as to which areas are important for its monetary policy decisions. For example, the ECB structures its analyses in the monthly bulletins into the categories 'the external environment of the euro area', 'monetary and financial developments', 'prices and costs', 'output demand and the labour market', and 'exchange rate and balance of payments developments'.

After having defined the categories used in the analysis of the central bank's monetary policy, the next step consists of identifying and collecting statements in which the central bank assesses (part of) these categories. Statements in economic statistical bulletins mostly do not refer directly to a specified category but instead assess several *key-variables* from the defined category. For example, a category 'real economic activity' is assessed, *inter alia*, with variables like 'investment', 'industrial production', and 'employment'. Each collected statement gives a hint as to how the central bank assesses at the time the assessment is given (part of) the information that is available about the state of the according category.

Assessments might refer to variables' past, current or expected future

[8] See Dyiobek and Jin (2002).

[9] It is straightforward to extend the coverage of assessment indicators outlined in this chapter beyond capturing information from economic statistical bulletins only, for example, via using statements given during press conferences, interviews etc.

developments. Central banks often refer to past values of variables because the data provided by the statistical offices are mainly available with a certain time lag. However, all statements evaluated in a defined category reflect the motives for the central bank's monetary policy decisions at the time the assessment is given, that is, in t, and will thus be used in the following to set up the assessment indicator for each category in t.

At this stage of analysis one has available for each point in time, that is for each issue of the economic statistical bulletin of the analyzed central bank, numerous statements in each defined category.

The next sub-section outlines how an ordinal index mark is assigned to each of these collected statements.

1.2.2 The Ordinal Index

To reduce arbitrariness in the evaluation of statements, the procedure outlined in the following only uses three option ordinal index numbers and confines evidence containing information about changes in the monetary policy stance to the occurrence of *key-words*.[10] When assigning ordinal index numbers to the collected statements it is important (i) to determine whether a statement's subject variable is out-of-trend (deviates from its normally expected state), and if so (ii) whether the variable is positively or negatively correlated with the category it is assigned to. The following two paragraphs outline when a variable is judged out-of-trend and how its correlation with the according category can be determined.

Statements using key-words that put emphasis on the central bank's assessment of the variable under consideration, for example, 'high', 'weak', 'markedly', 'extraordinarily', or alike, indicate that this variable is out-of-trend. For example, the statement "The growth of the monetary aggregate M3 is weak" indicates that the variable 'M3' (in the category 'monetary activity') is below trend.

The correlation of a variable with the according category depends on whether the variable's deviation from trend indicates that the category it

[10] The approach to generate the ordinal index draws partly upon Bluhm (2007).

is assigned to deviates into the same direction (positive correlation) or into the opposite direction (negative correlation). For example, the variable 'unemployment rate' is likely to be negatively correlated with the category 'real economic activity'. Higher than normal unemployment usually indicates that the economy underperforms. By contrast, the correlation of the variable 'industrial production' with the category 'real economic activity' is positive because high industrial production indicates that the real economy is used to capacity. Having outlined the relation between variables and their according category, the following paragraph describes how each statement is assigned an ordinal index mark, following the scheme depicted on Figure 1.1.

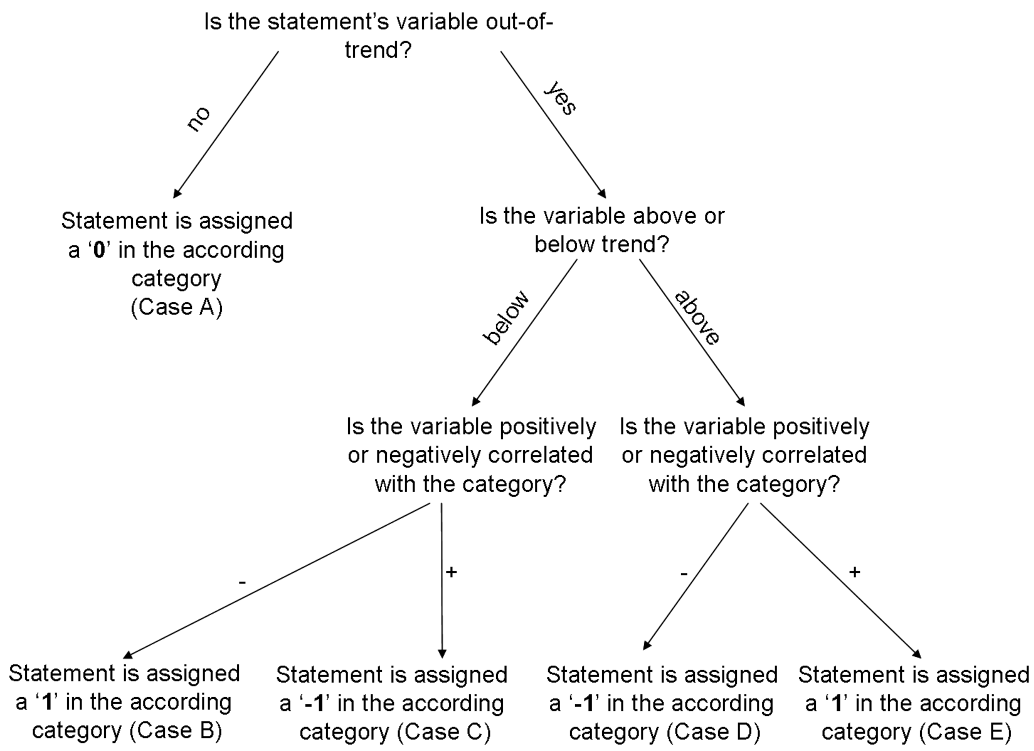


Figure 1.1: Assignement of Index Marks

First of all, one infers following the approach described in the previous paragraph whether a statement suggests that its subject variable is out-of-trend. If a statement is not judged to be out-of-trend it is assigned a '0' in the according category [case A on Figure 1.1]. If the statement suggests that the variable deviates from its normal state one has to figure out the variable's correlation with the according category. The statement is assigned a '1' ('−1') [case E(D) on Figure 1.1] if the variable positively deviates from its normal state and is positively (negatively) correlated with the category. The statement is assigned a '−1' ('1') [case C(B) on Figure 1.1] if the variable negatively deviates from its normal state and its correlation with the according category is positive (negative). In the following the evaluations '1' and '−1' are denominated 'out-of-trend marks' and the categorized and evaluated set of statements will be referred to as 'ordinal index data'.

At this stage of setting up the assessment indicators, each category of the ordinal index data contains for each point in time many index numbers, taking on the values '-1', '0', or '1'.

The next sub-section describes the method that is used to transform the ordinal index data into quantitative assessment indicators.

1.2.3 Transformation of the Ordinal Index Into Assessment Indicators

The ordinal index data have arranged the central bank's assessments of macroeconomic variables like 'real economic activity' in an accessible way. In the following, each individual index number is treated analogously to a response of the analyzed central bank to a question about its assessment of the state in the according category. This approach offers the possibility to transform the ordinal index data into quantitative assessment indicators with techniques known from public survey analyses.

Surveys are an important source to measure expectations – or, as in the case of this analysis, assessments – directly and offer up-to-date information about the state of the economy. They can be broadly divided into two classes, namely quantitative and qualitative surveys.[11] Quantitative surveys require precise quantitative answers. An example is the ECB's Quarterly Survey of Professional Forecasters which, *inter alia*, asks the participants for point

[11]Pesaran (1987).

estimates of Euro Area inflation expectations.[12] In contrast, qualitative surveys do not directly ask the respondents for a precise figure concerning the variable under consideration. Instead, respondents are asked to give a qualitative indication. The latter is widely used in surveys because responses to qualitative questions are more reliable than more precise questions, there is believed to be some sort of trade-off between the loss of information consequent on qualitative questions and the cost in terms of response rate and therefore possible bias from asking more precise questions.[13]

A special form of qualitative survey is the business tendency survey which asks respondents about recent developments and the current situation of their business as well as their plans and expectations for the near future. One example for this kind of survey is the Industrial Confidence Indicator published by the European Commission.[14] For example, repondents are asked whether they consider their current stock of finished products to be 'too large (above normal)', 'adequate (normal)', or 'too small (below normal)'. Another question asks respondents whether they expect their production to 'increase', 'remain unchanged', or 'decrease' over the next 3 months. The ordinal index data described in the previous sub-section are set up in the spirit of such a tendency survey as they also consist of three-option replies. Note that the ordinal index numbers assigned can be based on statements related to levels as well as changes of relevant variables.

There exist mainly three approaches to convert qualitative survey data into quantitative data: The balance statistic approach, the regression approach, and the Carlson-Parkin method.[15] While the latter two are rather complex and based on distributional assumptions, the balance statistic approach is not outperformed as there is a very high correlation between all three approaches when three-option replies are used.[16] The European Com-

[12] Garcia (2003).

[13] Pesaran and Weale (2005).

[14] An overview on the methodology of the Confidence Indicators used by the European Commission is given in European Commission, DG for Economic and Financial Affairs (2006).

[15] An overview about these transformation methods can be found in Pesaran and Weale (2005).

[16] OECD (2003).

mission, for example, makes use of the balance statistic to set up the Industrial Confidence Indicator. The balance statistic is also the method which is used in this chapter to transform the ordinal index data into time series of quantitative assessment indicators. It is calculated following Equation (1.1):

$$bs_{jt} = u_{jt} - d_{jt} \tag{1.1}$$

where bs_{jt} denotes the balance statistic, u_{jt} denotes the proportion of statements that indicate a positive deviation from trend, and d_{jt} denotes the proportion of statements that indicate a negative deviation from trend, all with respect to category j at time t.

Equation (1.1) thus shows how the ordinal index data are transformed into quantitative assessment indicators restricted to the interval (-1,1) for each defined category and point in time. If no statements are available in a category at a given point in time it is assumed that the assessment indicator is in line with trend, that is, the assessment indicator is assigned a value of '0'.

Note that the assessment indicators contain information about the central bank's assessment of past and currently available data as well as on its expectations about data in the future. The indicators obtained from this information set hence contain real time information available to the central bank at the time the assessment was given and are thus not subject to the informational problems when using revised data vintages as outlined in Orphanides (2001).

The information content in the assessment indicators is limited, not at least because the indicators are based on three-option replies and are restricted to the interval (-1,1). However, the more statements are available for a category and point in time, the preciser will be the balance statistic. For example, if for a category and point in time there is only one statement, the assessment indicator can take three values, -1, 0, and 1. If instead there are two statements, the assessment indicator can additionally take the values -0.5 and 0.5, etc.[17] Effectively, the information content in the assessment in-

[17]Hence the analysis of Gerlach (2007) with ordinal index values that can take on 5

dicators gets less coarse if the number of statements in a category and point in time increases. However, no matter how many discrete values the indicators can take on, in tendency, they reveal the central bank's assessment of categories underlying its monetary policy decisions.[18]

Figure 1.2 gives an overview of the method outlined throughout this chapter.

Monthly bulletin at time t

↓

Statements containing assessments of category j at time t

↓

Ordinal index for assessments of category j at time t

↓

Transformation method: balance statistic

↓

Quantitative assessment indicator of category j at time t

Where t covers the time dimension, and j denotes different specified categories.

Figure 1.2: Method to Generate Assessment Indicators

In the next section the proposed method will be applied to re-investigate the monetary policy of the Deutsche Bundesbank.

distinct values can be seen as an example for the case where one collects exactly two statements for each category in each monthly bulletin analyzed.

[18]It is possible that the number of variables evaluated in a defined category varies between different issues of economic statistical bulletins if the central bank does not always receive data in time or if variables are only analyzed from a certain point in time onward. For example, when growth in money funds became very large in the 1990s, the Deutsche Bundesbank created a new monetary aggregate for analysis, 'M3 extended', that contained these funds.

1.3 Analysis of the Deutsche Bundesbank's Monetary Policy Using Assessment Indicators

The Deutsche Bundesbank continues to be considered as a benchmark for many central banks in light of its success in maintaining price stability. One distinctive feature of its monetary policy was the strategy of monetary targeting which the Deutsche Bundesbank officially followed since 1975. However, whether monetary aggregates indeed played a role in its monetary policy strategy is subject to debate because analyses show mixed evidence. While Clarida, Gali, and Gertler (1998) and Bernanke and Mihov (1997) find that monetary aggregates did not play a significant role for the Deutsche Bundesbank's monetary policy from 1979 to 1993, Gerberding, Worms, and Seitz (2005) find that the Deutsche Bundesbank indeed took its monetary targets seriously from 1979 to 1998 and Clausen and Meier (2005) find that monetary aggregates played a small but significant role for the Deutsche Bundesbank's interest rate decisions between 1973 and 1998.

As an application of the method proposed in this chapter the monetary policy strategy of the Deutsche Bundesbank is re-investigated using a new data set. The dataset consists of assessment indicators that capture the Deutsche Bundesbank's assessment of monetary and real economic developments following the approach outlined in the previous section. The assessment indicators are then used to estimate a monetary policy rule.

This analysis might also be relevant for the debate about the two pillar strategy of the ECB. The ECB was established much in the spirit of the Deutsche Bundesbank, also as regards the monetary policy strategy. In particular prior to the financial crisis that began in 2007, it has been subject to criticism for using monetary aggregates in its second pillar to assess the trends in medium- to long-term inflation. If the Deutsche Bundesbank actually was a monetary targeter its eminent track record concerning price stability might suggests that incorporating monetary aggregates in a central bank's policy strategy cannot be labelled as improper right away.

The following sub-section outlines the monetary policy strategy of the Deutsche Bundesbank.

1.3.1 The Deutsche Bundesbank's Monetary Policy

The Deutsche Bundesbank Act from 1957 mandated the Deutsche Bundesbank to 'safeguard the currency' which was ultimately interpreted as maintaining price stability.[19] To achieve this goal, the Deutsche Bundesbank's policy consisted of pre-announcing annual targets for growth in broad money since 1975. From 1975 to 1987 the target was defined as the central bank monetary stock, that is, currency in circulation and required reserves and from 1988 to 1998 the Deutsche Bundesbank targeted growth in the monetary aggregate M3. To cross-check and verify the information content provided by the targeted aggregate, the Deutsche Bundesbank always included other monetary and real indicators in its monetary policy analyses. The monetary targeting strategy was implemented via controlling the quantity of money indirectly by influencing the day-to-day money market rate in the interbank market through rediscount and lombard policies, minimum reserve policy, and open market operations.[20]

The Deutsche Bundesbank determined the money growth target for the following year via adding growth of potential output, the 'unavoidable' inflation over the medium term, and the trend rate of change in the velocity of money. The reasoning behind this approach was that if the money stock could be kept on this target path, the monetary conditions should be met for corresponding real growth to be compatible with monetary stability.[21] Although the Deutsche Bundesbank announced the growth target on a yearly basis it frequently stressed the medium-term nature of the approach – the Deutsche Bundesbank did not apply its monetary policy mechanically but accepted short-run deviations from target growth if neccessary. With a few technical modifications this approach has been followed since the start of this policy in 1975 although the Deutsche Bundesbank regarded monetary targeting as an experiment in the first few years.[22]

[19] On several occasions the Deutsche Bundesbank stated that price stability is its statutory final goal, for example, in Bundesbank (1995).

[20] Bundesbank (1995).

[21] Issing (1997).

[22] Schmid (1999).

Despite the fact that the Deutsche Bundesbank attained only 13 of 24 money stock targets, it impressively achieved its ultimate goal of safeguarding price stability with an annual inflation rate of 3% on average between 1975 and 1998.[23]

The following sub-section outlines how the assessment indicators for the Deutsche Bundesbank are are set up.

1.3.2 Assessment Indicators for the Deutsche Bundesbank

As outlined in Section 1.2, policy relevant statements can be extracted from the analyzed central bank's economic statistical bulletin. The monthly bulletin was the Deutsche Bundesbank's main instrument of communication with the public. Prior to the emergence of European Monetary Union (EMU) the monthly bulletins of the Deutsche Bundesbank had an outstanding position in Germany in the field of regular economic publications. Since 1970 the Deutsche Bundesbank regularly incorporated economic reports in its monthly bulletins. Every quarter, two monthly bulletins contained abridged economic reports and one monthly bulletin gave a detailed report on the economic situation in Germany.[24] These parts of the monthly bulletin touched upon the different fields the Deutsche Bundesbank judged to be of importance for its monetary policy. They were organized into sub-sections analyzing 'monetary development', 'public finances', 'economic situation', 'balance of payments', and 'stock and bond markets'. All monthly bulletins contained a statistical appendix with economic key data and infrequently essays on economic questions of interest.

To construct the assessment indicators for the Bundebank, only the abridged reports and editorials of the economic outlook in the monthly bulletins are taken into account because in these parts the Deutsche Bundesbank

[23] Own calculation: Mean year-on-year percentage change of the consumer price index; from 1975 to 1991 only for West Germany, from 1992 to 1998 for re-united Germany.

[24] The Deutsche Bundesbank issued economic reports prior to 1970 but not on a regular monthly basis: within a year there were several issues of monthly bulletins containing only economic key-data.

explained its policy decisions in the context of its analyses of economic and monetary aspects in a condensed form. As the structure of the monthly bulletins had undergone only minor changes since January 1970 this date is chosen as the starting point of the sample analyzed. The endpoint of the sample is December 1998 because it marks the last month of an independent monetary policy of the Deutsche Bundesbank.

All statements from the abridged reports and the editorials of the monthly bulletins from 1970 to 1998 that express the Deutsche Bundesbank's assessment for one or several of the categories, 'monetary activity', 'real economic activity', 'fiscal activity', 'foreign trade activity', and 'price activity' have been collected.[25] Table 1.1 summarises the assumed correlation of the variables appearing most frequently in statements about one or several of the defined categories. In the sample analyzed, the average number of assessed statements per month amounts to 8.68 for the category 'real economic activity', 8.63 for the category 'monetary activity', 5.89 for the category 'fiscal activity', 4.49 for the category 'foreign trade activity', and 2.41 for the category 'price activity'.

Following the proposed method outlined in the previous section, assessment indicators for the five defined categories are set up. Several examples for the evaluation of statements are given in Appendix 1.A at the end of this chapter.[26] As a showcase Figure 1.3 displays the assessment indicator for monetary activity (left scale), its mean value (left scale), and the number of statements in each month (right scale). The time series shows little persistence and the number of statements assessed reflects that the editorials and short reports in the monthly bulletins became more extensive over the years. While the analyzed parts covered only three to five pages in a bulletin in the 1970s, the amount of pages to be analyzed from a bulletin of the end of the 1990s increased up to seven pages. This development took place gradually in the course of time. As previously outlined, this makes the assessment indicators' information content less coarse for later issues of the monthly bulletins and provides a more differenciated picture of the Deutsche

[25]In the following these five fields will be referred to as categories.
[26]Part of the statements has been taken from Bluhm (2007).

Category	Variables Positively Correlated With the category	Variables Negatively Correlated With the category
Monetary activity	Monetary expansion Monetary inflows from abroad Volume of money in circulation Monetary aggregates Credits	Long-term deposits Monetary outflows to abroad
Real economic activity	Industrial production Investments Business cycle Labour market Economic activity Volume of orders Domestic orders	Unemployment
Fiscal activity	Public debt Public spending / investment Public borrowing Public deficit	Inland tax revenues
Foreign trade activity	Orders from abroad Exports Active trade balance Sales abroad	Inland orders for abroad Imports Passive trade balance
Price activity	Producer prices Year-on-year percentage change of the Consumer Price Index (CPI) Import prices	

Table 1.1: Variables and Their Relation to the Assessed Category

Bundesbank's assessment about the economy. According figures for the assessment indicators of the other categories are provided in Appendix 1.B at the end of this chapter.

Theoretically, deviations from trend captured by the assessment indicators should be zero on average. However, the mean values of all assessment indicators are positive, ranging from 0.06 (assessment indicator for foreign trade activity) to 0.17 (assessment indicator for monetary activity). This might reflect higher vigilance of the Deutsche Bundesbank towards upward risks to price stability as compared to downward risks if the Deutsche Bundesbank did not assess upward or downward deviations from trend symmetrically. In other words, the Deutsche Bundesbank might have perceived an upward deviation from trend in a category as sizeable because this puts upward pressure on prices while the Deutsche Bundesbank might not have perceived a downward deviation of similar magnitude as sizeable if it was not as sensible as regards downward risks to price stability.

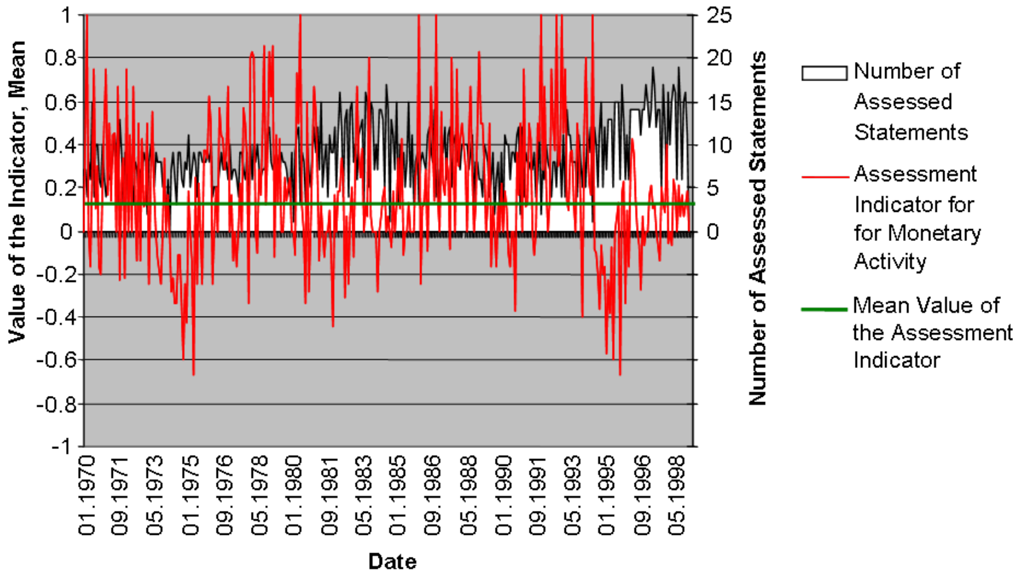


Figure 1.3: Assessment Indicator for Monetary Activity

Except for the real economic activity indicator and the fiscal activity indicator the assessment indicators are not correlated with each other. This provides evidence that the indicators capture distinct information sets. The correlation coefficient between the real economic activity indicator and the fiscal activity indicator amounts to -0.30 which might be due to countercyclical policies of German governments. It is very likely that in addition to the normal economic stabilizers, such as unemployment compensations, deficit spending strategies were implemented when the economy was in a recession.

In the following sub-section a monetary policy rule based on the outlined assessment indicators is estimated for the Deutsche Bundesbank.

1.3.3 A Monetary Policy Rule for the Deutsche Bundesbank

Investigating the properties of monetary policy rules, Levin, Wieland, and Williams (1998) show that first difference rules perform reasonably well in comparison to several alternatives and are robust to model uncertainty. In their analysis they employ the first differenced U.S. federal funds rate as dependent variable and a measure for the deviation of inflation from target and the output gap as independent variables. Other authors also use first difference rules to investigate the monetary policy of the Federal Reserve System of the U.S. or the ECB. For example, Judd and Rudebusch (1998) estimate a policy rule for the Fed with the U.S. federal funds rate in first-differences as dependent variable and measures for the output gap and deviation of inflation from target as independent variables. Gerlach (2007) estimates a policy rule for the ECB using first differences of the repo rate as dependent variable and different measures capturing real economic activity, inflation, money growth, and the exchange rate as independent variables.

To investigate the monetary policy of the Deutsche Bundesbank, a Taylor-type rule will be estimated that explains the first-differenced German day-to-day money market rate[27] with the generated assessment indicators following

[27] Clarida and Gertler (1996) use a vector autoregressive analysis to identify the German day-to-day money market rate as the relevant policy instrument of the Deutsche Bundesbank as well as measures for inflation and output gaps as explanatory variables. Similarly, Clarida, Gali, and Gertler (1998) employ the German day-to-day money market rate as dependent variable in an estimation of a monetary policy rule for the Deutsche Bundesbank, with, *inter alia*, measures for the output gap and deviation of inflation from target as explanatory variables.

Equation (1.2).[28]

$$\Delta i_t = c + \beta_1 \cdot money_t + \beta_2 \cdot real_t + \beta_3 \cdot fiscal_t + \beta_4 \cdot trade_t + \beta_5 \cdot price_t + \epsilon_t \quad (1.2)$$

where 'Δi' is the first-differenced German day-to-day money market rate (monthly averages), 'c' is a constant, 'money' denotes the deviation of monetary activity from trend and is captured by the assessment indicator for monetary activity, 'real' denotes the deviation of real economic activity from trend and is captured by the assessment indicator for real economic activity, 'fiscal' denotes the deviation of fiscal activity from trend and is captured by the assessment indicator for fiscal activity, 'trade' denotes the deviation of foreign trade activity from trend and is captured by the assessment indicator for foreign trade activity, 'price' denotes the deviation of price activity from trend and is captured by the assessment indicator for price activity, and 'ϵ' is an error term. Intuitively one would expect the coefficients of the explanatory variables in equation (1.2) to be positive since high values of the assessment indicators are indicative of upward risks to price stability.

To avoid a spurious regression it is important to determine the order of integration of the time series under consideration. All time series used are stationary at a 5% significance level when applying the Dickey-Fuller test.[29]

The time span covered in the analysis, January 1970 to 1998, might contain structural breaks, for example, the breakdown of the Bretton-Woods system in March 1973, the beginning of the monetary targeting strategy of

[28] The assessment indicators can also be used to augment Taylor-type rules which already contain standard statistical data for the output gap and deviation of inflation from target, thus turning them into 'hybrid rules'. In the case of the Deutsche Bundesbank such hybrid rules feature a better model fit with respect to standard Taylor-type rules as measured by the adjusted R-squared. A systematic comparison of such hybrid versus non-hybrid rules would be interesting to pursue but is beyond the scope of this paper. See also Sturm and de Haan (2009) and Heinemann and Ullrich (2007) for an analysis using mixed data.

[29] Note that all following results as regards significance and breakpoint tests also hold qualitatively when estimating the Taylor-type rule not as a first-difference rule but with the level of the day-to-day money market rate as dependent variable and the lagged dependent variable as well as the assessment indicators as explanatory variables. However, since the level of the dependent variable features high persistence at a monthly frequency, it follows a unit root process.

the Deutsche Bundesbank in January 1975, and German re-unification in October 1990. Bai and Perron (1998) propose a procedure that allows to estimate the number and the position of breakpoints and tests linear models with multiple structural changes for a given data set. In the following this method will be applied to the estimation of a monetary policy rule for the Deutsche Bundesbank to detect potential breakpoints in the sample. An outline of the procedure is provided in Appendix 1.C at the end of this chapter.

The procedure selects March 1975 as the only breakpoint.[30] Table 1.2 displays the estimation results for the two samples ranging from January 1970 to March 1975, and April 1975 to December 1998. Regarding the first sample, only the indicator for real economic activity is significant.[31] Given its coefficient, the target rate's first difference rose by 2.84 percentage points if, *ceteris paribus*, all variables from the category real economic activity were assessed to be above trend (that is, the according indicator has a value of 1). The relatively high coefficient estimates are likely due to the volatility of the dependent variable during the breakdown of the Bretton-Woods system. Figure 1.4 displays the day-to-day money market rate for the period of analysis. Several large changes took place only during and shortly after the period of Bretton-Woods.

Regarding the second sample, all assessment indicators except those for foreign trade activity and fiscal activity are significant and have the expected sign. If all assessments in one of the categories, monetary activity, real economic activity, or price activity, *ceteris paribus*, were assessed to be above trend, the day-to-day money market rate rose by 0.16, 0.22, or 0.19 percentage points, respectively.

A central result is the significance of the assessment indicator for monetary activity in the sample that starts in April 1975. It provides evidence that the Deutsche Bundesbank indeed took into account the development of

[30] As a robustness check here and in the following the procedure has been implemented with several values of the parameter that determines the minimal length of a sub-sample (see Appendix 1.C). For reasonable values of this parameter the selected breakpoint is always March 1975.

[31] Significance is indicated by an absolute t-value of 1.96 or larger. All t-statistics are computed with robust standard errors.

Sample:	Jan 1970 - Mar 1975	Apr 1975 - Dec 1998
Constant	-0.61	-0.09 ***
	[1.53]	[3.22]
Monetary activity	-1.75	0.16 **
	[1.41]	[2.09]
Real economic activity	2.84 **	0.22 ***
	[2.17]	[3.78]
Fiscal activity	1.65	0.05
	[1.47]	[0.79]
Foreign trade activity	-0.46	0.09
	[0.59]	[1.76]
Price activity	-0.25	0.19 ***
	[0.36]	[2.60]
No. of obs.	63	285
Adjusted R-squared	0.078	0.067

t-statistics are displayed in square brackets underneath the coefficient estimates. A '**' indicates significance at the 5% level and a '***' indicates significance at the 1% level. The dependent variable is the first difference of the day-to-day money market rate. Estimated equation: $\Delta i_t = c + \beta_1 \cdot money_t + \beta_2 \cdot real_t + \beta_3 \cdot fiscal_t + \beta_4 \cdot trade_t + \beta_5 \cdot price_t + \epsilon_t$.

Table 1.2: Regression Results of the Taylor Rule for the Deutsche Bundesbank

monetary aggregates for the conduct of its monetary policy. The analysis does not allow to disentangle to which extent this outcome is directly driven by the Deutsche Bundesbank's policy rate setting or indirectly via influencing market expectations through its communication within the framework of its monetary policy strategy.[32] However, monetary aggregates played a significant role in the practical implementation of the Deutsche Bundesbank's monetary policy strategy. Similar to Gerberding, Worms, and Seitz (2005) and Clausen and Meier (2005) the results also give evidence that the Deutsche Bundesbank was not a pure monetary targeter but took into consideration real economic activity and inflation developments as well.

Besides the Deutsche Bundesbank, several other central banks incorporated monetary targeting elements in their policy strategies – with different degrees of success. Switzerland successfully followed a strategy of monetary targeting from 1975 to 2000. The Federal Reserve System of the United

[32]For an analysis of the money growth targeting approach of the Deutsche Bundesbank in light of a communication strategy see von Hagen (1999).

States adhered to a policy strategy with monetary targeting elements at the beginning of the 1980's, and the Bank of England pursued a strategy that focused on monetary targeting at the end of the 1970's and in the 1980's. However, the latter two central banks more or less abandoned monetary targeting elements in their strategies after several years. In the United States a large literature has criticised the practice of monetary targeting because of the macroeconomic turbulence of that period and of the severity of the recession that followed.[33] The authors claim that accurate control of the money stock is not feasible or that control induces extreme volatility to money market rates. The practical implementation of the monetary targeting strategy followed by the Deutsche Bundesbank might be a reason why criticism directed against monetary targeting does not convincingly apply in the case of the German experience. The Deutsche Bundesbank never claimed to be able to completely control money growth and even frequently missed its target growth rate. In large part this should be due to the medium-term orientation of the Deutsche Bundesbank's strategy but also to a certain degree of pragmatism which is revealed by also taking real economic and inflation developments into consideration.

In the words of Issing (1997), "*[s]ome occasions when targets were missed may well be interpreted as showing that at these points in time the Deutsche Bundesbank allowed itself additional room for discretion in the light of the then prevailing situation. Only rarely have money stock overshoots been of a completely involuntary nature; mostly rather they constituted deliberate monetary policy decisions. [...] Crucially though, monetary policy was always analyzed with a view to achieve the ultimate aim of safeguarding the currency. Such an approach may be termed 'pragmatic monetarism'...*"[34]

This also gives evidence why the pragmatic, flexible monetary targeting approach of the Deutsche Bundesbank did not induce extreme volatility to money market rates. The Deutsche Bundesbank did not mechanically try to achieve its medium target but claimed a certain discretionary margin when

[33] McCallum (1985).

[34] From 1990 to 1998 Otmar Issing was a member of the Board of the Deutsche Deutsche Bundesbank with a seat in the Central Bank Council.

judged neccessary. Figure 1.4 displays that the Deutsche Bundesbank did not bring extreme hikes or slumps about its target rate since the start of monetary targeting in 1975.

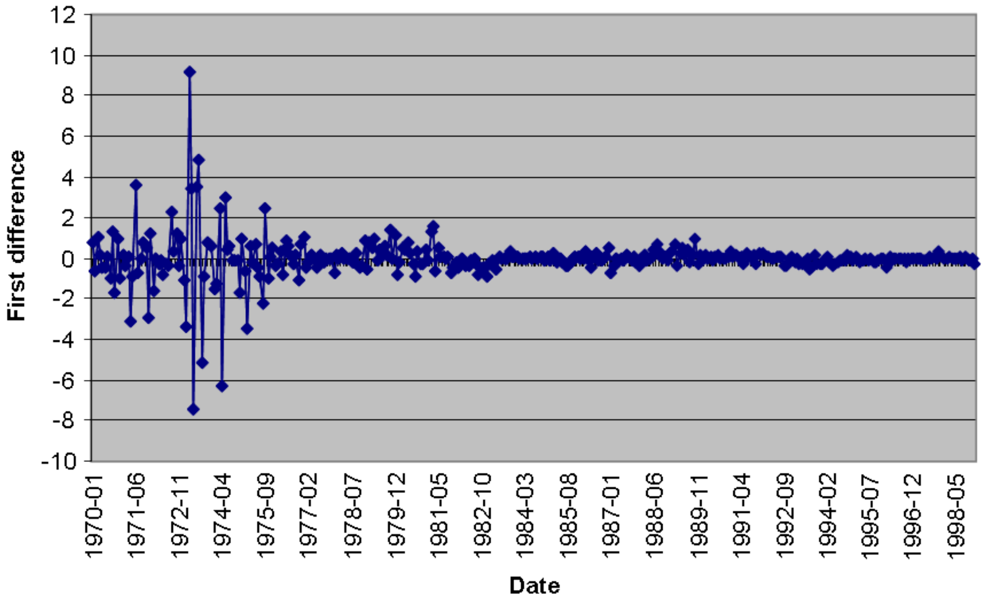


Figure 1.4: First Differences of the German Day-to-Day Money Market Rate (Monthly Averages)

Critics of monetary targeting also stress that practical difficulties coming up through technological changes and deregulations in the payment industry render monetary targeting practices unfeasible. These arguments do not apply in the German case as well. It is possible that money demand functions become unstable and that targeted monetary aggregates lose explanatory power and utility for forecasting. However, this was not the case for Germany as the liberalization of financial markets and cross-border money and capital movements was largely completed in Germany at the beginning of the 1970s. In addition, new financial products generally turned out to be of little relevance in Germany.[35]

The results of the analysis in this chapter give evidence that the Deutsche

[35]Issing (1997).

Bundesbank actually was a flexible monetary targeter. Its policy strategy was in large part operational due to a combination of the Deutsche Bundesbank's pragmatic approach and to a relatively stable financial environment in Germany after the period of Bretton-Woods.

The following section concludes.

1.4 Conclusion

This chapter outlined a novel method which allows to extract a central bank's assessment of macroeconomic key-variables from its public statements using the balance statistic approach. Since a central bank's assessment of macroeconomic key-variables is not contained in the information set when using readily available statistical data such as, for example, the percentage change of the CPI, the generated assessment indicators capture unique information and can be used to analyze a central bank's monetary policy.

The method is applied to re-investigate the Deutsche Bundesbank's monetary policy strategy with a new data set and gives evidence that the Deutsche Bundesbank actually was a flexible monetary targeter. When estimating a monetary policy rule with a sample ranging from April 1975 to December 1998 the assessment indicators for monetary activity, real economic activity, and price activity are significant and have the expected sign. Particularly for the monetary indicator this is an interesting result as it was claimed in several studies that the Deutsche Bundesbank actually did not involve monetary aggregates in the conduct of its policy.

These results indicate that the inclusion of monetary aggregates in a central bank's monetary policy strategy, as done by the ECB, might not be refuted as unreasonable right away. The example of the Deutsche Bundesbank gives evidence that successfully incorporating monetary targeting elements in a policy strategy is possible.

Appendix 1.A: Examples for the Evaluation of Statements

First of all, consider three examples for the category 'monetary activity'.

"*Das längerfristige Mittelaufkommen bei den Banken war [...] weit höher als gewöhnlich [...].*"[36]

The statement suffices to assign an out-of-trend mark as it describes the variable 'long-term deposits' to be much higher than usual. The correlation of long-term deposits with monetary activity is negative. Accordingly the statement is evaluated with '−1' (Case D in Figure 1.1).

"*Deutlicher noch als in den vorangegangenen Monaten beruht das starke Wachstum der Geldmenge im Juni des Jahres auf der kräftigen Expansion der Kreditgewährung der Banken an inländische Kunden.*"[37]

This statement assesses two variables: 'monetary quantity' and 'credits'. Both variables change sizeably into a positive direction. As the variables are positively correlated with the category both are evaluated with '1' (Case E in Figure 1.1).

"Insgesamt waren die Kredite [...] an inländischen Nichtbanken Ende Juli 1970 um 12.8 Prozent höher als vor einem Jahr."[38]

Nothing suggests that the variable 'loans' which are positively correlated with the category 'monetary activity' is out-of-trend. Hence the statement is evaluated with '0' (Case A in Figure 1.1).

Next consider three examples for the category 'real economic activity'.

"*Die Investitionstätigkeit der Unternehmen hielt sich in den vergangenen*

[36]"Long-term deposits were much higher than usual." *Monthly Bulletin of the Deutsche Bundesbank* (May 1975), p. 6.

[37]"The strong growth of the monetary quantity in June results more noticeably from a robust domestic credit expansion than in the previous months." *Monthly Bulletin of the Deutsche Bundesbank* (August 1976), p. 7.

[38]"Overall, at the end of July 1970 loans to domestic non-banks were 12.8% higher than in the previous year." *Monthly Bulletin of the Deutsche Bundesbank* (August 1970), p. 7.

Monaten auf hohem Niveau."[39]
The variable 'firm investments' is described to be on a high level which is sufficient to assign an out-of-trend mark. As the correlation of firm investments with the category 'real economic activity' is positive the statement is evaluated with '1' (Case E in Figure 1.1).
"*Das verarbeitende Gewerbe hat seine Produktion in den ersten beiden Monaten spürbar ausgeweitet.*"[40]
The positive change of the variable 'production in the manufacturing industries' is sizeable which turns the balance towards an out-of-trend mark. As the corellation of the variable with the category is positive the statement is evaluated with '1' (Case E in Figure 1.1).
"*Die Produktion des produzierenden Gewerbes ist im September tendenziell leicht gesunken.*"[41]
A 'slight decrease' is not sufficient to assign an out-of-trend mark for the variable 'industrial production'. The statement is evaluated with '0' (Case A in Figure 1.1).

The following three statements are examples for the evaluation in the category 'foreign trade activity'.

"*In den hohen Auslandsbestellungen spiegelt sich die fortschreitende Konjunkturbelebung in wichtigen Industrieländern wider.*"[42]
'Foreign export orders' are described to be high which is sufficient to assign an out-of-trend mark. As the correlation of the variable with the category 'foreign trade activity' is positive the statement is evaluated with '1' (Case E in Figure 1.1).

[39]"The investment activity of enterprises stayed on a high level during the past months." *Monthly Bulletin of the Deutsche Bundesbank* (December 1980), p. 6.

[40]"The manufacturing industries have noticeably expanded their production during the summer months." *Monthly Bulletin of the Deutsche Bundesbank* (October 1996), p. 6.

[41]"Industrial production tended to decline slightly in September." *Monthly Bulletin of the Deutsche Bundesbank* (November 1997), p. 10.

[42]"The high level of foreign export orders reflects the advancing economic recovery in important industrial countries." *Monthly Bulletin of the Deutsche Bundesbank* (June 1976), p. 5.

"*Saisonbereinigt waren die Exporte (...) im Mai nach dem recht umsatzstarken Vormonat ausgesprochen schwach.*"[43]
'Exports' are described to be markedly weak which points in the direction of being below trend. As exports and foreign trade indicator are positively correlated the statement is evaluated with '−1' (Case C in Figure 1.1).
"*Schaltet man die Saisonschwankungen aus, so waren Aus- und Einfuhren gleichermaßen dem Wert nach um 1% höher als im Februar 1983.*"[44]
The change of the variables 'exports' and 'imports' is not sizeable. Hence they are assumed to be in line with their trend. Both variables assessed are evaluated with '0' (Case A in Figure 1.1).

The next three examples are about the interpretation of assessments from the category 'fiscal activity'.

"*Demzufolge muss für 1980 auch mit einem weit höheren Gesamtdefizit der öffentlichen Haushalte gerechnet werden, als noch im Frühjahr erwartet worden war [...].*"[45]
'Public debt' is expected to be considerably above previous expectations which hints that the variable will be higher than normal in the future. Its correlation with the category is positive and consequently the statement is evaluated with '1' (Case E in Figure 1.1).
"*Der vorangegangene Monat November war für den Bund [steuerlich] ein außerordentlich einnahmeschwacher Monat gewesen [...].*"[46]
'Inland revenues' are assessed to be 'extraordinarily weak' which hints that they are below trend. The correlation of inland revenues with the category is

[43]"After the quite top-selling previous month seasonally adjusted exports (...) were markedly weak in May." *Monthly Bulletin of the Deutsche Bundesbank* (July 1978), p. 12.

[44]"After correcting for seasonal variations the values of imports and exports were 1% higher than in February 1983." *Monthly Bulletin of the Deutsche Bundesbank* (May 1983), p. 15.

[45]"As a result one should expect a much higher overall public deficit than the deficit which was expected in spring." *Monthly Bulletin of the Deutsche Bundesbank* (December 1980), p. 6.

[46]"Inland revenues in the previous month, November, were extraordinarily weak." *Monthly Bulletin of the Deutsche Bundesbank* (January 1975), p. 9.

negative. Consequently the statement is evaluated with '1' (Case B in Figure 1.1).

"*Auch im kommenden Jahr werden die staatlichen Defizite weiter steigen, aber sie werden voraussichtlich nicht die im Sommer des Jahres erwartete Größenordnung erreichen.*"[47]

Nothing suggests that the variable 'public deficit' which is positively correlated with the category 'fiscal activity' is out-of-trend. Hence the statement is evaluated with '0' (Case A in Figure 1.1).

The next three examples show the evaluation of statements from the category 'price activity'.

"*Die Zunahme der Außenhandels- und Leistungsbilanzüberschüsse [...] geht [...] ausschließlich auf die drastischen Rückgänge der Einfuhrpreise zurück.*"[48]

'Import prices' are positively correlated with the category 'prices'. They have declined drastically which indicates that (part of) the category is below trend. The statement is evaluated with '-1' (Case C in Figure 1.1).

"*[...] das Problem der Inflationsbekämpfung [stellt sich] mehr denn je.*"[49]

One can infer from this statement that inflation is considerably too high. This justifies an out-of-trend mark. As the variable is positively correlated with the category the statement is evaluated with '1' (Case E in Figure 1.1).

"*Die Einfuhrpreise sind im Mai saisonbereinigt wieder leicht gesunken.*"[50]

One cannot infer that the variable 'import prices' is out-of-trend. The state-

[47] "Public deficits will also rise in the forthcoming year but presumably they will not reach the magnitude that was expected in the summer of this year." *Monthly Bulletin of the Deutsche Bundesbank* (December 1978), p. 6.

[48] "The growth of the surpluses in the foreign trade balance and the current account balance [...] can be attributed to a drastic decline in import prices." *Monthly Bulletin of the Deutsche Bundesbank* (September 1986), p. 8. Note that this statement would also be evaluated in the category foreign trade activity because it assesses the variable "trade balance".

[49] "The problem of fighting inflation is bigger than ever." *Monthly Bulletin of the Deutsche Bundesbank* (February 1974), p. 6.

[50] "Seasonally adjusted import prices again slightly decreased in May." *Monthly Bulletin of the Deutsche Bundesbank* (July 1996), p. 14.

ment is evaluated with ‘0’ (Case A in Figure 1.1).

Appendix 1.B: Assessment Indicators, Mean Values, and Number of Assessed Statements

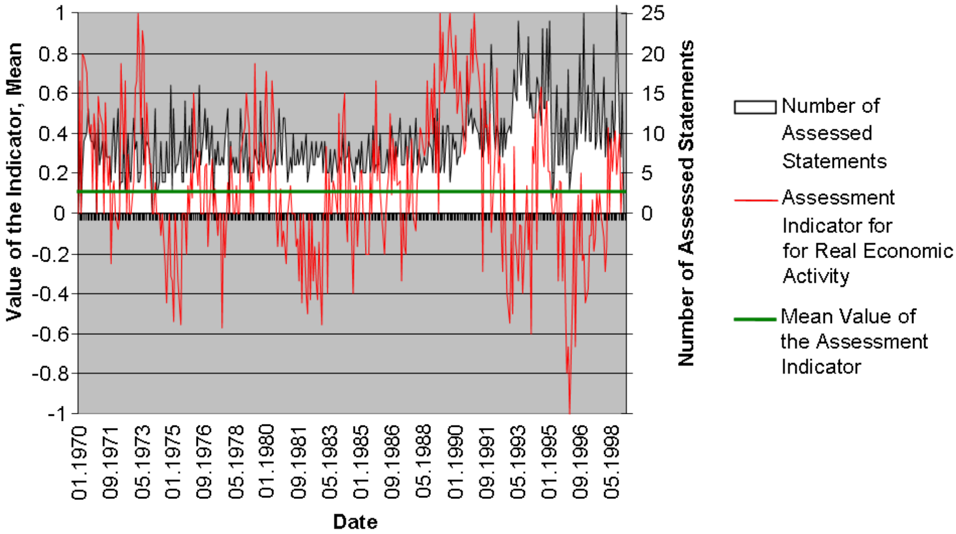


Figure 1.5: Assessment Indicator for Real Economic Activity

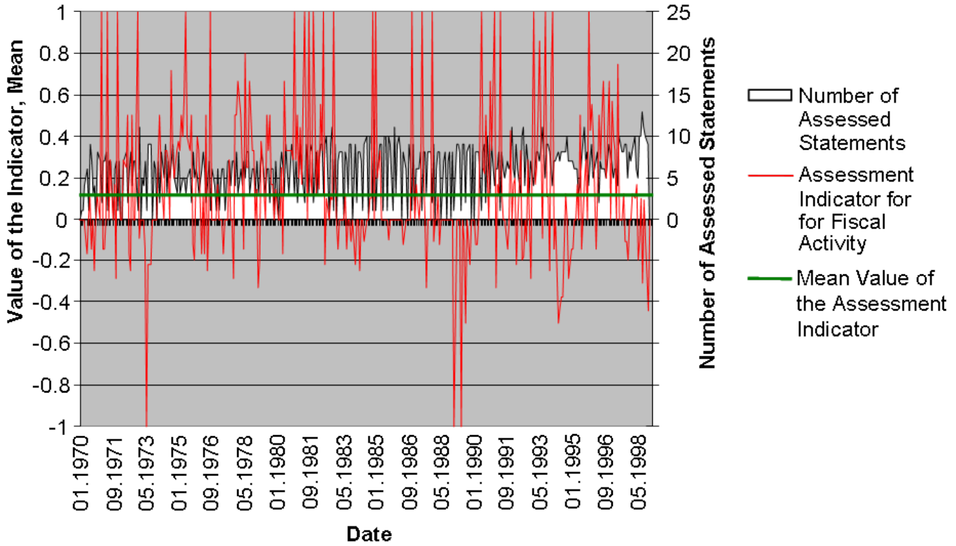


Figure 1.6: Assessment Indicator for Fiscal Activity

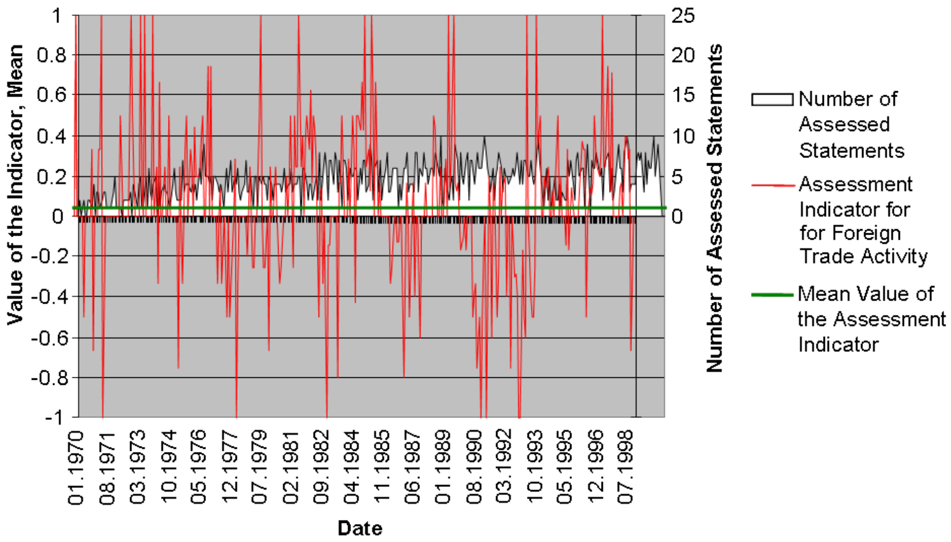


Figure 1.7: Assessment Indicator for Foreign Trade Activity

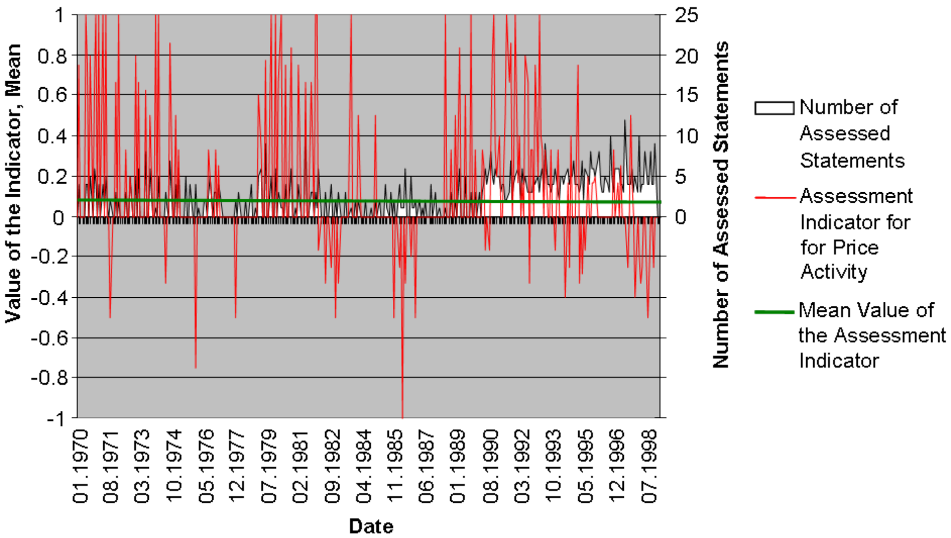


Figure 1.8: Assessment Indicator for Price Activity

Appendix 1.C: Testing for Structural Breaks

The following description is based on Bai and Perron (1998). In this application estimation is done within a pure structural change model, that is, all coefficients can be subject to shifts.

Consider the linear regression with m breakpoints, that is m+1 regimes:

$$y_t = \boldsymbol{z}_t'\boldsymbol{\delta}_j + u_t \tag{1.3}$$

where $j = 1, ..., m+1$, $t = T_{j-1}+1, ..., T_j$, $min(t) = h$, $T_0 = 0$, $T_{m+1} = T$, h denotes the minimal length of a regime, y_t is the dependent variable, $\boldsymbol{z}_t$ are the independent variables, $\boldsymbol{\delta}_j$ is a vector of coefficients, and u_t is an error term.

The following procedure estimates the unknown regression coefficients $\hat{\boldsymbol{\delta}}_j$ as well as the optimal position of the breakpoints $\hat{T}_j$. For each possible segment $(T_{j-1}+1, ..., T_j)$, denoted $\{T_j\}$, the corresponding least squares estimates of $\boldsymbol{\delta_j}$ are obtained by minimizing the sum of squared residuals $\sum_{i=1}^{m+1}\sum_{t=T_{i-1}+1}^{T_i}[y_t - \boldsymbol{z}_t'\boldsymbol{\delta}_i]^2$. Let $\hat{\boldsymbol{\delta}}(\{T_j\})$ denote the resulting estimates. Using the corresponding sum of squared residuals, denoted by $S_T(T_1, ..., T_m)$, for the $\hat{\boldsymbol{\delta}}(\{T_j\})$, the estimated breakpoints $(\hat{T}_1, ..., \hat{T}_m)$ are such that $(\hat{T}_1, ..., \hat{T}_m) = argmin_{T_1,...,T_m} S_T(T_1, ..., T_m)$.

In a nutshell, given the number of breakpoints m and the minimal length of a segment h, the procedure calculates the global sum of squared residuals for all possible positions of the breakpoints. The selected breakpoints are such that the sum of squared residuals over all segments is minimized. The $\hat{\boldsymbol{\delta}}(T_j)$ chosen are the corresponding coefficient estimates at the selected breakdates $\hat{\boldsymbol{\delta}}(\hat{T}_j)$.

The maximum number of breakpoints m is determined by h: $m = \theta - 1$ where θ is rounded to the nearest integer less or equal to $\frac{T}{h}$. To determine the optimal number of breakpoints one applies the above procedure for m=0, ..., $\theta - 1$. The optimal number of breakpoints chosen is the one that yields the smallest value of the Bayesian Information Criterion (BIC) defined as

$$BIC(m) = ln\ \hat{\sigma}^2(m) + [(m+1)q + m]\frac{ln\ T}{T}, \tag{1.4}$$

where q is the number of independent variables. According to Bai and Perron (1998) the BIC performs reasonably well when no serial correlation is present in the errors. In all estimations, Durbin's test provided no evidence of serial correlation.[51]

Bai and Perron (1998) do not give clear guidance as to how the parameter h which influences the position of selected breakpoints should be chosen. When choosing h too small, one ends up estimating for some segments with very few observations. However, in their application they always choose it to be in a range between 10% and 25% of all observations. The value of h chosen in this application is 48 observations, that is, a minimum sample size of four years, which is 14% of T. Note that the chosen value of h does not allow the inclusion of the breakdown of the Bretton Woods system as a breakpoint in the analysis covering data from January 1970 to December 1998.[52]

[51] See Durbin's test for serial correlation in Stata (2005).

[52] In the range of h=30 to 38 the beginning of 1973 is always a chosen breakpoint, however, this number of observations is considered too small to estimate six coefficients and several potential breakpoints. In the range h=39 to h=63, which allows for the inclusion of March 1975, that date is always the selected breakpoint.

Chapter 2

On the Conditional Effects of IMF Program Participation on Output Growth[1]

The IMF began its operations in 1945 and was conceived as an independent international organization helping to promote macroeconomic and financial stability as well as growth of the world economy. In the 1970s the IMF expanded its role towards providing on a conditional basis development assistance to countries that as a prerequisite for loan approval had to initiate economic and structural reforms as outlined by the IMF.[2] While the IMF has often been criticized for failures in carrying out such development policy, in the wake of the recent financial crisis a number of calls have been made for an expanded role of the IMF. This chapter re-considers the effects of a country's participation in IMF loan programs on its output growth, taking account of conditionality of these growth effects on the degree of program implementation as well as institutional factors such as quality of governance, internal stability, health, and educational attainment.

The IMF has been offering four types of loan arrangements involving policy conditions, the Stand-by Arrangement (SBA), the Extended Fund Facility

[1]This chapter is joint work with Michael Binder, Goethe-Universität Frankfurt am Main.

[2]For a more detailed exposition, see Fritz-Krockow and Ramlogan (2007).

(EFF), the Structural Adjustment Facility (SAF), and the Enhanced Structural Adjustment Facility (ESAF), subsequently replaced by the Poverty Reduction and Growth Facility (PRGF).[3] Most of the IMF's assistance is provided through SBAs. Designed in 1952 to help countries with addressing short-term balance of payments problems, SBAs typically cover periods of one to two years. The EFF was set up in 1974 to help countries encountering long-term balance of payments problems requiring fundamental economic reforms. EFF loan arrangements usually cover three to five years. The SAF has been used since 1986 and is designed to provide assistance for low-income countries. The ESAF only differs slightly from the SAF, but involves stricter conditionality criteria and larger loan amounts. The ESAF was used since 1986. After the East-Asian crisis this facility was relabeled PRGF, as it was broadened to include poverty reduction and to grant governments larger scope in negotiating the policy conditions. Typically PRGF programs are pursued for up to four years. When conditionality is involved, the IMF assesses whether a country complies with the conditionality requirements. If so, the country can draw on the loan funds in pre-specified intervals.[4]

The previous empirical evidence regarding the effects of a country's participation in IMF loan programs on its output growth is rather mixed. Using political economy variables as instruments to address endogeneity issues, Barro and Lee (2005) find that the IMF loan program participation rate has a negative effect on output growth.[5] Vreeland (2003), using counterfactual analysis, also finds evidence that program participation leads to a reduction of output growth. In contrast, Dicks-Mireaux, Mecagni, and Schadler (2000), also using counterfactual analysis, find positive output growth effects of IMF program participation.

[3]An overview on these programs involving conditionality is provided in Fritz-Krockow and Ramlogan (2007).

[4]For the empirical work in this chapter we will not discriminate between these different loan arrangement schemes. While SBAs in contrast to the other schemes cover elements of structural reforms only to a limited extent, for example in the form of exchange rate and pricing policies, SBAs often precede one of the other schemes simply because "there has not [...] been enough time to assemble all the necessary elements of a comprehensive structural package" (Polak, 1991).

[5]Barro and Lee (2005) define the loan participation rate as the fraction of months during a five-years interval that a country operated under IMF loan programs.

In this chapter we provide new insights regarding the effects of a country's IMF program participation on its output growth by constructing and estimating a state-dependent panel data model accounting in particular for sample selection, for the endogeneity of program participation, and for the potential conditionality of the output growth effects of IMF program participation on a country's degree of program implementation and institutional factors such as quality of governance, internal stability, health, and educational attainment. We argue that capturing sample selection, program participation endogeneity, and state dependence of the effects is critical for properly measuring the effects of a country's IMF program participation on output growth. To cope with sample selection issues, we work with an equation system composed both of a program participation selection and an output growth (participation effects) equation. Within this equation system, we account for the endogeneity of the program participation measure in the output growth equation using a two-step maximum likelihood estimator. We capture country-specific effects under the two alternatives of a random and a fixed effects model. To account for the state dependence of the output growth effects of IMF program participation, we use semi-parametric conditional pooling techniques to condition the effects of participation in IMF programs on a country's degree of program implementation and its institutional features as measured by our index comprising measures of quality of governance, internal stability, health, and educational attainment.

Using this novel econometric framework and a sample of annual data for 86 countries over the time period from 1975 to 2004, we provide evidence that the effects of IMF program participation on output growth vary systematically with the degree of program implementation as well as our index of institutional factors, and that these effects are positive only if IMF program participation is at a sufficiently advanced stage, or if the program participation is coupled with sufficient progress in improving institutional quality.

The remainder of this chapter is structured as follows: Section 2.1 provides a review of the previous literature. Sections 2.2 and 2.3 describe our panel econometric framework, with Section 2.2 focussing on sample selection and endogeneity issues, and Section 2.3 describing our approach to modelling state dependence of the effects of IMF program participation. Section 2.4 describes the construction of our variables for modelling the state dependence of the effects of IMF program participation on a country's output growth. Section 2.5 presents our empirical results. Finally, Section 2.6 concludes. Further details regarding our econometric modelling framework and inference approach, further results checking on the robustness of our main findings and some details concerning the data set we collected for this chapter are described in several appendices at the end of the chapter.

2.1 Review of Previous Literature

There are a number of notable contributions to the literature concerned with measuring the effects of a country's IMF loan program participation on output growth. Most of the contributions can be characterized as following one of three approaches: (i) the 'before-after'-approach, (ii) the 'with-without'-approach, and (iii) regression-based approaches.[6]

The 'before-after'-approach is based on the idea that, *ceteris paribus*, output growth that a country has experienced before/after entering an IMF loan program may be compared with output growth that the country experiences during participation in an IMF loan program. For example, Evrensel (2002) investigates the effects of IMF loan programs for a sample of 109 countries over the time period from 1971 to 1997 using lags of up to three years before and after program participation to conduct a 'before-after' analysis. With respect to the output growth effects of program participation, she argues that the evidence is inconclusive. The main problem with the 'before-after' approach, in any case, is that in practice it does not allow to fully account for country-specific factors that have bearing on the output growth effects of program participation.

The 'with-without' approach rests on the assumption that the core features of countries that participate in IMF loan programs are the same as those of countries not participating in IMF loan programs. For example, using matching methods, Hutchison (2004) analyzes the differences in output growth between countries participating and those not participating in IMF loan programs, for a panel of 25 countries over the time period 1975 to 1997. Hutchison's (2004) results suggest that, once sample selection is controlled for using observed variables only,[7] participation in IMF loan programs has no adverse effects on output growth. However, Hutchison's (2004) matching methods do not take into account any selection based on unobserved variables, and so his results may still be subject to sample selection bias.

[6] See also Vreeland (2003) and Dreher (2006) for a similar categorization of the literature.

[7] See, for example, Heckman, Ichimura, and Todd (1998) for a distinction between selection based on observed variables versus selection based on unobserved variables.

Bordo and Schwartz (2000) compare the performance of 24 Asian and Latin-American countries over the time period 1973 to 1999 and find that before the onset of currency or banking crises, output growth declines more strongly in countries not participating in IMF loan programs, though not to levels as low as of those countries participating in IMF loan programs. They find furthermore that countries not participating in IMF loan programs recover faster after currency and banking crises.

The majority of contributions to the empirical literature on the effects of IMF loan program participation on output growth employ regression-based approaches. Dicks-Mireaux, Mecagni, and Schadler (2000) perform a counterfactual analysis using a panel data set for 74 countries over the time period from 1986 to 1991. Taking into account sample selection issues, they find significant, positive effects of IMF loan program participation on output growth. In contrast, Vreeland (2003) using a similar methodology for a panel of 79 countries over the time period from 1970 to 1990,[8] finds a negative impact of IMF program participation on output growth. Bordo and Schwartz (2000), also using counterfactual analysis, find negative but insignificant effects on output growth during the onset of a currency or banking crisis, but positive and significant effects a year later. Their data set comprises 24 Asian and Latin-American countries and covers the time period from 1973 to 1998. Hutchison and Noy (2003), distinguishing between IMF program approval and successful completion of IMF programs, analyze the effects of IMF program participation on output growth in a sample of 65 developing countries over the time period from 1975 to 1997. Using counterfactual analysis, they find that participation in IMF loan programs results in short-run output growth losses, though noting that these results appear entirely driven by the Latin-American countries in their sample. Finally, Barro and Lee (2005), using a set of political economy variables as instruments to correct for regressor endogeneity problems in a panel comprising 86 countries over the time period from 1975 to 2000 find that participation in IMF loan programs has a significantly negative effect on output growth.

The following section outlines the econometric framework to investigate

[8] Vreeland (2003) also uses a larger data set, ranging from 1950 to 1990.

the conditional effects of IMF program participation on output growth.

2.2 Panel Data Models with Sample Selection and Censored Endogenous Variables

When using a regression framework to estimate the effects of IMF program participation on a country's output growth, two issues that need to be addressed are (i) endogeneity of the program participation measure in the output growth equation and (ii) sample selection. The first issue arises when explaining output growth with, *inter alia*, a country's participation in IMF loan programs, as one will need to distinguish whether a country's economic performance is causal for IMF program participation, or vice versa. The second issue arises when using non-randomly selected samples for model estimation, as then the fact that the output growth performance of countries that participate in IMF programs may systematically differ from that of those countries that do not participate needs to be addressed.[9] Countries tend to participate in IMF loan programs when they encounter economic problems, which implies that they are likely to experience an output growth process that is different from that of countries that do not turn to the IMF for assistance. It is thus sensible to analyze the output growth process of participating countries – that are likely to be in a situation of economic crisis – separately from the output growth process of non-participating countries, which in turn necessitates to correct for sample selection. As noted by Vella (1998), while sample selection has in the literature been commonly confronted in purely cross-sectional analyses, it is less frequently considered to be of concern in the estimation of panel models. This may in part be due to the perception that a panel model incorporating random or fixed effects will eliminate most forms of unobserved heterogeneity. However, consistency of the fixed effects estimator of a default fixed effects model not explicitly capturing the selection mechanism requires that the selection operates purely through the time-invariant country-specific terms, which appears to be rather unlikely. Consistency of the random effects estimator of the default random effects panel model requires the additional condition that the time-invariant

[9]As is well known, the investigation of such sample selection effects was pioneered in empirical microeconomics by Heckman (1979).

country-specific effect and the model's disturbance term are uncorrelated.

The next two sub-sections describe the random and fixed effects panel models which will be used for our analysis and take account of sample selection and endogeneity.

2.2.1 Random Effects Panel Model with Sample Selection and Endogeneity

In the following we will first outline a random effects model to correct for sample selection as well as endogeneity of the IMF program participation measure in the output growth equation. Our exposition of this random effects model draws strongly upon Vella (1998) and Vella and Verbeek (1999).[10] Consider the following random effects panel data model with sample selection and endogeneity:

$$y_{it}^* = \mu_i + d_{it}\theta + \boldsymbol{x}_{it}'\boldsymbol{\beta} + e_{it} \tag{2.1}$$

('participation effects equation'),

$$d_{it}^* = \alpha_i + \boldsymbol{z}_{it}'\boldsymbol{\gamma} + v_{it} \tag{2.2}$$

('participation selection equation'), with

$$d_{it} = \begin{cases} d_{it}^* \text{ if } d_{it}^* > 0, \\ 0 \text{ otherwise,} \end{cases} \tag{2.3}$$

$$y_{it} = \begin{cases} y_{it}^* \text{ if } d_{it} > 0, \\ \text{`unspecified' otherwise,} \end{cases} \tag{2.4}$$

[10] Vella and Verbeek (1999) discuss a model that *inter alia* allows for a broader range of functional forms than we wish to consider in this chapter. Our model specification also differs from theirs in that unlike Vella and Verbeek (1999) we wish to allow for a larger number of regressors in the participation selection equation than in the participation effects equation.

$i = 1, 2, ..., N$, and $t = 1, 2, ..., T_i$, where y_{it}^* and d_{it}^* are latent endogenous variables for country i and time period t with observed counterparts y_{it} (output growth – participation effects measure) and d_{it} (IMF loan-quota ratio – measure of participation intensity).[11] Also note that $\boldsymbol{x}_{it}$ is a subset of $\boldsymbol{z}_{it}$, and throughout our exposition in this section $\boldsymbol{z}_{it}$ will be taken to be strictly exogenous.

Let us write the unobserved component of each equation as the sum of the country-specific random effect (μ_i in Equation (2.1) and α_i in Equation (2.2)) and the time-specific idiosyncratic error term (e_{it} in Equation (2.1) and v_{it} in Equation (2.2)):

$$\epsilon_{it} = \mu_i + e_{it}, \tag{2.5}$$

and

$$u_{it} = \alpha_i + v_{it}. \tag{2.6}$$

Defining $\boldsymbol{u}_i$ as the stacked $(T_i \times 1)$ vector of u_{it}'s for country i, $\boldsymbol{X}_i = (\boldsymbol{x}_{i1}, \boldsymbol{x}_{i2}, ..., \boldsymbol{x}_{iT_i})'$, and $\boldsymbol{Z}_i = (\boldsymbol{z}_{i1}, \boldsymbol{z}_{i2}, ..., \boldsymbol{z}_{iT_i})'$, we assume that

$$\boldsymbol{u}_i | \boldsymbol{Z}_i \overset{iid}{\sim} N(0, \sigma_\alpha^2 \boldsymbol{\iota\iota}' + \sigma_v^2 \boldsymbol{I}), \tag{2.7}$$

with $\boldsymbol{\iota}$ being a $T_i \times 1$ vector of ones. Equation (2.7) restricts α_i and v_{it} to be independent across i, and v_{it} is restricted to be intertemporally uncorrelated and homoskedastic. We also assume that

$$E(\epsilon_{it} | \boldsymbol{Z}_i, \boldsymbol{u}_i) = \tau_1 u_{it} + \tau_2 \bar{u}_i, \tag{2.8}$$

where $\bar{u}_i = T_i^{-1} \sum_{t=1}^{T_i} u_{it}$ and τ_1 as well as τ_2 are parameters. Note that Equation (2.8) allows for d_{it} and ϵ_{it} to be correlated, capturing endogeneity of the IMF loan-quota ratio in the output growth equation as arising through the program participation selection mechanism specified in Equation (2.2). Also,

[11] While the availability of data on output growth is per se not tied to a country participating in an IMF loan program (that is, $d_{it} \geq 0$), y_{it} under non-participation is unobserved from the perspective of the sample selection model equations in (2.1) and (2.2), in that it is then driven by a different model of output growth.

through $\tau_2 \neq 0$ Equation (2.8) allows e_{it} to be intertemporally correlated and heteroskedastic.

Conditioning Equation (2.1) on the selection outcomes, $\boldsymbol{d}_i$, as well as the regressors in $\boldsymbol{X}_i$, and observing Equation (2.8) yields

$$\begin{aligned} E(y_{it}^*|\boldsymbol{Z}_i, \boldsymbol{d}_i) &= d_{it}\theta + \boldsymbol{x}_{it}'\boldsymbol{\beta} + E(\epsilon_{it}|\boldsymbol{Z}_i, \boldsymbol{d}_i) \\ &= d_{it}\theta + \boldsymbol{x}_{it}'\boldsymbol{\beta} + \tau_1 u_{it} + \tau_2 \bar{u}_i. \end{aligned} \tag{2.9}$$

To obtain the sample selection correction terms in u_{it} and $\bar{u}_i$ on the right-hand side of Equation (2.9), Vella and Verbeek (1999) propose to compute

$$E[u_{it}|\boldsymbol{Z}_i, \boldsymbol{d}_i] = \int [\alpha_i + E(v_{it}|\boldsymbol{Z}_i, \boldsymbol{d}_i, \alpha_i)] f(\alpha_i|\boldsymbol{Z}_i, \boldsymbol{d}_i) d\alpha_i, \tag{2.10}$$

where $f(\alpha_i|\boldsymbol{Z}_i, \boldsymbol{d}_i)$ denotes the conditional density of α_i and v_{it} in terms of its expectation conditional on $\boldsymbol{Z}_i, \boldsymbol{d}_i$ and α_i is the generalized residual from estimation of the panel Tobit model in Equation (2.2).[12] The conditional density of α_i can be obtained from

$$f(\alpha_i|\boldsymbol{Z}_i, \boldsymbol{d}_i) = \frac{f(\boldsymbol{d}_i|\boldsymbol{Z}_i, \alpha_i) f(\alpha_i)}{f(\boldsymbol{d}_i|\boldsymbol{Z}_i)}, \tag{2.11}$$

with f generically denoting density functions, and where

$$f(\boldsymbol{d}_i|\boldsymbol{Z}_i) = \int \prod_{t=1}^{T_i} f(d_{it}|\boldsymbol{Z}_i, \alpha_i) f(\alpha_i) d\alpha_i. \tag{2.12}$$

After obtaining the conditional expectation of u_{it} in Equation (2.10), the output growth equation in (2.1) can be estimated, including u_{it} and $\bar{u}_i$ as additional variables to correct for sample selection while also allowing for endogeneity of d_{it}. The functional form of Equation (2.10) as well as details concerning the computation of the standard errors for the estimates of $\theta, \boldsymbol{\beta}, \tau_1$, and τ_2 can be found in Appendix 2.A at the end of the chapter.

If e_{it} is restricted to be intertemporally uncorrelated, then Equation (2.8)

[12] See Gourieroux, Monfort, Renault, and Trognon (1987) for a definition of the generalized residuals we work with here.

reduces to

$$E(\epsilon_{it}|\boldsymbol{Z}_i, \boldsymbol{u}_i) = \tau_1 u_{it}, \tag{2.13}$$

implying that Equation (2.10) simplifies to

$$E[u_{it}|\boldsymbol{Z}_i, d_{it}] = \int [\alpha_i + E(v_{it}|\boldsymbol{Z}_i, d_{it}, \alpha_i)] f(\alpha_i|\boldsymbol{Z}_i, d_{it}) d\alpha_i. \tag{2.14}$$

The following sub-section describes the fixed effects panel model.

2.2.2 Fixed Effects Panel Model with Sample Selection and Endogeneity

Semykina and Wooldridge (2010) propose a fixed effects specification of a panel data model closely related to Equations (2.1) to (2.4). In what follows we will invoke Semykina and Wooldridge's (2005) modelling of the fixed effects, decomposing the fixed effects into a systematic component driven by observables (in the following the variables in $\boldsymbol{g}_i$) as well as a random unobserved component, and then embed the resultant model within the estimation and inference procedure discussed in Sub-Section 2.2.1.[13]

Following Semykina and Wooldridge (2010), let us thus invoke a Mundlak (1978) type decomposition of the country-specific fixed effect in Equation (2.2):

$$\alpha_i \quad = \quad \zeta + \boldsymbol{g}_i' \boldsymbol{\kappa} + r_i, \tag{2.15}$$

where r_i is a random effect. Defining

$$\tilde{u}_{it} = r_i + v_{it}, \tag{2.16}$$

[13]Semykina and Wooldridge (2010) provide a different two-step estimation and inference procedure for a panel model with a Probit specification of the selection mechanism than we propose in this sub-section for a panel model with a Tobit specification of the selection mechanism. For our data set, the procedure we outline here appears to be more robust to the selection of variables in $\boldsymbol{g}_i$ than the Semykina and Wooldridge (2010) procedure. A systematic comparison of our procedure with that of Semykina and Wooldridge (2010) would be interesting to pursue but is beyond the scope of this chapter.

we assume in analogy to Equation (2.7) that

$$\tilde{\boldsymbol{u}}_i|\boldsymbol{Z}_i, \boldsymbol{g}_i \overset{iid}{\sim} N(0, \sigma_r^2 \boldsymbol{\iota}\boldsymbol{\iota}' + \sigma_v^2 \boldsymbol{I}). \tag{2.17}$$

Note that the systematic component in α_i, $\boldsymbol{g}_i$, consists of cross-sectional means over time, that is, country-specific constants.

Clearly, the Mundlak (1978) and Semykina and Wooldridge (2010) fixed effects specification restricts the systematic variation of the country-specific effect to only arise through the vector of observables $\boldsymbol{g}_i$. This is a more restrictive specification of the fixed effect than often adopted in other panel data models, for example in the linear dynamic panel data literature.[14]

Let us use a similar decomposition as specified in Equation (2.15) for the country-specific effect in the participation selection equation also for the country-specific effect in the output growth (participation effects) equation (that is, Equation (2.1)):

$$\mu_i = \psi + \boldsymbol{q}_i'\boldsymbol{\xi} + \chi_i, \tag{2.18}$$

where χ_i is a random effect and $\boldsymbol{q}_i$ is a subset of $\boldsymbol{g}_i$. Defining

$$\tilde{\epsilon}_{it} = \chi_i + e_{it}, \tag{2.19}$$

we now also assume in analogy to Equation (2.8) that

$$E(\tilde{\epsilon}_{it}|\boldsymbol{Z}_i, \tilde{\boldsymbol{u}}_i, \boldsymbol{g}_i) = \tilde{\tau}_1 \tilde{u}_{it} + \tilde{\tau}_2 \bar{\tilde{u}}_i. \tag{2.20}$$

Under Equations (2.15) to (2.20), we therefore allow for a less restrictive specification of the country-specific effects than in Vella and Verbeek (1999) and capture a fixed effects specification in the spirit of Mundlak (1978) and Semykina and Wooldridge (2010), augmenting both the program selection equation, Equation (2.2), and the output growth equation, Equation (2.1), with the regressors in $\boldsymbol{q}_i$ and $\boldsymbol{g}_i$, but otherwise pursuing the estimation and in-

[14] See, for example, Binder, Hsiao, and Pesaran (2005) for an unrestricted formulation of fixed effects within a linear dynamic panel data model.

ference procedure of Sub-Section 2.2.1. We will discuss the choice of elements in $\boldsymbol{g}_i$ in Section 2.5.

Finally, the null of the random effects specification of Sub-Section 2.2.1 can be tested against the fixed effects specification of this section by investigating whether $\boldsymbol{\kappa} = \mathbf{0}$ and $\boldsymbol{\xi} = \mathbf{0}$.

The next section outlines the methodological approach which allows for conditioning the effect of IMF loan program participation in our panel econometric framework.

2.3 Conditioning the Effect of IMF Loan Program Participation

The fixed effects model of Sub-Section 2.2.2 still involves the restriction that the systematic differences in the output growth processes across participating countries can be captured through the country-specific effects and different realizations of the regressors in d_{it} and $\boldsymbol{x}_{it}$. This is a rather strong assumption. To analyze the effects of IMF program participation, it clearly seems desirable to allow for systematic differences in these effects themselves across countries. To do so in a parsimonious form that also allows us to learn about the sources of the variations of the effects across countries, we consider here the conditional pooling (state dependence) approach of Binder and Offermanns (2007). This approach allows us to model the conditionality of the growth effects of IMF loan programs on a country's degree of program implementation or on its institutional quality with a minimal set of assumptions regarding the functional form of this conditionality. The approach consists of modelling the state dependence with flexible functional form polynomials, as a (cross-sectionally) homogeneous function of the relevant conditioning variable. Denoting the conditioning variable by w_{it} and the flexible functional form polynomial by $\theta(w_{it})$, Binder and Offermanns (2007) propose to specify $\theta(w_{it})$ using a parametric function of flexible form, and in particular choose Chebyshev polynomials as one specification of orthogonal polynomials:

$$\theta(w_{it}) = \sum_{s=0}^{\tau} \eta_s^{(\theta)} c_s(w_{it}), \qquad (2.21)$$

with the Chebyshev polynomials $c_s(w_{it})$ recursively defined as $c_{s+1}(w_{it}) = 2w_{it}c_s(w_{it}) - c_{s-1}(w_{it})$, $s = 1, 2, ..., \tau$, $c_0(w_{it}) = 1$, $c_1(w_{it}) = w_{it}$, and where $\eta_s^{(\theta)}$, $s = 0, 1, ..., \tau$, are coefficients that are homogeneous across countries.[15]

To condition an independent variable's effect, the variable may be multiplied with the Chebyshev polynomial $\theta(w_{it})$, and estimation can then be

[15] Chebyshev polynomials belong to the class of orthogonal polynomials and thus can address collinearity problems that could arise under $\tau > 1$.

carried out as usual with the resultant augmented set of variables.

The following section describes the variables which are used to condition the effects of IMF loan program participation in our panel econometric framework.

2.4 Conditioning Variables

Under the conditional pooling approach (some of) the model coefficients are a function of a conditioning variable. According to the IMF, "[c]onditionality refers to policies and actions that a borrowing member agrees to carry out as a condition for the use of IMF resources. The purpose of conditionality is to ensure assistance to members [...] in a manner that [...] establishes adequate safeguards for the temporary use of the IMF's resources."[16] In practice, the IMF only disburses installments of funds agreed to in the loan program if the country initiates specific reforms, that is, complies with conditionality of the loan program. Hence, one way to model compliance with conditionality is to consider the ratio of loans actually drawn relative to loans originally agreed upon.[17] Provided that the IMF consistently disburses funds only to countries that are sufficiently successful in advancing economic reforms, the loans-drawn-to-agreed ratio should be a useful proxy as to whether a country is successful in implementing the economic reforms advocated by the IMF.

We also consider a more direct measure of structural conditionality. Structural conditionality according to the IMF since the 1980s has involved changes in policy processes, legislation, and institutional reforms.[18] In line with this, the IMF is arguing that "the implementation of IMF-supported programs depends to a significant extent on the domestic political and institutional environment".[19] By fostering institutional development, the IMF in effect acknowledges that efficient outcomes in market-oriented economies are most likely to occur when the non-market institutions are functioning well. Rodrik (2009) distinguishes between five types of institutions that allow markets to perform well: (i) private property rights give entrepreneurs the security of claiming the gains from investment and innovations; (ii) regulatory institutions prevent market failures that can arise from fraudulent behavior and incomplete information; (iii) institutions for macroeconomic stabilization are

[16] See Fritz-Krockow and Ramlogan (2007), p. 25.

[17] This measure was initially suggested as a proxy for compliance with conditionality by Killick (1995)

[18] See Nsouli, Atoyan, and Mourmouras (2006).

[19] See A. Moody and A. Rebucci (2006).

neccessary to alleviate shocks that hit the economy; (iv) institutions for social security render a market economy compatible with social coherence and stability; and (v) institutions of conflict management are neccessary to prevent social conflicts from creating uncertainty and diversion of ressources from economically productive activities. To capture a broad range of aspects of institutional quality, we construct for this chapter an index incorporating measures of bureaucracy quality, absence of corruption, law and order, government stability, absence of ethnic tensions and internal conflicts, and add two further dimensions by also taking account of health (life expectancy) and educational attainment. The set up of the index is described in what follows.[20] The index is constructed on the basis of the mean of the i-th country's index elements relative to the mean of the same index elements for a base-country year (the United States in 2000):

$$index_{it} = \frac{\sum_{s=1}^{m} \ s\text{-}th \ variable_{it}}{\sum_{s=1}^{m} \ s\text{-}th \ \text{variable}_{\text{base-country, base-year}}}, \tag{2.22}$$

where m denotes the number of variables that enter into the construction of the index. To be able to calculate this index, we replace missing observations using interpolated values. If for, say, country i a time series is missing entirely, we proxy it via a 'rank-matching' procedure: For each time period for country i, first a preliminary index is calculated on the basis of Equation (2.22) involving only those variables that are actually available for country i. We then also calculate the same preliminary index for all other countries for time period t, excluding those variables that are completely missing for country i. Using these preliminary indices, we then calculate the period t relative rank (that is, $\frac{rank_{it}}{number\ of\ countries_t}$) of the preliminary index value of country i among the set of all countries that can be considered for the preliminary index values in period t. We then proxy for time period t the variable in country i that is entirely missing with the value of that variable for which the period t relative rank is closest to the relative rank calculated for country i's preliminary index for period t.

[20] A listing including a description of all variables used for construction of our index is given in Appendix 2.B at the end of the chapter.

Finally, we impute those variables for which there are no observations either at the beginning or at the end of the series backward or forward, respectively, using the percentage changes of, again, a preliminary index that contains only the variables that are available for the country in the missing time period. At this point we then have for each country a balanced set of variables that can be used to calculate the index as outlined in Equation (2.22).

Our approach to index calculation ensures that there are no mean-shifts in the index if for a country the time series for some variable begins later or ends earlier than the time series for some other variables for that country. Our approach furthermore preserves all the information about the variation in the time series we exploit. It should be noted that due to the imputation procedure it is possible that an index value may become larger than one.

The next section outlines our empirical results as regards the conditional effects of IMF program participation on output growth.

2.5 Empirical Results

We begin by discussing empirical results obtained when taking into account sample selection and regressor endogeneity by means of considering the fixed effects panel model without state dependence of effects, as outlined in Sub-Section 2.2.2.[21] The selection equation, Equation (2.2) is a fixed effects Tobit model, as the loan-quota ratio is left-censored at zero.[22] It contains country years with and without participation in IMF loan programs. Note that when later we turn to considering state dependence of effects, the estimated models involve different sets of observations than considered here, depending on the conditioning variable chosen.[23] Table 2.1 displays our estimation results when estimating Equation (2.2), with the full set of observations available.

As can be seen from Table 2.1, the estimated coefficients on the investment share, measure of democracy, inflation, and mean economic proximity to major Europe are significantly negative. If the investment share or the measure for democracy decline by one percentage point or by one unit, then the ratio of IMF lending to a country's quota increases by 1.686 or 3 per-

[21] The set of regressors for all equations was chosen on the basis of the Akaike Information Criterion (AIC). Since the AIC turned out to always select the fixed effects specification, in what follows we focus our discussion on the fixed effects model. Potential candidates for the Mundlak variables, g_i and q_i, were a country's fertility rate, freedom of the press, freedom status of society, economic proximity to the U.S., and economic proximity to major Europe. Results for the random effects specification are provided as robustness check in Appendix 2.D at the end of the chapter. Potential candidates for $\boldsymbol{z}_{it}$ and $\boldsymbol{x}_{it}$ were a country's cumulative number of years in IMF loan programs, quota share at the IMF, staff share at the IMF, political proximity to the U.S., political proximity to major Europe, reserve position, current account position, trade openness, democracy index rating, investment share of Gross Domestic Product (GDP), Government share of GDP, and inflation.

[22] The IMF loan-quota ratio captures the average, on a monthly basis, of funds agreed upon in all loan programs (SBA, EFF, SAF, ESAF/PRGF) divided by the country's quota at the IMF. Note that Dreher (2006) only covers those arrangements that have been active for at least five months in a given calendar year. Our results do not change if we adjust the loan-quota ratio accordingly. Similar to Vreeland (2003), we consider consecutive agreements with the IMF as part of the same spell, since governments most of the time have several consecutive agreements with the IMF. A description of all variables used is provided in Appendix 2.B at the end of the chapter.

[23] One of the conditioning variables, the (growth rate of the) index of institutional quality, is available only for a sub-set of the observations in our sample. When using this sub-set of observations the results of the selection equation do not change qualitatively, however.

Independent Variables	**Coefficients**
Investment Share	−1.686** [2.579]
Reserves	−0.053 [0.374]
Government Share	0.432 [1.014]
Current Account	−0.077 [0.207]
Openness	−0.094 [0.859]
Democracy Index	−0.030** [2.371]
Number of Years under IMF Programs	0.020*** [4.358]
Inflation	−0.027** [2.771]
Mean Fertility Rate	0.556* [1.875]
Mean Economic Proximity to Major Europe	−0.132** [2.032]
Number of Observations for the selection equation:	1640

Note: Estimation results are obtained by estimating Equation (2.2), augmented with the Mundlak variables capturing fixed effects. The dependent variable is the loan-quota ratio. The F-test of joint significance of the Mundlak variables is significant at the 5% significance level. The McFadden pseudo R-squared for the regression equals 0.017. t-statistics are displayed in square brackets underneath the coefficient estimates. A '*' indicates significance at the 10% level, a '**' indicates significance at the 5% level, and a '***' indicates significance at the 1% level. The regression uses annual data, the sample extends from 1975 to 2004 and the number of countries considered is 68. A description of all variables used is provided in Appendix 2.B at the end of the chapter.

Table 2.1: Regression Results for the Participation Selection Equation, FE Specification

centage points, respectively.[24] If the inflation rate or the mean economic proximity to Major Europe increase by one percentage point, then the loan-quota ratio decreases by 0.027 or 0.132 percentage points, respectively. The

[24] Note that differentiating the latent variable (denoted here generically as y^*) with respect to the independent variable (denoted here generically as x, entering into the Tobit model with a coefficient of β), we of course have

$$\frac{\partial E(y^*|x)}{\partial x} = \beta.$$

The marginal effect for the observed dependent variable needs to be corrected for censoring, multiplying β with the probability that the loan-quota ratio is strictly positive. All reported effects are average marginal effects evaluated at the independent variables' sample means.

effect of a country's mean fertility rate and the number of years a country has been under IMF loan programs are significantly positive. If the mean fertility rate increases by one percentage point or the number of years under IMF loan programs increases by one year, then the loan-quota ratio increases by 0.556 and 2 percentage points, respectively.

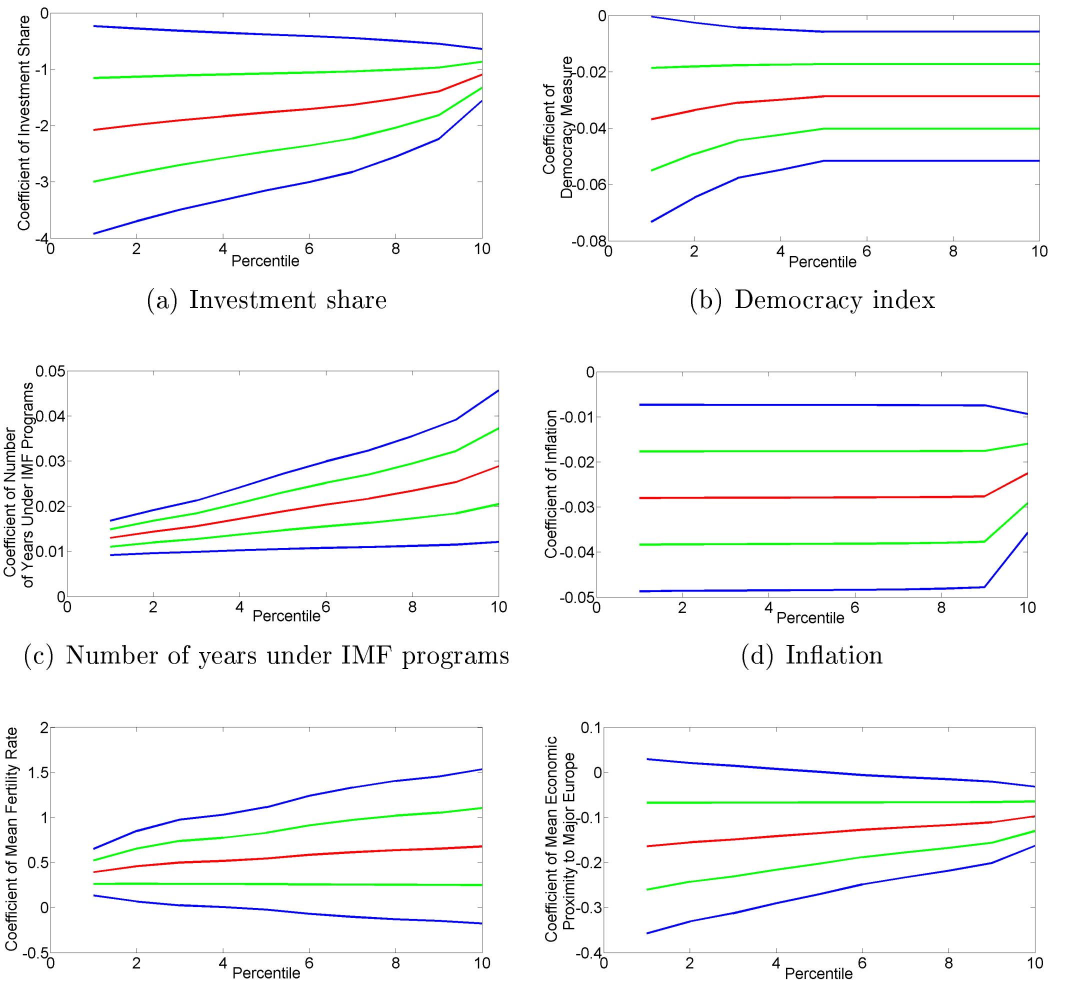
Figure 2.1 displays the marginal effects (red curve) of the significant variables from Table 2.1 as well as the corresponding one-standard deviation (green) and two-standard deviation (blue) bands.

The residual obtained from estimating the participation selection equation can be used to generate correction terms that, as described in Sub-Section 2.2.1, in addition to correcting for sample selection also correct for endogeneity when estimating the effects of the loan-quota ratio on the output growth of countries participating in IMF loan programs. Table 2.2 displays our estimation results for the fixed effects participation effects model (without state dependence) of Sub-Section 2.2.2, using the growth rate of real GDP per capita as the dependent variable and the IMF loan-quota ratio, as well as a set of explanatory variables as independent variables.[25] The estimated coefficient on the investment share is significantly positive. An increase of the investment share by one percentage point increases a country's growth rate of real GDP per capita by 0.09 percentage points. The coefficients on inflation and the mean of a country's fertility rate are significantly negative. An increase of inflation by one percentage point and an increase of the mean fertility rate by one unit lead to a decrease of the real GDP per capita growth rate by 0.003 and 0.035 percentage points, respectively.

Two further issues are worth noting: First, τ_1 (not displayed in the table) is significant at the 10% level, providing evidence for a sample selection mechanism. Second, the coefficient on the loan-quota ratio is positive but not significant.[26]

[25] All standard errors reported in the following tables are corrected for first-step sampling uncertainty affecting second-step inference. See also Appendix 2.A at the end of the chapter.

[26] When estimating the participation effects equation without the sample selection correction terms (which we can do for a total of 938 observations), then the coefficient on the loan-quota ratio has negative sign (-0.003), with a t-statistic of -1.522.



(a) Investment share (b) Democracy index

(c) Number of years under IMF programs (d) Inflation

(e) Mean fertility rate (f) Mean economic proximity to Major Europe

Figure 2.1: Marginal Effects in the Participation Selection Equation, FE Specification

To address the issue of heterogeneity bias in the loan program participation effects estimates when state dependence of the effects is ignored, in our next step of analysis we condition the effects of the loan-quota ratio on output growth on the amount-drawn-to-amount-agreed ratio, which, as discussed in Section 2.4, may serve as a useful proxy for measuring state dependence of effects. Taking into account such state dependence may also on its own contribute to alleviating the endogeneity problem: One may expect

Independent Variables	**Coefficients**
Loan-Quota Ratio	0.004 [1.083]
Investment Share	0.090 ** [1.962]
Inflation	−0.003 *** [4.488]
Reserves	0.017 [1.300]
Mean Fertility Rate	−0.035 ** [2.315]
Number of Observations:	849

Note: Estimation results are obtained by estimating Equation (2.1), augmented with the Mundlak variables to capture fixed effects. The F-test of joint significance of the correction terms, τ_1 and τ_2, is not significant, but τ_1 is individually significant at the 10% significance level, indicating correlation between the idiosyncratic error terms. The dependent variable is real GDP per capita growth. The adjusted R-squared for the regression equals 0.041. t-statistics are displayed in square brackets underneath the coefficient estimates. A '*' indicates significance at the 10% level, a '**' indicates significance at the 5% level, and a '***' indicates significance at the 1% level. The regression uses annual data, the sample extends from 1975 to 2004, and the number of countries considered is 68. A description of all variables used is provided in Appendix 2.B at the end of the chapter.

Table 2.2: Regression Results for the Participation Effects Equation, FE Specification

that a higher degree of compliance with conditionality causes higher (lower) output growth if the reforms implemented promote higher (lower) output growth. However, output growth should have a negligable effect on compliance with conditionality. It appears sensible to conjecture that lower output growth raises a country's willingness to accept painful economic reforms. In this case, lower output growth should be associated with a higher degree of compliance. In any case, the amount-drawn-to-amount-agreed ratio and real GDP per capita growth in our data set feature a correlation of -0.05 only.

Table 2.3 provides our estimation results when using Chebyshev polynomials of order one and the amount-drawn-to-amount-agreed ratio as capturing state dependence.

Conditioning the output growth effects of the loan-quota ratio on the proxy for compliance with conditionality has a considerable effect on the estimation results: If a participating country were not to comply with conditionality at all, the effect of loan program participation on output growth is negative. An increase in the loan-quota ratio by 1 percentage point lowers

Independent Variables	**Coefficients**
Loan-Quota Ratio	-0.005 [1.046]
*Loan-Quota Ratio * Drawn Ratio*	0.012 ** [2.333]
Investment Share	0.070 [1.642]
Inflation	−0.003 *** [4.241]
Reserves	0.021 [1.591]
Current Account	−0.046 [1.272]
Mean of Fertility Rate	−0.045 *** [3.144]
Number of Observations:	849

Note: Estimation results are obtained by estimating Equation (2.1), augmented with the Mundlak variables to capture fixed effects. The F-test of joint significance of the correction terms, τ_1 and τ_2, is not significant, but τ_1 is individually significant at the 10% significance level, indicating correlation between the idiosyncratic error terms. The conditioning variable, amount-drawn-to-agreed ratio, has been used as control variable (not displayed) and is not significant. The dependent variable is real GDP per capita growth. The adjusted R-squared for the regression equals 0.053. t-statistics are displayed in square brackets underneath the coefficient estimates. A '*' indicates significance at the 10% level, a '**' indicates significance at the 5% level, and a '***' indicates significance at the 1% level. The regression uses annual data, the sample extends from 1975 to 2004, and the number of countries considered is 68. A description of all variables used is provided in Appendix 2.B at the end of the chapter.

Table 2.3: Regression Results for the Participation Effects Equation with the Actual Degree of Program Implementation as Conditioning Variable, FE Specification

the growth rate of real GDP per capita by 0.005 percentage points. (If such a country does not receive any funds from the IMF, because it does not set in effect the required reforms, the output growth effect obviously would be zero.) However, the higher the compliance ratio, the smaller in absolute terms the negative output growth effect of the loan-quota ratio. If the compliance ratio is larger than 42%, then the effect of IMF program participation turns positive.[27] If all funds originally agreed upon are drawn, that is, there is full compliance with IMF conditionality, then an increase of the loan-quota ratio

[27]Note that this ratio is sizeably smaller than in Killick (1995), who sets a threshold value for successful IMF program implementation at 80%, arguing that this cut-off point is closely associated with successful program implementation based on a survey between 1980 and 1992.

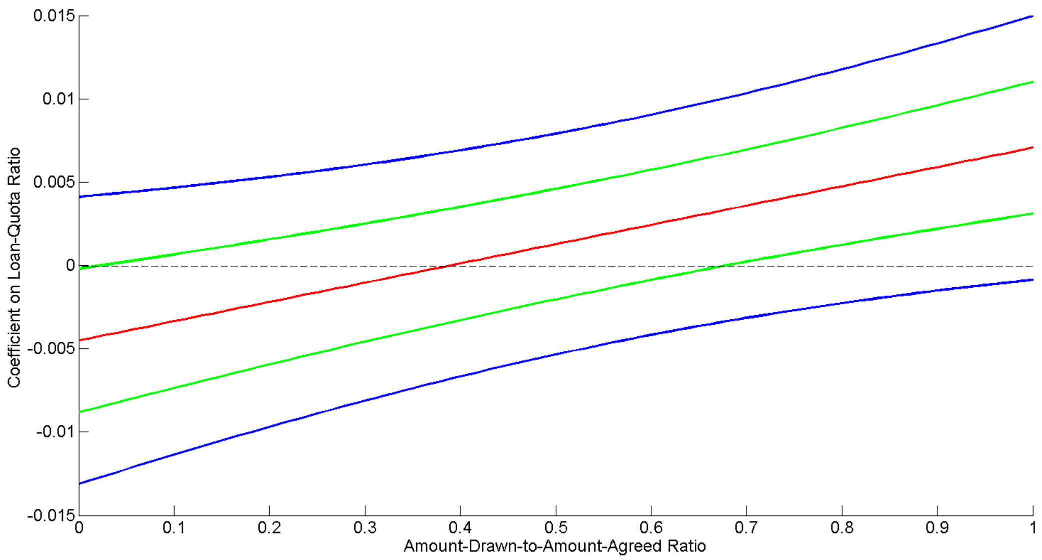


Figure 2.2: Effect of Program Participation Conditional on Actual Degree of Program Implementation, FE Specification

by 1 percentage point leads to an increase of real GDP per capita growth by 0.007 percentage points. These results are in line with IMF arguments stressing that compliance with conditionality is important for the success of IMF loan programs. Figure 2.2 plots the coefficient on the loan-quota ratio conditional on the amount-drawn-to-amount-agreed ratio (red curve) with the one standard deviation (green) and two standard deviation (blue) bands.

To provide a different measure of quantification of the output growth effects of IMF loan programs, Table 2.4 displays the average contribution of the various regressors to a country's real GDP per capita growth net of individual-specific effects, as implied by the state-dependent panel model in Table 2.3:

The overall contribution of the loan-quota ratio to real GDP per capita growth net of individual-specific effects is equal to 7.49%. The investment share contributes most to a participating country's real GDP per capita growth, at almost 50%.

To investigate the state dependence of the output growth effects of IMF

Variables	Mean Effect	Contrib. in %
Loan-Quota Ratio	−0.005	−30.39
Loan-Quota Ratio * Drawn Ratio	0.006	37.88
Investment Share	0.008	49.98
Inflation	−0.001	− 7.94
Reserves	0.006	36.70
Current Account	0.002	13.78
Sum	0.015	100.00

Table 2.4: Growth Accounting with the Actual Degree of Program Implementation as Conditioning Variable, FE Specification

program participation on a country's institutional quality directly, we next use our index of institutional quality as described in Section 2.4. Since structural conditionality is measured in changes by the IMF, we include the index of institutional quality in percentage changes ('institutional development') as our conditioning variable.

Table 2.5 displays results when using Chebyshev polynomials of order one and institutional development as the conditioning variable.

Conditioning the effect of the loan-quota ratio on institutional development yields significant results: If a country cannot improve its institutional quality, the effect of program participation on output growth is negative: An increase of the loan-quota ratio by 1 percentage point lowers the growth rate of real GDP per capita by 0.004 percentage points. At the same time, the estimated coefficient increases systematically with the magnitude of institutional development. Figure 2.3 displays the coefficient on the loan-quota ratio conditional on the progress in institutional development. If the progress in institutional development exceeds 0.12, the effect of IMF loan program participation on output growth turns significantly positive at the 5% level.

Table 2.6 displays the average contribution of the various regressors to a country's real GDP per capita growth net of individual-specific effects, as implied by the state-dependent panel model in Table 2.5.

Having analyzed the effect of a country's participation in IMF loan programs on its output growth, we next turn our focus to analyses of counterfactuals and intertemporal effects involving IMF loan programs. To get

Independent Variables	**Coefficients**
Loan-Quota Ratio	0.004 [1.024]
*Loan-Quota Ratio * Institutional Development*	0.049** [2.002]
Investment Share	0.070 [0.865]
Inflation	−0.003*** [4.257]
Democracy	0.002 [1.059]
Mean Fertility Rate	−0.038** [2.070]
Number of Observations:	773

Note: Estimation results are obtained by estimating Equation (2.1), augmented with the Mundlak variables to capture fixed effects. The F-test of joint significance of the correction terms, τ_1 and τ_2, is not significant. The conditioning variable, institutional development, has also been considered as a control variable (not displayed) and is not significant. The dependent variable is real GDP per capita growth. The adjusted R-squared for the regression equals 0.053. t-statistics are displayed in square brackets underneath the coefficient estimates. A '*' indicates significance at the 10% level, a '**' indicates significance at the 5% level, and a '***' indicates significance at the 1% level. The regression uses annual data, the sample extends from 1975 to 2004, and the number of countries considered is 60. A description of all variables used is provided in Appendix 2.B at the end of the chapter.

Table 2.5: Regression Results for the Participation Effects Equation with the Progress in Institutional Quality as Conditioning Variable, FE Specification

an idea about the magnitude of the effect of IMF program participation on countries' output growth, Tables 2.7 and 2.8 display counterfactual analyses for the panel models reported in Tables 2.3 and 2.5.

Table 2.7 reports that during participation in IMF loan programs countries between 1975 and 2004 had on average a real GDP per capita growth rate of 0.56%. The predicted value of this growth rate using the coefficients from the sample estimated only with country years under participation equals this 0.56%, while the fitted value using the same coefficients, but counterfactually setting the loan-quota ratio to zero, amounts to 0.45%. The predicted value using the coefficients from the sample estimated only with country years not under participation amounts to 1.40%. Non-participating countries actually had on average a real per capita GDP growth of 1.63%. The predicted value using the coefficients from the sample estimated only with country years not under participation amounts to 1.63% while the fitted value

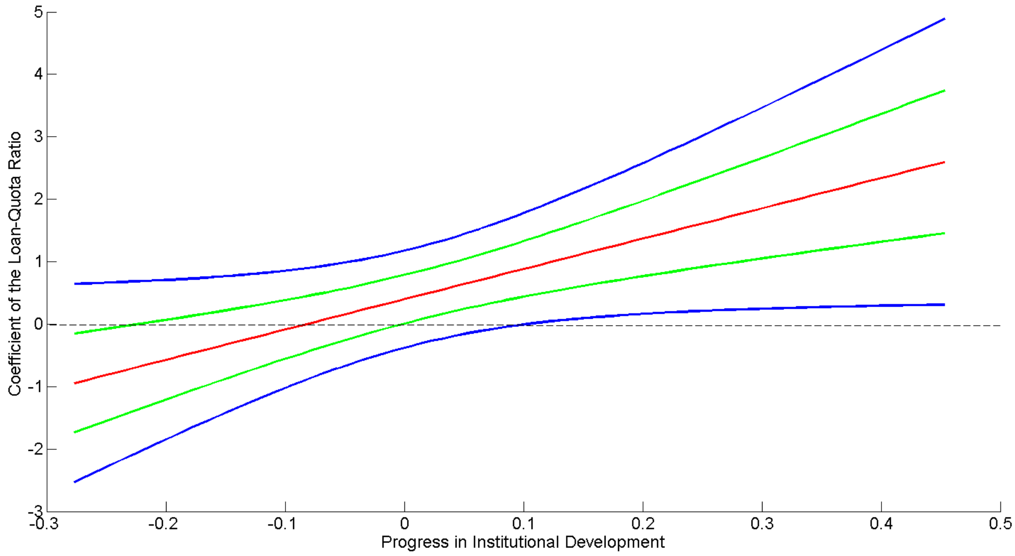


Figure 2.3: Effect of Program Participation Conditional on a Country's Progress in Institutional Development, FE Specification

Variables	Mean Effect	Contrib. in %
Loan-Quota Ratio	0.004	19.89
Loan-Quota Ratio * Instit. Dev.	0.001	2.33
Investment Share	0.007	35.11
Inflation	−0.001	− 6.06
Democracy	0.010	48.73
Sum	0.021	100.00

Table 2.6: Growth Accounting with the Progress in Institutional Quality as Conditioning Variable, FE Specification

Country years	Actual [a)]	Predicted[b)]	Predicted[c)]	Predicted[d)]
Particip.	0.56%	0.56%	0.45%	1.40%
Non-Particip.	1.63%	—	2.03%	1.63%

a) Actual average growth.

b) Coefficient estimates used to compute the counterfactual are taken from the model specification involving only country years with participation in IMF loan programs.

c) Coefficient estimates used to compute the counterfactual are taken from the model specification involving only country years with participation in IMF loan programs. The independent variable loan-quota ratio is always set to zero.

d) Coefficient estimates used to compute the counterfactual are taken from the model specification involving only country years without participation in IMF loan programs.

Table 2.7: Counterfactual Analysis with the Degree of Program Implementation as Conditioning Variable, FE Specification

Country years	Actual [a)]	Predicted[b)]	Predicted[c)]	Predicted[d)]
Particip.	0.52%	0.52%	0.05%	1.43%
Non-Particip.	1.53%	—	2.08%	1.53%

a) Actual average growth.

b) Coefficient estimates used to compute the counterfactual are taken from the model specification involving only country years with participation in IMF loan programs.

c) Coefficient estimates used to compute the counterfactual are taken from the model specification involving only country years with participation in IMF loan programs. The independent variable loan-quota ratio is always set to zero.

d) Coefficient estimates used to compute the counterfactual are taken from the model specification involving only country years without participation in IMF loan programs.

Table 2.8: Counterfactual Analysis with the Progress in Institutional Quality as Conditioning Variable, FE Specification

using the coefficients from the sample estimated only with countryyears under participation, but counterfactually setting the loan-quota ratio always to zero, amounts to 2.03%.

Three points are worth highlighting here. First, the second column of Table 2.7 highlights the fact that country years under IMF loan participation are times of (economic) crises. On average, countries had much lower output growth during years of participation in IMF loan programs. For this reason, it is imperative to properly capture the direction of causation in growth regressions involving development aid. Second, countries in economic crisis are, on average, better off when turning to the IMF and participating in IMF loan programs. The annual percentage gain amounts to 0.11% real per capita GDP growth per year. Nevertheless, as our results make clear, it is important for a country to comply with conditionality and improve upon its institutional quality. Third, according to our counterfactuals, countries that participated in IMF loan programs would have had an average growth rate of 1.40% had they not participated. This number is almost three times as high as their actual average growth rate and thus seems rather unrealistic. Our counterfactuals thus appear to provide evidence in favor of the presumption underlying our estimation strategy that countries entering IMF loan programs in times of crises have fundamentally different growth regimes than those countries that do not.

To learn more about the dynamic effects of IMF loan-program participation on a country's output growth, we finally turn to estimating the country's growth rates between $t-1$ and $t-1+i$, $i = 1, 2, ..., 5$, that can be attributed to IMF loan participation in year t.[28] Figures 2.4 and 2.5 display the intertemporal effects when taking the optimal specification of the fixed effects model with the amount-drawn-to-amount-agreed ratio or the progress in institutional development as conditioning state variable, respectively.

Tables 2.9 and 2.10 display the corresponding coefficients and their significance levels for all time periods.

The output growth effects of participation in IMF loan programs are sig-

[28] Note that it is not yet possible to use a dynamic model structure, in particular in the growth equation, in our sample selection model.

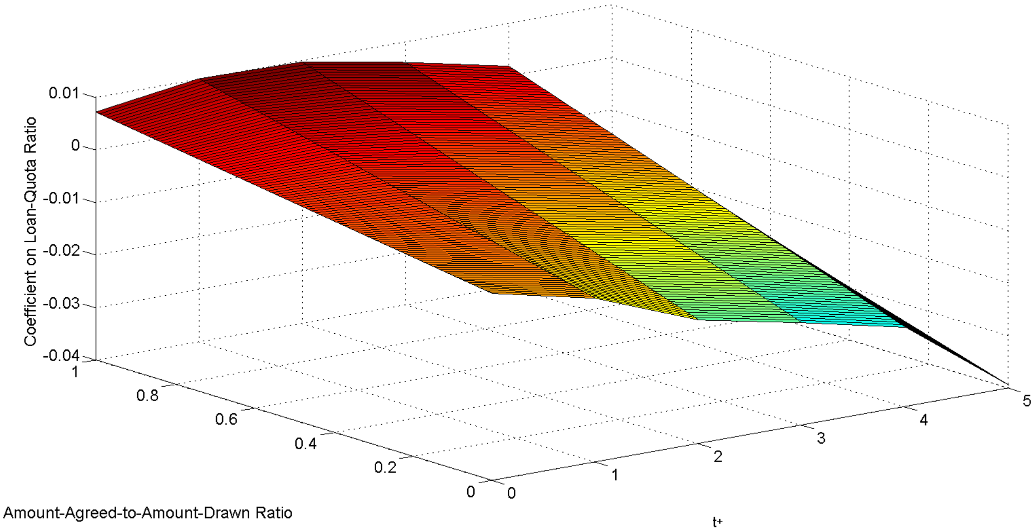


Figure 2.4: Effect of Program Participation in an Intertemporal Perspective with the Actual Degree of Program Implementation as Conditioning Variable, FE Specification

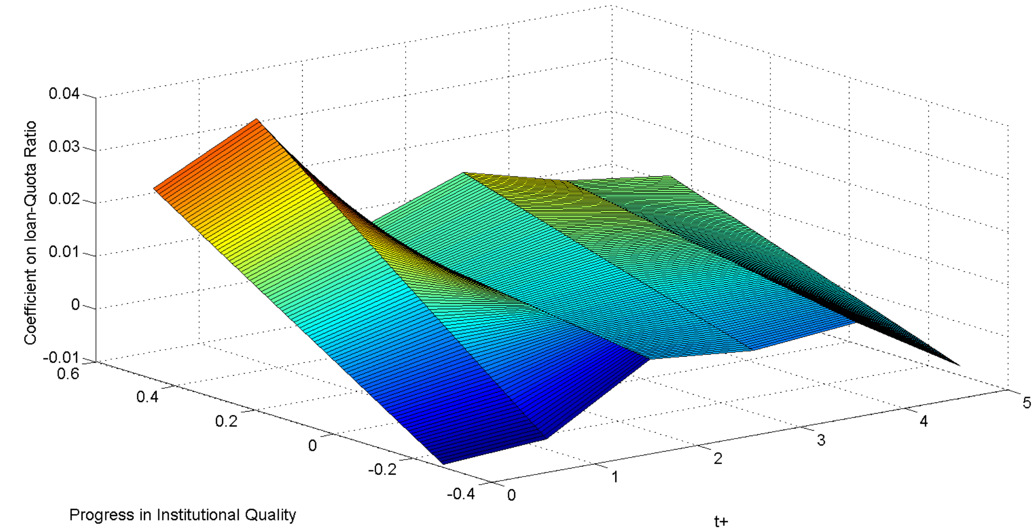


Figure 2.5: Effect of Program Participation in an Intertemporal Perspective with the Progress in Institutional Quality as Conditioning Variable, FE Specification

Dep. Variable	Loan-Quota Ratio	Loan-Quota Ratio*Drawn Ratio
$\frac{y_t - y_{t-1}}{y_{t-1}}$	-0.005 [1.046]	0.012** [2.333]
$\frac{y_{t+1} - y_{t-1}}{y_{t-1}}$	-0.009 [0.863]	0.019* [1.923]
$\frac{y_{t+2} - y_{t-1}}{y_{t-1}}$	-0.017 [0.932]	0.026** [2.166]
$\frac{y_{t+3} - y_{t-1}}{y_{t-1}}$	-0.021 [0.868]	0.027* [1.809]
$\frac{y_{t+4} - y_{t-1}}{y_{t-1}}$	-0.025 [0.765]	0.027 [1.336]
$\frac{y_{t+5} - y_{t-1}}{y_{t-1}}$	-0.040 [0.832]	0.023 [0.809]

Note: T-statistics are displayed in square brackets. A '*' indicates significance at the 10% level and a '**' indicates significance at the 5% level.

Table 2.9: Effect of Program Participation in an Intertemporal Perspective with the Degree of Program Implementation as Conditioning Variable, FE Specification

Dep. Variable	Loan-Quota Ratio	Loan-Quota Ratio*Instit. Dev.
$\frac{y_t - y_{t-1}}{y_{t-1}}$	0.004 [1.024]	0.049** [2.002]
$\frac{y_{t+1} - y_{t-1}}{y_{t-1}}$	0.008 [0.981]	0.060* [1.737]
$\frac{y_{t+2} - y_{t-1}}{y_{t-1}}$	0.006 [0.401]	0.110 [0.265]
$\frac{y_{t+3} - y_{t-1}}{y_{t-1}}$	0.008 [0.372]	0.023 [0.294]
$\frac{y_{t+4} - y_{t-1}}{y_{t-1}}$	0.007 [0.265]	0.014 [0.165]
$\frac{y_{t+5} - y_{t-1}}{y_{t-1}}$	-0.001 [0.028]	0.026 [0.333]

Note: T-statistics are displayed in square brackets. A '*' indicates significance at the 10% level and a '**' indicates significance at the 5% level.

Table 2.10: Effect of Program Participation in an Intertemporal Perspective with the Progress in Institutional Quality as Conditioning Variable, FE Specification

nificant for up to three years after participation in an IMF loan program. For all time periods the output growth effects of participation in IMF loan programs are more favorable if a country complies with conditionality / improves on institutional development.

The following section concludes.

2.6 Conclusion

Through modelling conditionality of the output growth effects of IMF program participation, in this chapter we have shed light on what appears to be a major reason as to why previous empirical studies have arrived at mixed results, ranging from positive output growth effects to no effects to negative effects from IMF program participation. Allowing the effects of IMF program participation to vary systematically with the degree of program implementation or an index of institutional development, we find that there are significant positive effects of IMF program participation on a country's output growth only if the IMF programs are implemented to a sufficient degree or if the program participation is coupled with sufficient progress in institutional quality.

With regards to the magnitude of these output growth effects, our growth accounting calculations provide evidence that IMF loans have a sizeable impact. Their output growth effect, in absolute size, is larger than that of inflation, for example, though much smaller than that of investment in physical capital.

Our counterfactual analysis provides evidence that countries participating in IMF loan programs would on average have had lower output growth, had they not participated in IMF loan programs. The higher the degree of program implementation and improvement in institutional quality, the higher the potential gains from participating in IMF loan programs. We also find that output growth effects of IMF program participation are significant for up to three years after program participation, and are significantly positive if participating countries comply with conditionality. Countries that decide to turn to the IMF for funding appear well advised to comply with IMF conditionality and to make every effort in improving their institutional environment.

Appendix 2.A: Computation of Conditional Expectations and of Standard Errors

In this appendix we first discuss the computation of the conditional expectation in Equation (2.10) needed to correct the output growth equation, that is Equation (2.1), under the random effects specification for sample selection bias, while also allowing for endogeneity of d_{it}.[29] The conditional expectation of v_{it} given $\boldsymbol{Z}_i, \boldsymbol{d}_i$, and α_i on the right hand side of Equation (2.2) is calculated as follows:

$$E(v_{it}|\boldsymbol{Z}_i, \boldsymbol{d}_i, \alpha_i) = [d_{it} - (\alpha_i + \boldsymbol{z}'_{it}\boldsymbol{\gamma})]\, 1_{(d_{it}>0)} - \left(\sigma_v \frac{\phi(\frac{\alpha_i + \boldsymbol{z}'_{it}\boldsymbol{\gamma}}{\sigma_v})}{\Phi(\frac{-\alpha_i - \boldsymbol{z}'_{it}\boldsymbol{\gamma}}{\sigma_v})} \right) 1_{(d_{it}=0)}, \tag{2.23}$$

where ϕ and Φ denote the standard normal probability and cumulative density functions, respectively, and $1(\cdot)$ denotes the indicator function.

Using this expression, the conditional expectation of u_{it} given $\boldsymbol{Z}_i$ and $\boldsymbol{d}_i$, Equation (2.10), can be obtained as:

$$E(u_{it}|\boldsymbol{Z}_i, \boldsymbol{d}_i) = \int \left\{ \alpha_i + [d_{it} - (\alpha_i + \boldsymbol{z}'_{it}\boldsymbol{\gamma})]\, 1_{(d_{it}>0)} - \sigma_v \frac{\phi(\frac{\alpha_i + \boldsymbol{z}'_{it}\boldsymbol{\gamma}}{\sigma_v})}{\Phi(\frac{-\alpha_i - \boldsymbol{z}'_{it}\boldsymbol{\gamma}}{\sigma_v})} 1_{(d_{it}=0)} \right\} \cdot \frac{\left[\prod_{t=1}^{T} \Phi(\frac{-\alpha_i - \boldsymbol{z}'_{it}\boldsymbol{\gamma}}{\sigma_v}) 1_{(d_{it}=0)} \frac{1}{\sigma_v}\phi(\frac{d_{it} - \alpha_i - \boldsymbol{z}'_{it}\boldsymbol{\gamma}}{\sigma_v}) 1_{(d_{it}>0)}\right]}{\int \left[\prod_{t=1}^{T} \Phi(\frac{-\alpha_i - \boldsymbol{z}'_{it}\boldsymbol{\gamma}}{\sigma_v}) 1_{(d_{it}=0)} \frac{1}{\sigma_v}\phi(\frac{d_{it} - \alpha_i - \boldsymbol{z}'_{it}\boldsymbol{\gamma}}{\sigma_v}) 1_{(d_{it}>0)}\right]} \cdot \frac{\frac{1}{\sigma_\alpha}\phi(\frac{\alpha_i}{\sigma_\alpha})}{\frac{1}{\sigma_\alpha}\phi(\frac{\alpha_i}{\sigma_\alpha}) d\alpha_i} d\alpha_i \quad . \tag{2.24}$$

When obtaining standard errors for the estimates of the parameters of the output growth equation under the two-step procedure of Section 2.2, the sampling uncertainty that has entered the construction of the correction factors $\hat{u}_{it}$ and $\hat{\bar{u}}_i$ needs to be observed. The following estimator of

[29] Note that the conditional expectation $E(\tilde{u}_{it}|\boldsymbol{Z}_i, \boldsymbol{d}_i, \boldsymbol{g}_i)$ arising under the fixed effects specification can be computed in analogous fashion, and thus need not be considered separately.

the variance-covariance matrix of $\boldsymbol{\pi} = (\theta\ \boldsymbol{\beta}'\ \tau_1\ \tau_2)'$ reflects this sampling uncertainty:

$$\hat{Var}_N = \frac{1}{N}\hat{\boldsymbol{G}}_N^{-1}\left(\hat{\boldsymbol{V}}_N + \hat{\boldsymbol{D}}_N\hat{\boldsymbol{W}}_N\hat{\boldsymbol{D}}_N'\right)\hat{\boldsymbol{G}}_N^{-1}, \tag{2.25}$$

where $\hat{\boldsymbol{W}}_N = \hat{Var}_N(\hat{\boldsymbol{\gamma}})$,

$$\hat{\boldsymbol{G}}_N = \frac{1}{N}\sum_{i=1}^{N}\boldsymbol{R}_i'\boldsymbol{R}_i, \tag{2.26}$$

$$\hat{\boldsymbol{V}}_N = \frac{1}{N}\sum_{i=1}^{N}\boldsymbol{R}_i'\hat{\boldsymbol{e}}_i\hat{\boldsymbol{e}}_i'\boldsymbol{R}_i, \tag{2.27}$$

$$\hat{\boldsymbol{D}}_N = \frac{1}{N}\sum_{i=1}^{N}\boldsymbol{R}_i'\frac{\partial\left[(\hat{\boldsymbol{u}}_i\ \hat{\hat{u}}_i\boldsymbol{\iota})\ \hat{\boldsymbol{\tau}}\right]}{\partial\boldsymbol{\gamma}}\,|_{\boldsymbol{\gamma}=\hat{\boldsymbol{\gamma}}}, \tag{2.28}$$

with

$$\boldsymbol{R}_i = \left(\boldsymbol{d}_i\ \boldsymbol{x}_i'\ \hat{\boldsymbol{u}}_i\ \hat{\hat{u}}_i\boldsymbol{\iota}\right), \tag{2.29}$$

$$\boldsymbol{\tau} = (\tau_1\ \tau_2)', \tag{2.30}$$

and $\boldsymbol{\iota}$ is again a vector of ones of size T_i. Note that if $\tau_2 = 0$ is imposed in the estimation, then it appears sensible to also impose that $\hat{\boldsymbol{e}}_i\hat{\boldsymbol{e}}_i'$ is a diagonal matrix (reflecting that e_{it} is restricted to be intertemporally uncorrelated).

Computation of the standard errors of the growth equation parameter estimates under the fixed effects specification can proceed in analogy to Equations (2.25) and (2.30).

Appendix 2.B: Description of Variables

Variables	Source
Amount-drawn-to-amount-agreed ratio: The amount of all IMF loan program funds a country actually draws expressed as a share of the original amount agreed upon with the IMF.	International Financial Statistics and own calculations
Bureaucracy quality: Assesses the institutional strength and quality of the bureaucracy.	International Country Risk Guide
Corruption: Assesses corruption within the political system.	International Country Risk Guide
Democracy index: Based of the Legal Index of Electoral Competitiveness (LIEC); Codified with 1 if it has a value of 6 or larger which is the threshold for democratic systems.	World Bank Political Institutions Dataset
Economic proximity to major Europe: Bilateral trade with major Europe (France, Germany, United Kingdom), expressed as a ratio to GDP.	Barro and Lee (2005)
Educational attainment: Total population aged 15 and over, average years of school.	Worldbank
Ethnic tensions: Assesses the degree of tension within a country attributable to racial, nationality, or language divisions.	International Country Risk Guide
Fertility rate: Number of children that are born to a woman if she lives to the end of her childbearing years and bears children in accordance with current age-specific fertility rates.	World Development Indicators 2006 CD-ROM
Freedom of the press: Assesses the degree of freedom of the press in a country.	Freedom House
Freedom status: Assesses political rights and civil liberties in a country.	Freedom House
Government share of real GDP: Percentage in 2000 constant prices.	Penn World Tables 6.2
Government stability: Assesses the government's ability to carry out its declared program(s) and its ability to stay in office.	International Country Risk Guide
Inflation: Annual percentage change of the consumer price index.	World Development Indicators 2006 CD-ROM
Institutional index: Set up from the variables educational attainment, life expectancy, government stability, bureaucracy quality, corruption, law and order, ethnic tensions, and internal conflict	International Country Risk Guide and own calculations
Internal conflict: Assesses the political violence in the country and its actual or potential impact on governance.	International Country Risk Guide
Investment share of real GDP: Percentage in 2000 constant prices.	Penn World Tables 6.2
Law and order: Assesses the strength and impartiality of the legal system as well as the popular observance of the law.	International Country Risk Guide
Life expectancy at birth: Expresses the number of years a newborn can be expected to live if prevailing patterns of mortality at the time of its birth are the same throughout its life.	World Development Indicators 2006 CD-ROM
Loan-quota ratio: Sum of all current IMF loans a country is eligible to as a share of its quota at the IMF.	International Financial Statistics and own calculation
Openness in constant prices: Percentage in 2000 constant prices.	Penn World Tables 6.2
Political proximity to major Europe: Fraction of UN votes along with major Europe (France, Germany, United Kingdom).	Barro and Lee (2005)
Quota: Countries' quota in millions of standard drawing rights (SDR).	International Financial Statistics
Real GDP per capita: International Dollar in 2000 constant prices, thousand dollars.	Penn World Tables 6.2
Total reserves in months of imports: Amount of reserves in terms of the number of months of imports of goods and services which can be paid.	World Development Indicators 2006 CD-ROM

Appendix 2.C: Countries Contained in Data Set[30]

Country	Start : end of sample	Years with Program Participation	Country	Start : end of sample	Years with Program Participation
Algeria	1977:1991	1989:1991	**Liberia**	1979:1987	1979:1985
Argentina	1976:2004	1976:1978; 1983:2004	**Madagascar**	1975:2003	1977:1978; 1980:1992; 1996:2003
Australia	1975:2004	%	**Malawi**	1981:2002	1981:1986; 1988:2002
Austria	1975:2004	%	**Malaysia**	1975:2003	%
Bangladesh	1987:2003	1987:1993; 2003:2003	**Mali**	1989:2003	1989:2003
Belgium	1975:2001	%	**Mexico**	1979:2004	1979:1979; 1983:1993; 1995:1997; 1999:2000
Bolivia	1976:2003	1980:1980; 1986:2003	**Morocco**	1975:2003	1980:1993
Botswana	1976:2003	%	**Mozambique**	1988:2003	1988:2003
Brazil	1981:2003	1983:1986; 1988:1990; 1992:1993; 1998:2003	**Namibia**	2003:2003	%
Burkina Faso	1975:2001	1991:2001	**Netherlands**	1975:2004	%
Cameroon	1977:1995	1988:1992; 1994:1995	**New Zealand**	1975:2004	%
Canada	1975:2004	%	**Nicaragua**	1977:2004	1979:1979; 1991:2004
Chile	1975:2004	1975:1976; 1983:1990	**Niger**	1975:2003	1983:1991; 1994:2003
Colombia	1975:2003	1999:2003	**Nigeria**	1977:2004	1987:1987; 1989:1992; 2000:2001
Congo, Rep.	1986:2003	1986:1988;1990:1992; 1994:1999	**Norway**	1975:2004	%
Costa Rica	1977:2004	1977:1977; 1980:1983; 1985:1997	**Pakistan**	1976:2004	1977:1978; 1980:1983; 1988:1991; 1993:2004
Cote d'Ivoire	1975:2003	1981:1992; 1994:2003	**Panama**	1977:2003	1977:1987; 1992:2002
Cyprus	1976:2004	1980:1981	**Papua New Guinea**	1976:2001	1990:1992; 1995:1997; 2000:2001
Denmark	1975:2004	%	**Paraguay**	1975:2003	2003:2003
Dominican Republic	1975:2003	1983:1986; 1991:1994; 2003:2003	**Peru**	1977:2003	1977:1980; 1982:1985; 1993:2003
Ecuador	1976:2004	1983:1992; 1994:1995; 2000:2001; 2003:2004	**Philippines**	1977:2004	1977:1981; 1983:2000
Egypt, Arab Rep.	1977:2003	1977:1981; 1987:1988; 1991:1998	**Portugal**	1976:2004	1977:1979; 1983:1985
El Salvador	1976:2003	1980:1983; 1990:2000	**Senegal**	1975:2003	1979:1992; 1994:2003
Finland	1975:2004	1975:1976	**Sierra Leone**	1977:2003	1977:1982; 1984:1989; 1994:1998; 2001:2003
France	1975:2004	%	**Singapore**	1975:2004	%
Gambia, The	1978:1997	1978:1980; 1982:1991	**South Africa**	1975:2004	1976:1977; 1982:1983
Germany	1992:2004	%	**Spain**	1975:2004	1978:1979
Ghana	1975:2003	1979:1979; 1983:1992; 1995:2003	**Sri Lanka**	1975:2003	1975:1975; 1977:1981; 1983:1984; 1988:1995; 2001:2003
Greece	1976:2004	%	**Sudan**	1977:2003	1979:1985
Guatemala	1977:2003	1981:1984; 1988:1990; 1992:1994; 2002:2003	**Sweden**	1975:2004	%
Guinea-Bissau	1988:2003	1988:1990; 1995:1998; 2000:2003	**Syrian Arab Rep.**	1977:1988	%
Haiti	1975:2000	1975:1990; 1995:1999	**Thailand**	1975:2003	1978:1979; 1981:1983; 1985:1986; 1997:2000
Honduras	1975:2004	1979:1983; 1990:1997; 1999:2002; 2004:2004	**Togo**	1975:2003	1979:1998
India	1975:2003	1981:1984; 1991:1993	**Trinidad and Tobago**	1975:2003	1989:1991
Indonesia	1981:2004	1997:2003	**Tunisia**	1984:2004	1986:1992
Ireland	1975:2004	%	**Turkey**	1975:2004	1978:1985; 1994:1996; 1999:2004
Israel	1975:2004	1975:1977	**Uganda**	1981:2003	1981:1984; 1987:2003
Italy	1975:2004	1975:1975; 1977:1978	**United Kingdom**	1975:2004	1975:1978
Jamaica	1976:2003	1977:1996	**United States**	1975:2004	%
Japan	1977:2004	%	**Uruguay**	1978:2004	1978:1987; 1990:1993; 1996:2004
Jordan	1975:2003	1989:1990; 1992:2003	**Venezuela, RB**	1975:2004	1989:1993; 1996:1997
Kenya	1975:2003	1975:1986; 1988:1994; 1996:2003	**Zambia**	1986:2000	1986:1987,1995:2000
Korea, Rep.	1976:2004	1976:1977; 1980:1987; 1997:2000	**Zimbabwe**	1980:1994	1981:1984; 1992:1994

[30] Major oil exporting countries, centrally planned economies, and island economies have been excluded.

Appendix 2.D: Results for the Random Effects Panel Model

Independent Variables	**Coefficients**
Investment Share	-1.174^{***} [4.013]
Inflation	-0.016^{**} [2.798]
Government Share	0.513^{**} [2.359]
Number of Years under IMF Programs	0.021^{***} [7.562]
Staffshare at IMF	-0.029 [1.630]
Political Proximity to Major Europe	-0.123^{**} [2.682]
Reserves	-0.047 [0.692]
Current Account	-0.173 [0.903]
Openness	-0.123^{**} [2.257]
Democracy	-0.013^{**} [1.967]
Number of Observations for the selection equation:	2439

Note: Estimation results are obtained by estimating Equation (2.2). The dependent variable is the loan-quota ratio. The McFadden pseudo R-squared for the regression equals 0.031. t-statistics are displayed in square brackets underneath the coefficient estimates. A '*' indicates significance at the 10% level, a '**' indicates significance at the 5% level, and a '***' indicates significance at the 1% level. The regression uses annual data, the sample extends from 1975 to 2004, and the number of countries considered is 73. A description of all variables used is provided in Appendix 2.B at the end of the chapter.

Table 2.12: Regression Results for the Participation Selection Equation, RE Specification

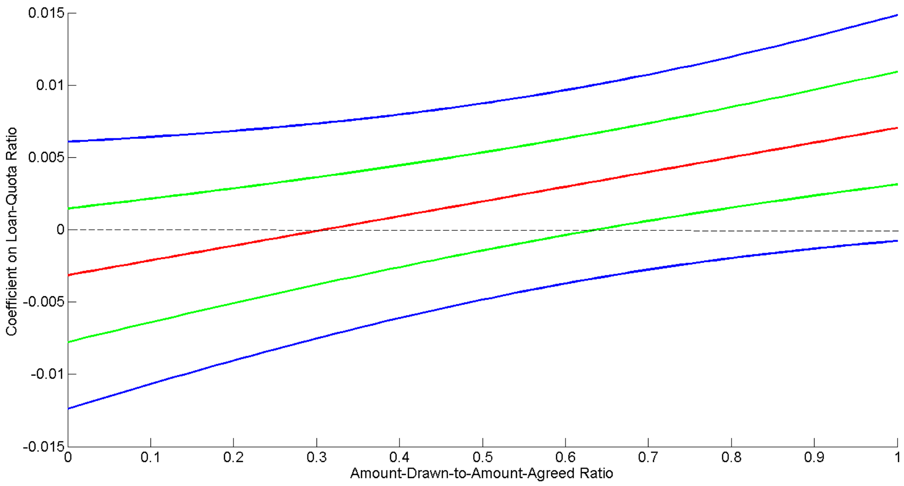


Figure 2.6: Effect of Program Participation Conditional on Actual Degree of Program Implementation, RE Specification

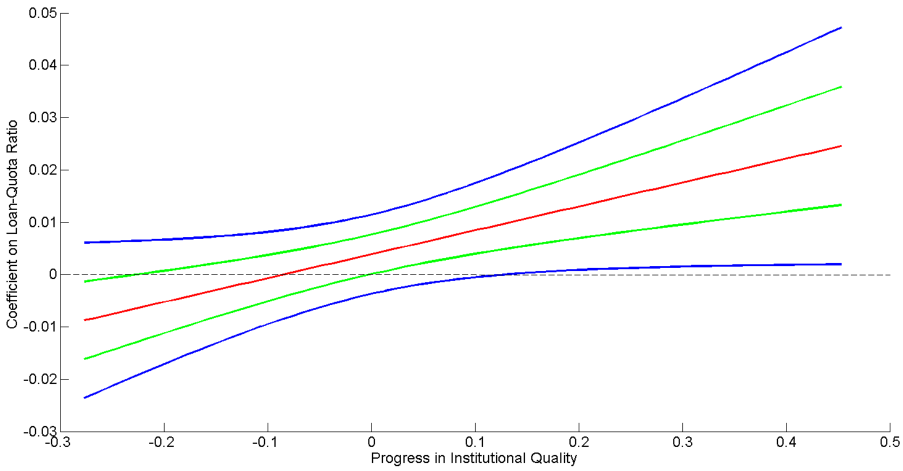


Figure 2.7: Effect of Program Participation Conditional on a Country's Progress in Institutional Quality, RE Specification

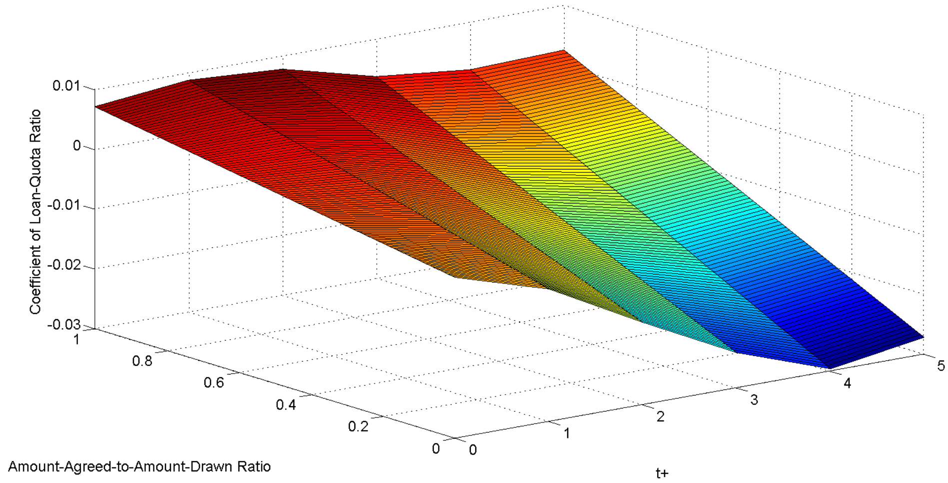


Figure 2.8: Effect of Program Participation in an Intertemporal Perspective with the Actual Degree of Program Implementation as Conditioning Variable, RE Specification

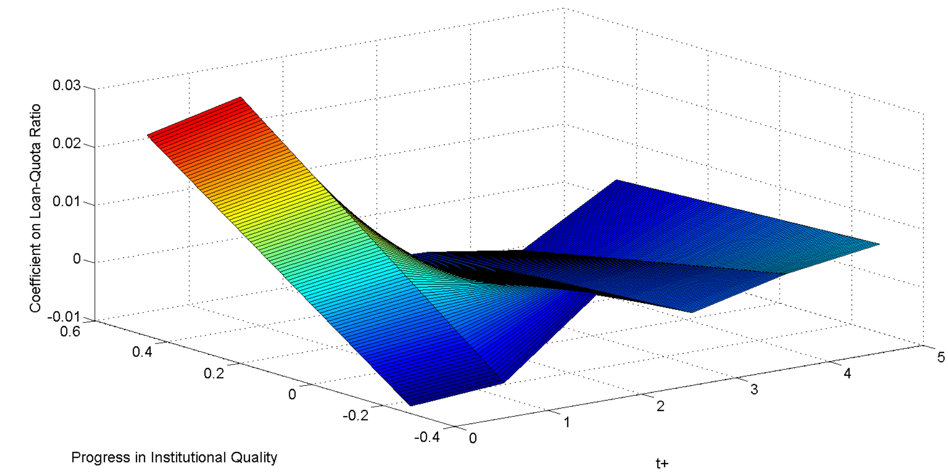


Figure 2.9: Effect of Program Participation in an Intertemporal Perspective with the Progress in Institutional Quality as Conditioning Variable, RE Specification

Independent Variables	**Coefficients**
Loan-Quota Ratio	−0.003 [0.682]
*Loan-Quota Ratio * Drawn Ratio*	0.010* [1.955]
Investment Share	0.138** [2.910]
Inflation	−0.003*** [4.873]
Reserves	0.022* [1.882]
Number of Observations:	931

Note: Estimation results are obtained by estimating Equation (2.1). The F-test of joint significance of the correction terms, τ_1 and τ_2, is not significant, but τ_1 is individually significant at the 10% significance level, indicating correlation between the idiosyncratic error terms. The conditioning variable, amount-drawn-to-agreed ratio, has been used as control variable also (not displayed), and is not significant. The dependent variable is real growth per capita GDP. The adjusted R-squared for the regression equals 0.051. t-statistics are displayed in square brackets underneath the coefficient estimates. A '*' indicates significance at the 10% level, a '**' indicates significance at the 5% level, and a '***' indicates significance at the 1% level. The regression uses annual data, the sample extends from 1975 to 2004, and the number of countries considered is 73. A description of all variables used is provided in Appendix 2.B at the end of the chapter.

Table 2.13: Regression Results for the Participation Effects Equation with the Actual Degree of Program Implementation as Conditioning Variable, RE Specification

Variables	Mean Effect	Contrib. in %
Loan-Quota Ratio	−0.003	−14.29
Loan-Quota Ratio * Drawn Ratio	0.005	21.91
Investment Share	0.015	71.32
Inflation	−0.001	− 5.59
Democracy	0.006	26.64
Sum	0.021	100.00

Table 2.14: Growth Accounting with the Actual Degree of Program Implementation as Conditioning Variable, RE Specification

Independent Variables	**Coefficients**
Loan-Quota Ratio	0.004 [1.021]
*Loan-Quota Ratio * Institutional Development*	0.046 * [1.955]
Investment Share	0.140 * [1.953]
Inflation	−0.003 *** [4.011]
Democracy	0.002 [1.138]
Reserves	0.017 [1.404]
Number of Observations:	852

Note: Estimation results are obtained by estimating Equation (2.1). The F-test of joint significance of the correction terms, τ_1 and τ_2, is not significant. The conditioning variable, growth of the index of institutional quality, has been used as control variable also (not displayed), and is not significant. The dependent variable is real GDP per capita growth. The adjusted R-squared for the regression equals 0.057. t-statistics are displayed in square brackets underneath the coefficient estimates. A '*' indicates significance at the 10% level, a '**' indicates significance at the 5% level, and a '***' indicates significance at the 1% level. The regression uses annual data, the sample extends from 1975 to 2004, and the number of countries considered is 65. A description of all variables used is provided in Appendix B at the end of the chapter.

Table 2.15: Regression Results for the Participation Effects Equation with the Progress in Institutional Quality as Conditioning Variable, RE Specification

Variables	Mean Effect	Contrib. in %
Loan-Quota Ratio	0.004	12.21
Loan-Quota Ratio * Instit. Dev.	0.001	1.43
Investment Share	−0.001	− 4.04
Inflation	0.009	28.55
Democracy	0.004	13.68
Sum	0.021	100.00

Table 2.16: Growth Accounting with the Progress in Institutional Quality as the Conditioning Variable, RE Specification

Country years	Actual[a)]	Predicted[b)]	Predicted[c)]	Predicted[d)]
Particip.	0.61%	0.61%	0.44%	2.91%
Non-Particip.	2.09%	—	2.18%	2.09%

a) Actual average growth.

b) Coefficient estimates used to compute the counterfactual are taken from the model specification involving only country years with participation in IMF loan programs.

c) Coefficient estimates used to compute the counterfactual are taken from the model specification involving only country years with participation in IMF loan programs. The independent variable loan-quota ratio is always set to zero.

d) Coefficient estimates used to compute the counterfactual are taken from the model specification involving only country years without participation in IMF loan programs.

Table 2.17: Counterfactual Analysis with the Actual Degree of Program Implementation as Conditioning Variable, RE Specification

Country years	Actual[a)]	Predicted[b)]	Predicted[c)]	Predicted[d)]
Particip.	0.57%	0.57%	0.13%	2.61%
Non-Particip.	2.06%	—	2.27%	2.06%

a) Actual average growth.

b) Coefficient estimates used to compute the counterfactual are taken from the model specification involving only country years with participation in IMF loan programs.

c) Coefficient estimates used to compute the counterfactual are taken from the model specification involving only country years with participation in IMF loan programs. The independent variable loan-quota ratio is always set to zero.

d) Coefficient estimates used to compute the counterfactual are taken from the model specification involving only country years without participation in IMF loan programs.

Table 2.18: Counterfactual Analysis with the Progress in Institutional Quality as Conditioning Variable, RE Specification

Dep. Variable	Loan-Quota Ratio	Loan-Quota Ratio*Drawn Ratio
$\frac{y_t - y_{t-1}}{y_{t-1}}$	-0.003 [0.682]	0.010* [1.955]
$\frac{y_{t+1} - y_{t-1}}{y_{t-1}}$	-0.008 [0.861]	0.017 [1.669]
$\frac{y_{t+2} - y_{t-1}}{y_{t-1}}$	-0.016 [1.226]	0.024** [2.060]
$\frac{y_{t+3} - y_{t-1}}{y_{t-1}}$	-0.024 [1.390]	0.028** [2.074]
$\frac{y_{t+4} - y_{t-1}}{y_{t-1}}$	-0.030 [1.265]	0.032* [1.751]
$\frac{y_{t+5} - y_{t-1}}{y_{t-1}}$	-0.027 [0.925]	0.030 [1.325]

Note: T-statistics are displayed in square brackets. A '*' indicates significance at the 10% level and a '**' indicates significance at the 5% level.

Table 2.19: Effect of Program Participation in an Intertemporal Perspective with the Actual Degree of Program Implementation as Conditioning Variable, RE Specification

Dep. Variable	Loan-Quota Ratio	Loan-Quota Ratio*Instit. Dev.
$\frac{y_t - y_{t-1}}{y_{t-1}}$	0.004 [1.021]	0.046* [1.955]
$\frac{y_{t+1} - y_{t-1}}{y_{t-1}}$	0.006 [0.878]	0.049 [1.320]
$\frac{y_{t+2} - y_{t-1}}{y_{t-1}}$	0.002 [0.173]	-0.120 [0.274]
$\frac{y_{t+3} - y_{t-1}}{y_{t-1}}$	-0.020 [0.144]	-0.004 [0.050]
$\frac{y_{t+4} - y_{t-1}}{y_{t-1}}$	-0.001 [0.036]	-0.013 [0.161]
$\frac{y_{t+5} - y_{t-1}}{y_{t-1}}$	0.004 [0.181]	-0.003 [0.038]

Note: T-statistics are displayed in square brackets. A '*' indicates significance at the 10% level and a '**' indicates significance at the 5% level.

Table 2.20: Effect of Program Participation in an Intertemporal Perspective with the Progress in Institutional Quality as Conditioning Variable, RE Specification

Chapter 3

Systemic Risk in an Interconnected Banking System with Endogeneous Asset Markets[1]

In a manner unexpected only a few years ago, the global financial crisis which started in 2007 has demonstrated that a system of interconnected financial institutions may be subject to a systemic breakdown, with large effects on the real economy. In this chapter a numerical model is used to analyze a network of financial institutions subject to capital requirements. The model allows to replicate important stylized facts of systemic risk which emerged during the recent financial crisis. We then introduce the concept of a System Value at Risk (SVaR) which allows to simultaneously determine both, a fair risk charge as well as the optimal macroprudential capital endowment, for financial institutions in the system. Among other things we find that there is not necessarily a correspondence between a bank's[2] contribution to systemic risk – which determines its risk charge – and the capital that is optimally injected into it to make the financial system more resilient to systemic risk.

Depending on the sources of systemic risk assessed and the various potential consequences on the financial system as well as on the real economy,

[1]This chapter is joint work with Jan Pieter Krahnen, Goethe-Universität Frankfurt am Main.

[2]In the following 'banks' and 'financial institutions' will be used interchangeably.

there is not a single definition of systemic risk.[3] An early definition of systemic risk was given in Group of Ten: "Systemic financial risk is the risk that an event will trigger a loss of economic value or confidence in, and attendant increases is uncertainly about, a substantial portion of the financial system that is serious enough to quite probably have significant adverse effects on the real economy. Systemic risk events can be sudden and unexpected, or the likelihood of their occurrence can build up through time in the absence of appropriate policy responses. The adverse real economic effects from systemic problems are generally seen arising from disruptions to the payment system, to credit flows, and from the destruction of asset values."[4] Lo (2009) proposes analyzing a set of risk measures to capture systemic risk in the entire financial system. These risk measures capture the six dimensions 'leverage', 'liquidity', 'correlation', 'concentration', 'sensitivities', and 'connectedness'. The IMF defines systemic risk as "large losses to other financial institutions induced by the failure of a particular institution due to its interconnectedness"[5] and the Financial Stability Board, International Monetary Fund, and Bank for International Settlements describe systemic risk in a report to the G-20 as "a risk of disruption to financial services that is (i) caused by an impairment of all or parts of the financial system and (ii) has the potential to have serious negative consequences for the real economy".[6] Following closely the latter definition, in this chapter we define systemic risk as the danger that failures within the financial system will mean that an adequate supply of credit and financial services to the economy is no longer guaranteed, so that negative real effects will follow.

A main driver of the recent financial crisis was the constitution of the financial system.[7] Highly leveraged, to a large extent homogeneous (with

[3] See Chapter 2 of International Monetary Fund (2009) for a comprehensive discussion of different definitions of systemic risk.

[4] Group of Ten (2001), p. 126.

[5] Chapter 2 of International Monetary Fund (2010), p. 2.

[6] Financial Stability Board, International Monetary Fund, and Bank for International Settlements (2009), p. 2.

[7] For a general overview on the causes and consequences of the recent financial crisis see, *inter alia*, Issing, Asmussen, Krahnen, Regling, Weidmann, and White (2009), Borio (2008), Brunnermeier (2009), and Gorton (2010a).

respect to their portfolio structure) financial institutions, comprising the banking as well as the shadow-banking system,[8] with interconnected, mostly obscure balance sheets rendered the financial system fragile. In the course of the crisis numerous institutions had to be bailed out because their insolvency would have put the financial system at risk via triggering a cascade of other financial institutions' defaults. Arising systemic risk was essentially driven by three factors: (i) Size of financial institutions as well as the (ii) direct and (iii) indirect interconnectedness between financial institutions.

First of all, the default of a financial institution which is relatively large can put the financial system at risk. For example, in line with our definition of systemic risk, one can expect that the insolvency of the bank UBS would constitute a serious threat to the financial system and the real economy of Switzerland, the effects of interconnectedness with other institutions not even considered. Institutions of which a default would have threatened the financial system and the wider economy because of their mere size were called 'too-big-to-fail' in the recent financial crisis.

Second, banks that are highly interlinked with other financial institutions can also threaten the financial system through counterparty exposure. If such a bank defaults on its liabilities it can directly induce losses on its creditor banks which on their part might spread the shock further in case they also default. For example, during the recent financial crisis, the insurance company American International Group (AIG) was bailed out because it was highly interlinked with many financial institutions through Credit Default Swaps (CDS). A default of AIG would thus have exposed a large part of the financial system to huge potential losses.

Third, indirect connections between financial institutions can also make the financial system vulnerable. If banks invest in identical or correlated financial products their balance sheets can become correlated. Losses can induce one or several banks to deleverage via liquidating large parts of assets on the market, eventually resulting in a decline of prices for those assets.

[8]For an analysis of the role of the shadow banking system in the recent financial crisis see Gorton (2010b) who compares the breakdown of the shadow banking system to historical bank runs.

Other banks that have invested into the same or to some extent correlated assets then face a loss when marking their assets to market. Furthermore, these banks might thus also be induced to sell assets on the market which can further depress prices, eventually forcing other banks to also deleverage etc. Ultimately this cascade creates firesales[9] and indirectly transmit shocks between financial institutions with correlated balance sheets via markets. Shocks can thus spread directly and indirectly through the financial system. Institutions that threaten the financial system through a contagious casacade of defaults because of their interconnectedness with the financial system were labelled 'too-interconnected-to-fail' during the recent financial crisis.

Figure 3.1 gives an outline of how balance sheets of financial institutions are interconnected. Solid lines depict direct interconnections while dashed lines depict indirect interconnections. The direction of the arrows indicates exposure towards another bank. For example, the arrow from the interbank lendings of bank 2 to the interbank borrowings of bank 1 represents counterparty exposure of bank 2 towards bank 1.

On the stylized balance sheet from Figure 3.1 banks' assets consist of liquid and non-liquid assets as well as interbank lendings. Liquid assets are, for example, cash and cash equivalents. Non-liquid assets are, for example, Collateralized Debt Obligations (CDO) and need to be marked to market if they are held in a bank's trading book. Interbank lendings are, for example, credits given to other financial institutions. Distinguishing between liquid and illiquid assets is important because one of the main drivers of systemic risk during the recent financial crisis consisted of banks which were cut off from liquidity on the interbank markets and thus had to sell illiquid assets, resulting in self-energizing firesales. Banks' liabilities consist of deposits, interbank borrowings, and equity. Below the stylized balance sheets on Figure 3.1 in dashed lines are conditional assets and liabilities, for example CDS.

To mitigate the risk of future financial meltdowns it has become consensus that, in addition to microprudential supervision, supervisors need to set up an additional layer of macroprudential regulation and supervi-

[9]See Gorton and Metrick (2009) and Gorton (2009) for a detailed analysis of the mechanism underlying firesales.

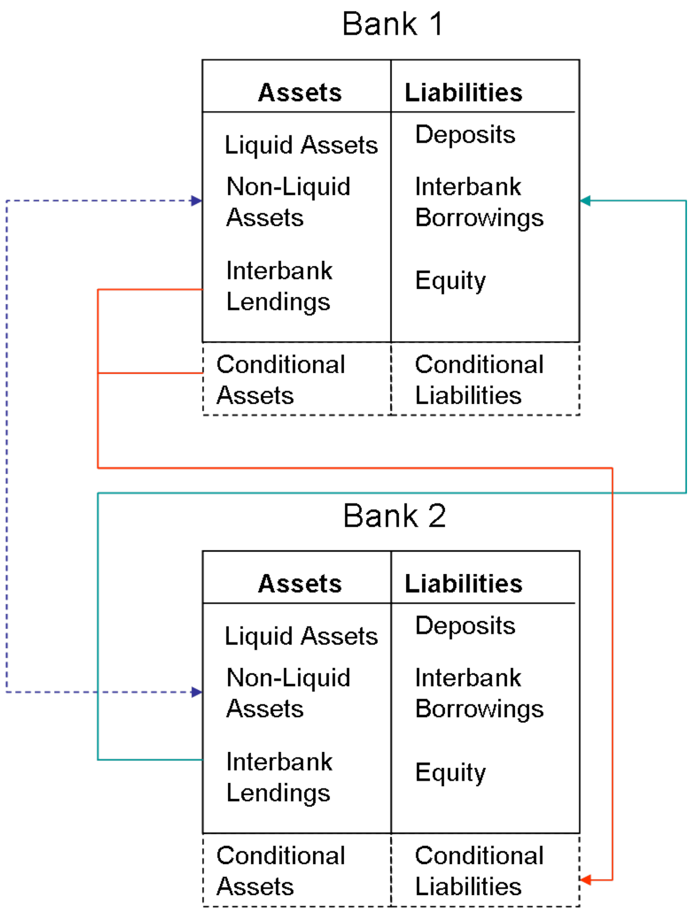


Figure 3.1: Interconnections Between Financial Institutions

sion which shall allow to identify system-wide risk drivers, monitor systemic risk, and react adequately to it. Systemic risk is a negative externality of financial institutions on the financial system. Without charging them for this negative externality, financial institutions are perversely incentivized to increase their contribution to systemic risk via becoming too-big-to-fail or too-interconnected-to-fail because it allows them to take advantage from resulting cheap refinancing opportunities.

To analyze systemic risk and banks' contributions to it, we develop a network of interrelated bank balance sheets with endogeneous asset markets. Our model reproduces the main stylized facts with regards to systemic risk that emerged during the recent financial crisis. We then introduce the concept of SVaR in which a Pigouvian tax is used to capitalize a systemic risk fund. The capital from the systemic risk fund is re-injected into the financial system to make it more resilient to systemic risk. The optimal amount of capital for the systemic risk fund as well as the necessary proportions of capital injected into financial institutions are determined with a parallelized simulated annealing approach.

Our analysis provides evidence that there is not neccessarily a correspondence between a bank's contribution to systemic risk – which determines its risk charge – and the capital that is injected into it to make the financial system more resilient to systemic risk. In addition, the analysis provides evidence that a systemic risk fund which is immediately re-injected into the financial system requires less capital than a systemic risk fund which stores the capital in a central depository and is used to bail out banks ex-post.

The remainder of the chapter is organized as follows: Section 3.1 gives an overview on the previous literature. Section 3.2 outlines our model, and Section 3.3 shows how it can be used to analyze systemic risk as well as individual institutions' contribution to systemic risk along various parameters. Using the outlined model, Section 3.4 develops and analyzes a proposed systemic risk charge and fund subject to our SVaR concept within a systemic risk management approach. Section 3.5 concludes. Further details regarding different model structures analyzed as well as the parallelized simulated annealing algorithm employed for analysis are described in several appendices at the end of the chapter.

3.1 Review of Previous Literature

To get a general overview on systemic risk, Haldane (2009) considers the financial network as a complex and adaptive system and applies several lessons from other disciplines such as ecology, epidemiology, biology, and engineering to gain insights to systemic risk in the financial system. More specifically and regarding the various approaches to assessing systemic risk it is sensible to distinguish between (i) 'market-based' and (ii) 'network-based' approaches.[10] While the former use correlations and default probabilities that can be extracted from market prices of financial instruments, the latter explicitely model linkages between financial institutions, mostly using balance sheet information.

As regards the market-based literature, Lehar (2005) uses standard tools which regulators require banks to use for their internal risk management – however at the level of the entire bank system – and shows that in a sample of international banks over the period from 1988 to 2002 the North American banking system increased its stability while the Japanese banking sector has become more fragile. Bartram, Brown, and Hund (2007) develop three distinct methods to quantify the risk of systemic failures in the global banking system. Using a sample of 334 international banks during 6 financial crises the authors come to the conclusion that the existing institutional framework could be regarded as adequate to handle major macroeconomic events. Bårdsen, Lindquist, and Tsomocos (2006) evaluate the usefulness of macroeconomic models for policy analysis from a financial stability perspective. They find that a suite of models is needed to evaluate risk factors because financial stability depends on a wide range of factors.

To measure systemic risk, more recent research from the market-based literature focuses mainly on detecting systemic risk in groups of financial institutions, in particular using multivariate measures such as tail risk indicators or multivariate distress dependences.[11] For example, Gray and Jobst (2010) find that using equity option information to calculate (joint) tail risk

[10] See the background paper of Financial Stability Board, International Monetary Fund, and Bank for International Settlements (2009) for a similar distinction.

[11] See Chapter Three of International Monetary Fund (2009) for a similar subsumption.

indicators between institutions yields timely information about the extent of systemic risk. Segoviano and Goodhart (2009) compute the multivariate density of a portfolio of banks to capture linear and non-linear distress dependences and apply their methodology to a number of country and regional examples. Among other findings they show that U.S. banks are highly interconnected, and that distress dependence rises in times of crises. Finally, Adrian and Brunnermeier (2009) propose CoVaR, defined as the value at risk of financial institutions conditional on other institutions being in distress to assess systemic risk in the financial system. Using this measure, the authors quantify the extent to which financial key figures such as the leverage ratio and maturity mismatch can predict systemic risk.

As regards the network-based literature, Upper and Worms (2004) use balance sheet information to analyze whether there is the risk of contagion in the German interbank market and find that the failure of a single bank can lead to a loss of up to 15% of the banking system's assets. Cifuentes, Ferrucci, and Shin (2005) integrate a mechanism of marking to market assets in a network model and show that liquidity requirements can serve as an effective means to forestall contagious defaults in the financial system. Elsinger, Lehar, and Summer (2006) use standard tools from risk management in combination with a network model of interbank loans. Applying their methodology to a dataset of all Austrian banks they provide evidence that correlations in banks' asset portfolios are a main source of systemic risk. Mueller (2006) employs a data set of bilateral bank exposures and credit lines in a network model and finds a substantial potential for contagion in the Swiss interbank market. Aikman, Alessandri, Eklund, Gai, Kapadia, Martin, Mora, Sterne, and Willison (2009) combine a network model of the financial system with funding liquidity risk and incorporate this to a suite of models that allow to model various aspects of systemic risk. The authors provide evidence that large losses at some banks can be exacerbated by liquidity feedbacks and thus can lead to system-wide instability.

Castaglionesi and Navarro (2007) study the endogeneous formation of financial networks and show that an efficient financial network and a decentralized financial network both display a core-periphery structure in which core banks are all connected among themselves and choose to hold a safe asset while periphery banks can eventually be connected to other banks and choose to hold a risky asset. Gai and Kapadia (2010) develop a network framework where asset prices are allowed to interact with balance sheets. The authors find that greater connectivity in financial systems reduces the likelihood of widespread default in case of relatively small shocks, while the impact on the financial system in case of large shocks increases this likelihood. Espinosa-Vega and Solé (2010) show how a cross-border network analysis can be used to efficiently monitor direct and indirect systemic linkages between countries, in particular in the face of different credit and funding shocks. The authors provide evidence that the inclusion of risk transfers can modify the risk profile of entire financial systems.

The recent financial crisis has revealed that individual financial institutions impact differently on systemic risk. There are particularly two reasons why it is important to assess financial institutions' individual contribution to systemic risk. First of all, to prevent the insecurity surrounding potential defaults such as the Lehmann bankruptcy in 2008, a supervisor should be able to assess the impact of individual institutions' defaults on the stability of the financial system. Second, as already outlined in the previous section, individual financial institutions should be charged to incentivize them to internalize the cost of their negative externality on the financial system. Tarashev, Borio, and Tsatsaronis (2009) use the Shapley value methodology to identify the contribution of individual financial institutions to systemic risk. The authors show that none of the drivers of contribution to systemic risk, such as the institution's size or its probability of default, in isolation provide a fully satisfactory proxy for systemic importance. Following the authors, it is thus important to carefully take into consideration the interactions between the various risk factors when analyzing systemic risk and the individual institutions' contribution to it. Gauthier, Lehar, and Souissi (2010) compare alternative mechanisms for allocating the overall risk of a banking system to its member banks. Using a data set of the Canadian banking system the authors find that capital allocations that are optimal with respect to systemic risk can differ by up to 50% from actually observed capital levels. Similarly to Tarashev, Borio, and Tsatsaronis (2009) these allocations are not trivially related to different risk factors.

The following section outlines the network model that will be used for our analysis.

3.2 Model of an Interrelated Financial Network

The model which is set up in this section captures important features of the financial system and replicates several stylized facts in relation to systemic risk that arose during the recent financial crisis. It consists of (i) a system of three interconnected financial institutions that adjust their portfolio to fulfill a capital requirement and (ii) the Rest of the World (ROW). Banks have deposits, lend to each other, and hold liquid assets (LA) and non-liquid assets (NLA) on their balance sheet. Non-liquid assets are marked to market[12] while liquid assets do not change their value on banks' balance sheets. The financial system is mapped with a matrix of assets and liabilities as displayed on Figure 3.2.

Assets →

Liabilities ↓

	Bank 1	Bank 2	Bank 3	ROW	
				NLA	LA
Bank 1				X	Y
Bank 2	W				
Bank 3					
ROW	Z				

Figure 3.2: Matrix of the Financial System Model

On Figure 3.2 a bank's assets are on the respective rows of the matrix. For example, the row designated to bank 1 contains bank 1's assets. Similarly, a bank's liabilities are captured on the respective columns of the matrix. The field 'W' on Figure 3.2, that is, interbank lending from bank 2 to bank 1, designates an asset for bank 2 and a liability for bank 1, and the field 'X' which could, for example, be CDOs, captures bank 1's investment in

[12]Note that there is no distinction between banking and trading book in the model, all non-liquid assets are marked to market in the model.

non-liquid asset products related to the rest of the world. The field 'Y', for example cash and cash equivalents, captures bank 1's holdings of liquid assets, and the field 'Z' captures the depositors and bondholders of bank 1 from the rest of the world.

Banks have to fulfill a capital requirement ratio, γ, which is calculated following Equation 3.1 for the i'th bank,

$$\gamma = \frac{\sum_j a_j + p \cdot b_i + c_i - \sum_j l_j - d_i}{\sum_j a_j + p \cdot b_i}, \tag{3.1}$$

where $i, j \in (1, 2, 3), i \neq j$, are indices for the three banks in the system, b_i are non-liquid assets, c_i are liquid assets, a_j are interbank lendings, l_j are interbank borrowings, p is the market price of the non-liquid asset, and d_i are deposits. Note that the liquid asset does not show up in the denominator of Equation 3.1 because banks do not have to hold capital for their liquid asset holdings.[13] If a bank's equity ratio is lower than the capital requirement, γ, it tries to net its interbank exposure and, if that is not sufficient to adequately recapitalize, sells non-liquid assets on the market. In both cases the denominator in Equation 3.1 sinks relatively to the nominator. If a bank cannot fulfill the capital requirement it defaults.

Equation 3.2 displays the new capital ratio if a bank engages in netting its interbank lendings with other banks by θ units.

$$\gamma^* = \frac{(\sum_j a_j - \theta) + p \cdot b_i + c_i - (\sum_j l_j - \theta) - d_i}{(\sum_j a_j - \theta) + p \cdot b_i} \tag{3.2}$$

Netting diminishes the denominator by θ units while the nominator remains unchanged. Note that in the model counterparties can net any amount that exists as cross-exposure as long as their balance sheet net-value is non-negative, that is $\sum_j a_j + p \cdot b_i + c_i - \sum_j l_j - d_i \geq 0$.[14] Here and in the following cross-exposure means that two banks have borrowed from and lent to each other. Note that a bank which has cross-exposure with another

[13] See Cifuentes, Ferrucci, and Shin (2005) for a similar set up.

[14] If a bank's liabilities exceed its assets the bank is taken into custody by the supervisor for creditor protection. In that case no netting is possible anymore.

bank can have net-exposure with the same bank. Here and in the following net-exposure is defined as one bank having lent more to another bank than borrowed from the same bank.

Solving Equation 3.2 for the amount of bank i's desired netting yields Equation 3.3

$$\theta_i^d = -\mathbf{1}_{[nv_i \geq 0]} \frac{(1-\gamma)(\sum_j a_j + p \cdot b_i + c_i - \sum_j l_j - d_i)}{\gamma}, \tag{3.3}$$

where $\mathbf{1}$ is an indicator function and nv_i is bank i's net-value defined as $\sum_j a_j + p \cdot b_i + c_i - \sum_j l_j - d_i$. The amount of netting the j'th bank is willing to accept with bank i is given by Equation 3.4

$$\theta_j^s = \mathbf{1}_{[nv_j \geq 0]} min(a_i, l_i). \tag{3.4}$$

Note that the minimum operator is used since only cross-exposures can be netted. The resulting amount netted between bank i and bank j is given by Equation 3.5

$$\theta_{ji} = min(\theta_j^s, \theta_i^d). \tag{3.5}$$

Note that in the model banks never increase their lending to each other.

Similarly to recapitalizing via netting, Equation 3.6 displays the capital ratio bank i expects to obtain if it engages in selling s_i units of its non-liquid asset.

$$\gamma^* = \frac{\sum_j a_j + p(b_i - s_i) + c_i + p \cdot s_i - \sum_j l_j - d_i}{\sum_j a_j + p(b_i - s_i)} \tag{3.6}$$

While netting has no further effect except increasing the involved banks' capitalization, recapitalization via selling non-liquid assets has further repercussions on all banks' balance sheets with non-liquid asset holdings. In the model, the market price of the non-liquid asset, p, is a function of supply and demand on the market. If banks decide to engage in liquidating (part of) their non-liquid assets, there are several effects on banks' balance sheets: selling banks obtain liquid assets and hence improve their capital ratio. However, at the same time an increased supply of non-liquid assets to the market decreases the market price of the non-liquid asset. This results in lowering the market value of their remainder portfolio of non-liquid assets. Furthermore, this price effect also puts pressure on other banks' balance sheets since the market value of their non-liquid assets decreases as well.

In the model the market price of the non-liquid asset is found via a tâtonnement process between demand and offer. Similar to Cifuentes, Ferrucci, and Shin (2005), the inverse demand function is assumed to follow Equation 3.7

$$p = exp(-\xi \sum_i s_i), \tag{3.7}$$

where ξ is a positive constant to scale the price responsiveness to non-liquid assets sold on the market and s_i is the overall amount of non-liquid assets sold by bank i on the market.

Solving Equation 3.6 for the amount of non-liquid assets sold by bank i to fulfill the capital requirement and noting that a bank can only sell non-liquid assets it owns[15] yields Equation 3.8 which shows bank i's supply of non-liquid assets on the market as a function of the market price.

$$s_i = min\left(b_i, \frac{-(1-\gamma)(p \cdot b_i + \sum a_i) - c_i + \sum l_i + d_i}{\gamma p}\right) \tag{3.8}$$

Since each s_i is decreasing in p, the aggregate sales function, $S(p)$, is also decreasing in p. The tâtonnement-process to find the equilibrium market price is depicted on Figure 3.3.

Prior to any shock, the market price equals 1 which is the price when all banks initially fulfill the capital requirement, and sales of the non-liquid asset are zero. A shock to bank i, say a certain loss of cash, c_i, shifts the supply curve upwards, resulting in $S(1) = s_i \succ 0$ because bank i starts selling non-liquid assets to fulfill its capital ratio. However, for $S(1)$ the bid price equals only $p(S(1))^{bid}$, while the offer price is one. The resulting market price is $p(S(1))^{mid}$, the midprice between bid and offer prices. Since the

[15] Note that banks do not engage in buying or short-selling non-liquid assets in the model.

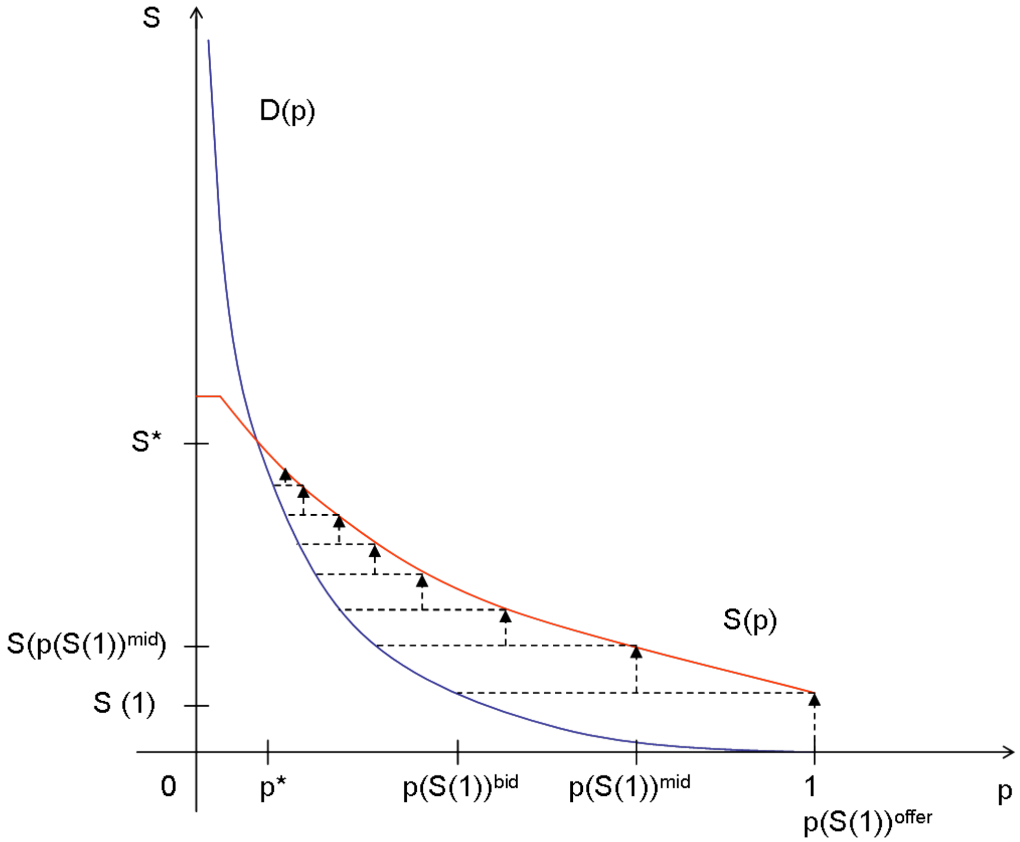


Figure 3.3: Tâtonnement Process in the Model

market price thus decreases and banks have to mark their non-liquid assets to market, additional non-liquid asset sales can result to fulfill the capital requirement. The step adjustment continues until the intersection of the demand and offer curves is reached at p^*. Note that the supply curve can become horizontal from a certain amount of non-liquid assets sold on the market onwards because there is only a limited amount of non-liquid assets on banks' balance sheets. Since a shock to one or several banks can only result in an upward shift of the supply curve, with the maximum price of the non-liquid asset equal to 1 in the initial equilibrium prior to the shock and the minimum market price equal to zero, a market price $p \in (0, 1)$ always exists.

In the outlined framework the two main shock transmission channels are the direct connections between banks via interbank holdings (credit risk) and indirect connections through marking to market the non-liquid assets on the balance sheet (market risk).

The following sub-section outlines how specific realizations of the financial network are set up.

3.2.1 Generating Specific Realizations of the Financial System Matrix

A specific set up of the financial system is a consistent matrix, that is, with all banks fulfilling the capital requirement ratio, of the financial system model depicted on figure 3.2, with concrete values for all assets and liabilities. Such a set up is determined by (i) the structure of the system, that is, defining which banks have counterparty exposure through, for example, interbank lending; (ii) banks' ratio between interbank lendings and other assets (that is, non-liquid and liquid assets), α, with α the overall amount lent to other banks and $1-\alpha$ the amount invested in other assets; (iii) the ratio between investment in non-liquid and liquid assets, β, with β the fraction invested in non-liquid assets and $1-\beta$ the fraction invested in liquid assets; (iv) the capital requirement, γ; and (v) an initial endowment of capital, A, that is allocated to banks' assets according to α and β. Note that $0 \leq \alpha \leq 1$ and $0 \leq \beta \leq 1$.

To determine all rows except the last row of the financial system matrix on Figure 3.2, one configures a structure of interlinkages, that is, determines which banks lend and/or borrow in the financial system, and assigns concrete values for α, β, A, and γ. In the model banks invest all the capital borrowed from other banks into liquid and non-liquid assets. The overall amounts bank i then holds in non-liquid assets and liquid assets are $((1-\alpha)\cdot A+\sum_j l_j)\beta$ and $((1-\alpha)\cdot A+\sum_j l_j)(1-\beta)$, respectively. The entry for the i'th bank in the last row of the financial system matrix, that is, its deposits, is determined such that it fulfills the capital requirement via combining the sum of its assets, its interbank liabilities, and the equity ratio using Equation 3.9

$$
\begin{aligned}
d_i = & A \cdot \alpha + \left((1-\alpha) \cdot A + \sum_j l_j \right) [\beta p + 1 - \beta] - \sum_j l_j \\
& - \gamma \left[A \cdot \alpha + (1-\alpha) A \cdot \beta \cdot p + \sum_j l_j \cdot \beta \cdot p \right] .
\end{aligned} \tag{3.9}
$$

The symmetric case, for example, is displayed on Figure 3.4. All banks are given the same amount of initial capital, A, borrow from and lend to each other, and have the same investment proportions, α and β.

	Bank 1	Bank 2	Bank 3	ROW	
				NLA	LA
Bank 1		Aα/2	Aα/2	Aβp	A(1-β)
Bank 2	Aα/2		Aα/2	Aβp	A(1-β)
Bank 3	Aα/2	Aα/2		Aβp	A(1-β)
ROW	d	d	d		

Figure 3.4: Symmetric Case of the Financial System Matrix

In the example on Figure 3.4 each bank's balance sheet then looks as displayed on Table 3.1.

Assets	Liabilities
LA: $A(1-\beta)$	Deposits: $A(\beta(p-1) - \gamma(\alpha + \beta p) + 1)$
NLA: $A\beta p$	Interbank borrowings: $A\alpha$
Interbank lendings: $A\alpha$	Equity: $A(\gamma(\alpha + \beta p))$
$\sum = A(\alpha + \beta(p-1) + 1)$	$\sum = A(\alpha + \beta(p-1) + 1)$

Table 3.1: Banks' Balance Sheets in the Symmetric Case

Note that with different interlinkage structures the relative size of banks vis-à-vis each other, measured by the sum of their assets, changes because borrowing money allows banks to leverage themselves, and increases the size of their balance sheets.

The next sub-section outlines how shocks to the financial system matrix are modeled.

3.2.2 Shocks in the Financial System Matrix and the Measure for Systemic Risk

As outlined at the beginning, we define systemic risk as the danger that failures within the financial system will mean that an adequate supply of credit and financial services to the economy is no longer guaranteed, so that negative real effects will follow. In our model, systemic risk conditional on a shock is defined as the proportion of the financial system that breaks down as measured by banks' balance sheet size, that is, the sum of their assets. When banks default, resulting liquidation costs but also the banks' overall importance with respect to financial services to the real economy will be closely related to this figure.

Shocks in the model always originate in a percentage loss of assets. Resulting systemic risk caused by the shock is then calculated as the ratio of assets from banks that default relative to system-wide assets, both prior to the shock. For example, if consecutive on a shock only bank 1 defaults, with the other banks in the financial system remaining solvent, systemic risk is calculated as $\frac{\text{Sum of Bank 1's Assets Prior to the Shock}}{\text{Sum of all Banks' Assets Prior to the Shock}}$.

As it is likely to be unclear which shocks will actually emerge in the financial system, a range of possible extreme shock events is taken into consideration. Note that these shocks shall in particular model strongly adverse scenarios, that is, unexpectedly high loss events. The reason for this is that systemic risk, involving defaults of parts of the financial system arises primarily in high loss events. Resulting expected systemic risk consecutive on a range of shocks is calculated as a weighted sum of the systemic risks under the different shocks with each weight given by the probability of the associated shock emerging. Equation (3.10) outlines this measure for expected systemic risk.

$$\Phi^E = \sum_j \frac{\text{Sum of Insolvent Bank's Assets Prior to Shock}_j}{\text{Sum of all Banks' Assets Prior to Shock}_j} \cdot prob_j \quad (3.10)$$

where Φ^E is expected systemic risk and $prob_j$ is the probability assigned to shock scenario j. This approach, with a range of different possible shocks to each bank and a probability assigned to each shock, on the one hand allows for a better identification of the different extents to which banks contribute to expected systemic risk but also to investigate the three main risk-channels, size, interconnectedness, and firesales, in a unified framework. While banks contribute to systemic risk via the firesales channel already at relatively small shocks, the interlinkage channel only comes into play from relatively large shocks onwards. On the other hand, modeling a range of shocks and probabilities offers the possibility to later on transfer the Value at Risk (VaR) concept,[16] a well established risk management concept from microprudential supervision, into a macroprudential framework with similar features, that is, the System-VaR (SVaR). In the following, expected systemic risk is the key measure which will be used to analyze systemic risk in the financial system.

Each possible shock to the banking system is modeled with a vector of percentage losses to a bank's (non-weighted) sum of assets over a discrete grid, ι, ranging from 1% to ς%, with ς being the highest conceivable shock. Taking all combinations of shocks for the three banks means there are ι^3 shock vectors, with each shock vector consisting of three entries, that is, the loss associated with the shock for each bank in the model. The probability of a shock realizing is captured by a multivariate normal distribution centered at a value between 1 and ς. The extent of correlation between the shocks is modeled with the variance-covariance matrix of the multivariate normal density function. The correlation between shocks in a given scenario, say a shock to banks 1 and 2 in scenario 1, is then calculated as $\frac{cov_{1,2}}{\sigma_1 \sigma_2}$, where $cov_{1,2}$ designates the covariance between shocks 1 and 2 and σ_1 and σ_2 the standard deviations of shocks to banks 1 and 2, respectively.[17] Since shocks

[16]See Jorion (2006) for an outline of the VaR methodology.

[17]Besides the firesales channel of non-liquid assets, the correlation between direct shocks

only range from 1 to ς, the multivariate normal density is rescaled such that the integral of the volume described by the discrete grid of shocks, ranging from 1 to ς in all three dimensions equals 1.

As previously outlined, if consecutive on a shock a bank cannot fulfill the capital requirement it first tries to net its counterparty exposures and then starts selling non-liquid assets, thus indirectly transmitting part of the shock through downward pressure on the market prices of non-liquid assets to other banks. If it cannot recapitalize to fulfill the capital requirement it defaults. When a bank's net-value, that is, its liabilities substracted from its assets, turns negative it transmits this difference to its liabilities. Respecting seniority, this first diminishes the interbank liabilities and ultimately deposits.

The clearing algorithm for shock transmission is an iterative process in which banks sequentially absorb the shock. Banks initially try to fulfill the capital requirement via netting counterparty exposures, and, after that stage, via selling non-liquid assets on the market. Banks with negative net-value then transmit a shock to their creditors, and the iterative process restarts. The process ends when shocks to solvent banks are absorbed. Figure 3.5 depicts the procedure of modeling the shock transmission.

Banks' assets are contracted by the initial shock (step A on Figure 3.5). Since netting has no negative repercussions on the balance sheet like the negative price effect from selling non-liquid assets, banks that do not fulfill the capital requirement first try to improve their capital ratio through netting interbank liabilities with other banks (step B on Figure 3.5). Next, banks that do still not fulfill the capital requirement start selling non-liquid assets on the market (step C on Figure 3.5).

Banks that are not able to fulfill the capital requirement default at this point. If insolvent banks have negative net-value they will transmit shocks to their creditors, that is, banks that have counterparty exposure to them or ultimately to depositors. A bank with negative net-value transmits shocks to its creditors, respecting seniority, until it has a net-value of zero. The overall shock prepared for transmission to the insolvent banks' creditors equals the

could be interpreted as an additional gauge of common exposure of banks in the financial system.

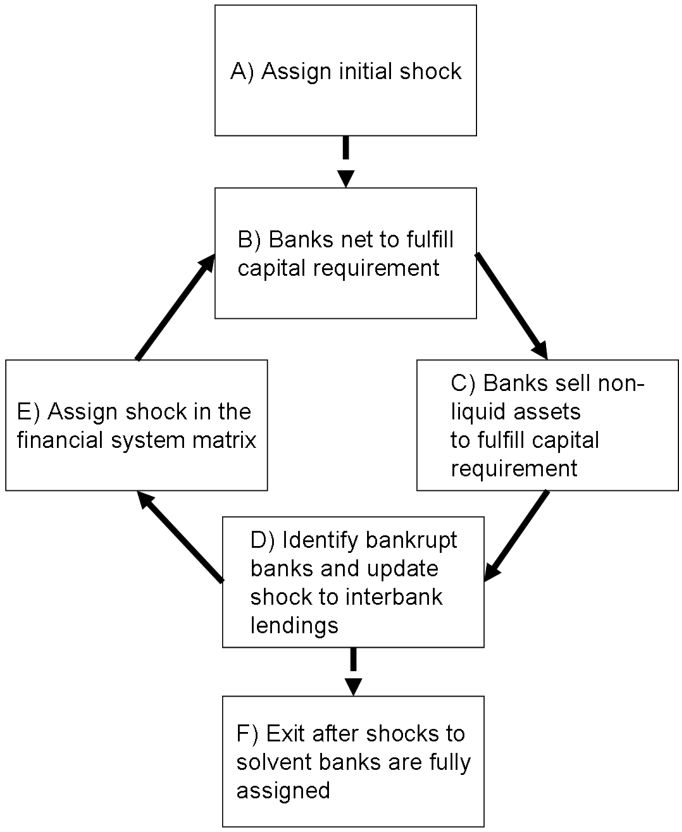


Figure 3.5: Shock Transmission in the Financial System Model

absolute value of their negative net-value and is assigned proportionally to a bankrupt's bank interbank liabilities as long as they are positive (step D on Figure 3.5).

In case the interbank liability shock matrix contains nonzero entries it is assigned (step E on Figure 3.5), and the iteration restarts (step A on Figure 3.5). If the interbank liability shock matrix is empty the shock has been assigned, and the resulting systemic risk is computed (step F on Figure 3.5).

The following sub-section outlines how the model can be used to analyze individual financial institutions' contribution to expected systemic risk.

3.2.3 Analyzing Banks' Contribution to Expected Systemic Risk

To find out an individual bank's contribution to expected systemic risk the Shapley value methodology can be employed.[18] In game theory this value is used to find the fair allocation of gains obtained by cooperation among players. For a game consisting of three players the Shapley value is defined as

$$\phi_i(v) = \frac{1}{3!} \sum_{K \ni i; K \subset N} v(K) - v(K - \{i\}), \tag{3.11}$$

where N is the set of all players, v(K) is the value obtained by coalition K including player i and $v(K - \{i\})$ is the value of coalition K without player i. The Shapley value for player i is the average contribution to the gain of the coalition over all permutations in which players can form a coalition.

The Shapley value has the following properties:

- Pareto efficiency: The total gain of a coalition is distributed;
- Symmetry: Players with equivalent marginal contributions obtain the same Shapley value;
- Additivity: If one coalition can be split into two sub-coalitions then the pay-off of each player in the composite game is equal to the sum of the sub-coalition games;
- Zero player: A player that has no marginal contribution to any coalition has a Shapley value of zero.

Since expected systemic risk is a cost to the financial network, in the model, the Shapley value is used to compute the marginal contribution of a player to this cost.

[18] See Shapley (1953). See also Tarashev, Borio, and Tsatsaronis (2009) who use the Shapley value to compute individual financial institutions' contribution to systemic risk. Note that in general also other measures for financial institutions' contribution to systemic risk could be employed, for example the CoVaR methodology from Adrian and Brunnermeier (2009). However, given the model set up in this chapter, the Shapley value methodology seems suited best.

In the financial network matrix the contribution of each of the three banks given a shock is calculated following Equation 3.11 as follows: As previously outlined, systemic risk conditional on the realization of a shock is defined as the proportion of the assets of banks that become insolvent due to the shock over system wide assets, both prior to the shock. $v(K)$ is the coalition K of 'all banks that can default and transmit shocks' and hence contribute to the measure for expected systemic risk, and $v(K - \{i\})$ is the coalition K without the i'th bank. Intuitively the latter can be imagined as the situation in which bank i cannot default and thus not transmit shocks to the financial system. In the model this is done via temporarily adding a large amount of liquid assets to a bank that shall not transmit shocks. Such a 'safe' bank does not try to net counterparty exposure[19] or sell non-liquid assets on the markets because it always fulfills the capital requirement. Following this approach, one calculates for each permutation of banks the systemic risk if only the first bank in the order can default, next the marginal contribution to systemic risk if the following bank can also default, and finally the marginal contribution to systemic risk if all three banks in the actual order can default. The Shapley value for a bank is then the average of its marginal contributions over all possible permutations. Since systemic risk is defined as a proportion here, its value and the Shapley values are restricted between 0 and 1.

Similar to calculating expected systemic risk as a weighted sum of systemic risk from a set of scenarios, Equation (3.12) outlines bank i's contribution to expected systemic risk from a weighted sum of its Shapley values.

$$\phi_i^E = \sum_j \phi_{ij} \cdot prob_j \tag{3.12}$$

where ϕ_{ij} is bank i's contribution to systemic risk in scenario j and $prob_j$ is the probability that scenario j realizes. Note that $\Phi^E = \sum_i^3 \phi_i^E$.

The following section outlines key results on expected systemic risk obtained from the model.

[19]Though it accepts netting requests from other banks.

3.3 Results from the Model

In the model banks' contribution to expected systemic risk is driven in particular by three channels: (i) banks' size in the financial system as well as the extent of (ii) direct and (iii) indirect connections between banks.[20] First of all, the size of an individual bank matters for its contribution to expected systemic risk because our measure for systemic risk, the sum of assets of banks that default relative to system-wide assets, both prior to the shock, increases with the size of the insolvent banks' balance sheets. Second, banks that have borrowed from other banks are likely to contribute more to expected systemic risk than banks that have not borrowed. If banks that have borrowed from other banks default on their liabilities they transmit shocks to their creditor banks. Third, non-liquid assets can make the financial system vulnerable to firesales. Large amounts of non-liquid assets on a bank's balance sheet on the one hand, make it vulnerable to market price decreases of non-liquid assets. On the other hand, banks which have invested to a large extent into non-liquid assets can themselves depress the market price if they have to liquidate part of their non-liquid assets consecutive on a loss, thus transmitting a shock via the market to other banks in the financial system. The following analyses will be taken out with a view on these three main risk-channels

Expected systemic risk will first be explored in a baseline specification of the model. Subsequent analyses will then investigate the impact of the main risk-channels outlined above. To shed some light on the role of banks' capitalization and its role as a major shock buffer, the effect of different capital requirement ratios on expected systemic risk will also be investigated.

In the baseline specification parameters are set such that banks' resulting balance sheets feature roughly the same proportions that can actually be found in the financial system. Regarding the relative amount of interbank lending, Upper and Worms (2004) note that in their study on the German interbank market banks lent on average 2.96 times the amount of their cap-

[20]Here and in the following expected systemic risk caused via direct and indirect exposure will also be referred to as 'interlinkage' and 'firesales' channels, respectively.

ital to other banks. Scaling the parameter α to 0.3 approximately results in this relative amount on banks' balance sheets in case they engage in lending. Furthermore, the proportion of non-liquid assets to cash and cash equivalents in the Deutsche Bank's total assets in 2009 was roughly 0.8.[21] Setting β to 0.8 in the model hence roughly mimicks this proportion. As regards banks' capitalization, following the Basel Commitee on Banking Supervision (2006), the capital requirement ratio, parameter γ, is set to 8% of risk weighted assets. The scaling parameter for the price responsiveness of non-liquid assets, parameter ξ, is set to 0.03 which results in a price decrease of approximately 7% of the market price if banks sell all their non-liquid assets on the market. Banks in the system are initially equipped with one unit of capital, parameter A. Since in the following exercises systemic risk is measured as a proportion, A is a scaling parameter and impacts results only if it is changed such that banks obtain different amounts of initial capital because this changes banks' relative size vis-à-vis each other.

Shocks that can impact individual banks are modeled as a loss of a bank's assets ranging from 1% to 9% of its balance sheet sum in discrete steps of 2%. Note that a shock always manifests in the form of a loss in liquid assets.[22] The multivariate normal shock distribution which determines the probability of a shock scenario realizing is centered at a loss of 6% of banks' assets. The main diagonal of the variance-covariance matrix is set to 3, and the covariances are set to yield a correlation coefficient of $\frac{1}{6}$ between shocks to banks.[23]

Note that the distribution of shock scenarios can influence the outcomes of the following analyses to some extent. For example, choosing the parameters

[21] See Deutsche Bank AG (2010).

[22] A direct loss assigned to non-liquid assets might affect the effect of the firesales channel in the model. A larger shock to an institution's non-liquid assets can theoretically cause lower risk in the financial system through a reduced extent of firesales. In the extreme case, if a bank loses all its non-liquid assets consecutive on a shock its potential to transmit the shock via the firesales channel has vanished.

[23] As regards the mean, and variance of the distribution of shocks, there is little guidance as to how these parameters can be chosen. Moody's Investor Service (2005) estimates the asset correlations for major structural finance sectors to range between 2% and 18%. Given that the recent financial crisis has demonstrated that correlations in the financial sector can be even higher than was previously assumed, a value slightly above the upper range of the interval has been chosen.

of the distribution such that small shocks receive a relatively high probability generally lowers the expected contribution of banks through the interlinkage channel. This feature comes up because banks only transmit shocks via this channel if a shock is large enough to reduce the sum of their assets below the sum of their liabilities, that is, their equity is entirely extinguished. Similarly, if very large shocks have a high probability, the size channel dominates the outcome as regards banks' contribution to expected systemic risk. In the extreme case when all banks lose all equity from an initial shock and cannot recapitalize, the whole banking system defaults and no contagion via fire-sales or interlinkages takes place. In this respect the variance and covariance between shocks matter as well. For example, to identify banks which contribute to expected systemic risk via the interlinkage channel it is necessary to model shock scenarios in which creditor banks are subject to a relatively small shock which does not cause their insolvency while at the same time their debtor banks are subject to a relatively big shock which makes them default on their liabilities, thus ultimately causing the default of the creditor banks. The distribution parameters hence influence expected systemic risk as well as banks' contribution via different channels to it.

Our choice of parameters governing the distribution of shock scenarios has been taken mainly with a view on generating shock scenarios which, on the one hand, allow for the emergence of systemic risk through all risk-channels, and, on the other hand, to identify through which of the channels banks primarily contribute to expected systemic risk. It is important to note that while the analyses are in some cases affected by distributional assumptions and interactions between the risk-channels themselves, the *insights* obtained from the *outcomes* of the experiments are qualitatively robust to changes in these underlying parameters because they are always corroborated with a view on the model's underlying mechanics. Furthermore, in case the distributional assumptions particularly matter, it will be pointed out in how far the results which are refered to are impacted.

Given that a bank can borrow to and lend from another bank at the same time there are 2^6 possible banking structures. Appendix 3.A at the end of the chapter gives an overview of all different structures of the financial network matrix that can emerge for analysis.

All following analyses consist of investigating expected systemic risk and bank 1's contribution to it. Omitting the other banks' contributions to expected systemic risk is without loss of generality because the interlinkage structures are redundant from the perspectives of different banks. For example, as can be seen in Appendix 3.A, structure 19 from the perspective of bank 1 is the same as structure 25 from the perspective of bank 3.

Finally note that all following analyses will frequently refer to specific structures of the financial system as well as to banks' size, counterparty exposure, and amount of non-liquid asset investment. Besides the general structural overview given in Appendix 3.A, the information refered to can be found in Appendix 3.B at the end of the chapter displaying specific set ups of structures and banks' relative sizes.

The following sub-section analyzes expected systemic risk in the baseline specification.

3.3.1 Expected Systemic Risk in the Baseline Specification

Figure 3.6 displays expected systemic risk in the baseline specification of the model. The upper panel shows the contribution of bank 1 to expected systemic risk (y-axis). The possible interlinkage structures outlined in Appendix 3.A have been ordered from lowest to highest contribution to expected systemic risk (x-axis).

In the baseline specification bank 1 contributes least to expected systemic risk in structure 31 (Table 3.13 in Appendix 3.B). Investigating the three main risk-channels, size, interlinkages, and firesales, indicates as to why this is the case. First of all, in this structure bank 1 is relatively small, it only constitutes 28% of the financial system. Second, it has no direct connections to other banks. This prevents it from being involved in shock emissions or transmissions through interbank lendings. Third, in this structure, bank 1 holds the same amount of non-liquid assets as the other two banks and thus is not particularly involved in the firesales channel. Bank 1 contributes most to expected systemic risk in structures 12 and 64 (Tables 3.7 and 3.16, respectively). In these structures bank 1 constitutes 36% of the financial system. It thus strongly contributes to expected systemic risk via the size channel. Furthermore, due to its interlinkages with other banks it can directly emit a shock but also transmit shocks from the bank it has exposure to, itself, both to its creditor bank. Finally, it has the second largest amount of non-liquid assets on its balance sheet thus giving it some potential to be involved in firesales.

As outlined at the beginning of this section, expected systemic risk and bank 1's contribution to it can depend on the distributional assumptions of the shock scenarios. Note, for example, that in structure 16 (Table 3.8), though bank 1 is the largest bank in the financial system (44%), two banks have net-exposure to it, and it has the largest holdings of non-liquid assets, it contributes slightly less to expected systemic risk than in structures 12 or 64. This result comes up because large shocks that are sufficient to make all banks default in structure 16 via a shock to bank 1 that is transmitted to banks 2 and 3 are at the extreme end of the shock distribution and thus receive relatively little weight in the calculation of expected systemic risk (Equation (3.10)) and bank 1's contribution to it (Equation (3.12)). By contrast, in structures 12 or 64 an eventual loss from bank 1 is transmitted more concentrated to its single creditor, thus making a sizeable shock transmission more likely at relatively smaller shocks which have a higher probability weight in the shock distribution.

The lower panel of Figure 3.6 displays expected systemic risk (y-axis) in the financial system over the different possible interlinkage structures (x-axis). The structures have been ordered according to their expected systemic risk value. In the baseline specification expected systemic risk is lowest in interlinkage structure 32 (Table 3.14), where banks are not connected by interbank lendings and are otherwise equal as regards size and non-liquid asset holdings. Expected systemic risk is highest in interlinkage structures with unidirectional links, as for example in structures 10 and 61 (Tables 3.6 and 3.15, respectively). Note that in these structures the arrows are 'pointing' into the same direction, that is, from bank 1 via bank 2 to bank 3, and from bank 3 back to bank 1, or vice versa, such that each bank can emit shocks via interbank linkages to all other banks in the financial system. In these two riskiest structures banks are equal as regards size and non-liquid asset holdings.

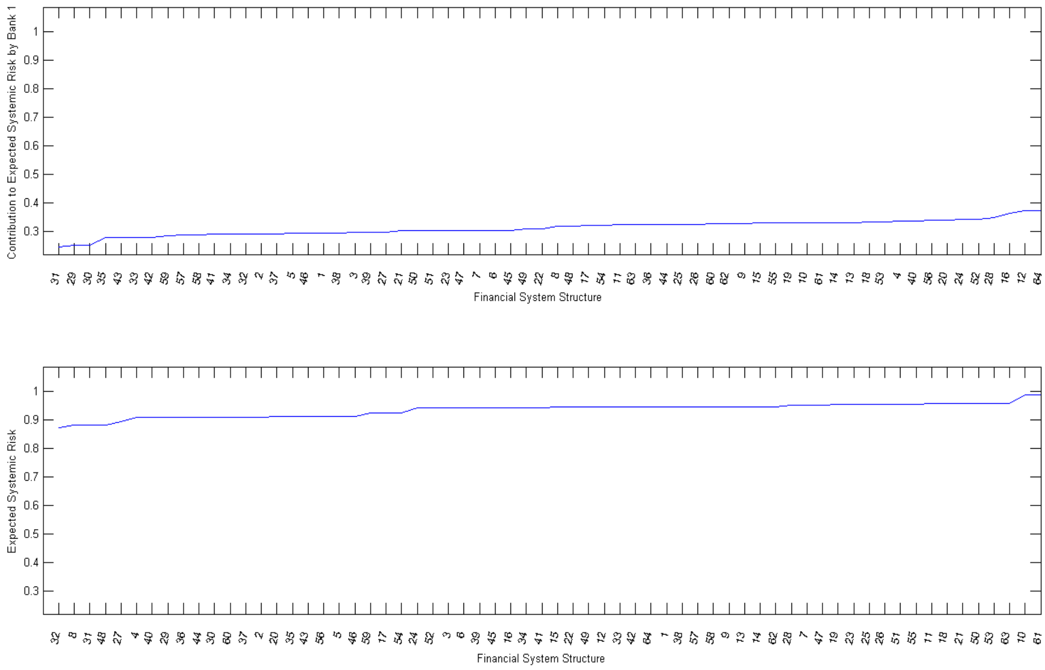


Figure 3.6: Expected Systemic Risk in the Financial System Model's Baseline Specification

To investigate the effects of the main risk-channels on expected systemic risk and banks' contribution to it they will be individually analyzed in the following, (partially) shutting down the other channels. Note that the size channel can only be influenced to some extent by varying the initial amounts of capital, parameter A, banks are endowed with. Some variations in banks' size depend on the financial system structure. For example, if banks borrow from each other they increase their size, measured by the sum of their assets relative to system-wide assets.

The next sub-section analyzes the effect of firesales on expected systemic risk.

3.3.2 The Effect of Firesales on Expected Systemic Risk

The effect of the 'firesales' channel on expected systemic risk can be analyzed if the 'interlinkage' channel is shut down and all banks start with the same amount of initial assets. This can be done using structure 32 (Table 3.14), where all banks have the same size with respect to the financial system and do not lend to each other. The price responsiveness of the non-liquid asset, parameter ξ, is increased from 0 to 0.05. If all non-liquid assets are sold on the market, the percentage loss of the price of the non-liquid asset then ranges from 0% to 11%, respectively. Figure 3.7 displays the effect of an increase in the price responsiveness of the non-liquid asset (x-axis) on expected systemic risk (y-axis) on the lower panel and bank 1's contribution to it (y-axis) on the upper panel, both in structure 32. With higher responsiveness of the

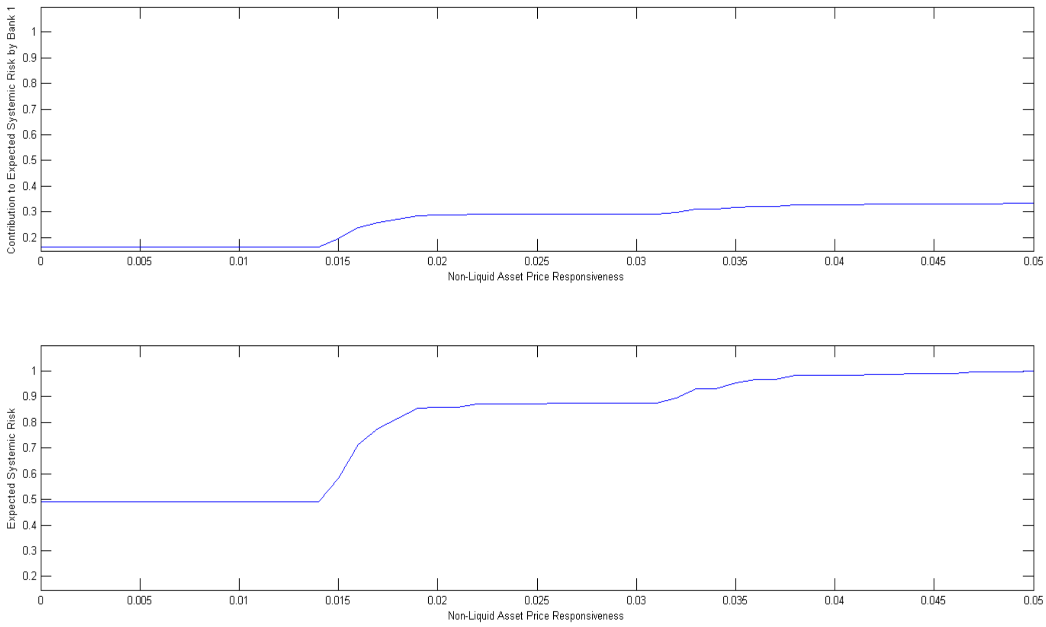


Figure 3.7: Effect of Firesales on Expected Systemic Risk in Financial System Structure 32

price the effect of marking to market gets more severe, increasing the impact of firesales. This leads to higher expected systemic risk as well as bank 1's contribution to it. From a parameter value of 0.05 onwards, even tiny shocks in the model lead to a default of the whole system because relatively small amounts of non-liquid assets sold to recapitalize lead to massive price effects, triggering firesale spirals.

Note that the functions displayed on Figure 3.7 do not follow a smooth pattern because of the coarseness of the grid of shocks which features a stepsize of 2% over a range of losses. For example, say, that with a given price responsiveness, a bank that loses 5% or more of its assets has no chance to recapitalize and thus always sells all its non-liquid assets on the market and defaults. If the price responsiveness is then *ceteris paribus* increased a bit, this bank would maybe already liquidate all its non-liquid assets at a loss of 4% or larger of its assets and default. However, since the next smaller shock considered is 3%, the price responsiveness needs to be raised sizeably to increase expected systemic risk and banks' contribution to it over some ranges of the grid. The result is that in some regions of the analyzed parameter space of ξ only a sizeable change in the price responsiveness may cause an increase of expected systemic risk and banks' contribution to it.

Overall, the analysis of the impact of firesales on expected systemic risk provides evidence that a stronger responsiveness of the price of non-liquid assets increases the risk of firesales. This leads to higher expected systemic risk as well as banks contribution to it.

The next sub-section analyzes the effect of interlinkages on expected systemic risk.

3.3.3 The Effect of Interlinkages on Expected Systemic Risk

As a first inspection of the effect of interlinkages on expected systemic risk, Figure 3.8 displays a boxplot of expected systemic risk (lower panel) as well as bank 1's contribution to it (upper panel) for each number of connections possible in the 64 possible financial system structures analyzed. Note that two banks are considered as being connected as soon as one of the banks lends to or borrows from the other. To get the effect of interbank connections without the effect of firesales and size, the parameter for price responsiveness has been set to zero, and all banks start with the same amount of initial assets. When investigating the medians (red lines), the figure displays that

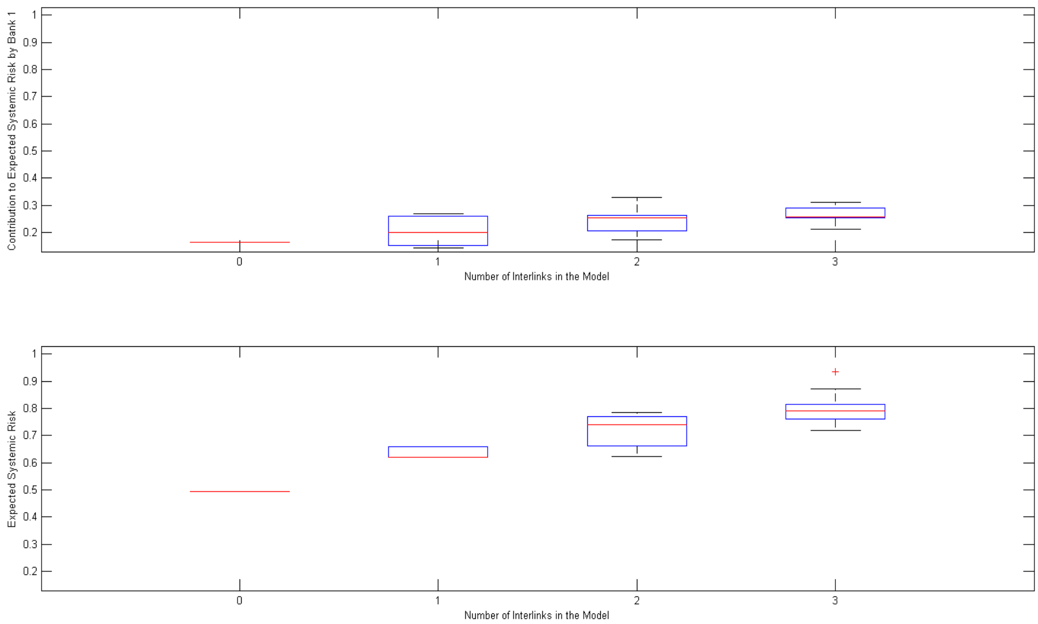


Figure 3.8: Effect of Number of Interlinks on Expected Systemic Risk

expected systemic risk as well as bank 1's contribution to it tend to increase with a growing number of interlinks. However, focusing on the upper and lower quartiles (designated by the blue boxes), the whiskers which extend to the most extreme data points not considered outliers (black lines), and an outlier (red plus symbol), one can see that more interconnections do not strictly result in higher expected systemic risk or contribution to it.

In the network literature this property is called 'robust yet fragile', meaning that with a growing number of interlinks the network can get more robust to small shocks and at the same time more vulnerable to large shocks. Since in this case the shock vectors are the same, the 'robust yet fragile' property

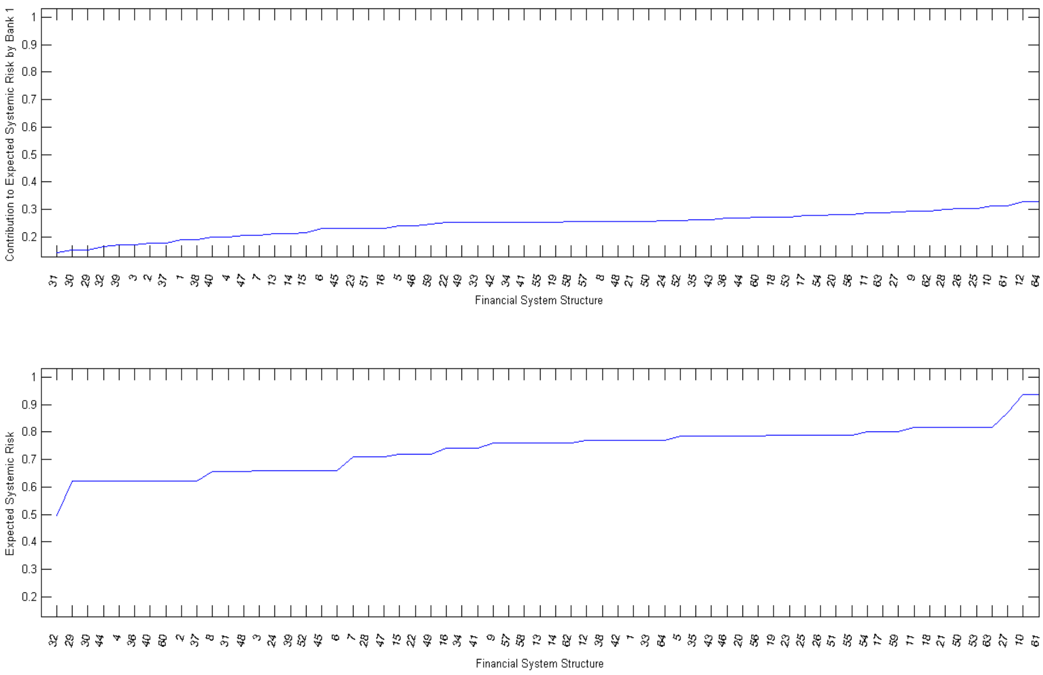


Figure 3.9: Effect of Financial System Structures on Expected Systemic Risk

comes up through another dimension, namely the specific set up of the interlinks, in particular depending on whether there is cross-exposure between two banks which is akin to an insurance between banks, or whether one of the banks has net-exposure to the other and can likely receive a shock through that exposure.

Overall, Figure 3.8 provides evidence that in tendency both expected systemic risk as well as a bank's contribution to it increase with more interlinks in the financial system.

As a second inspection of the effect of the interlinkage channel on expected systemic risk, Figure 3.9 displays a similar visualization as on Figure 3.6 for the baseline specification, but with the firesales channel shut down, that is, the parameter for price responsiveness, ξ, set to zero, and all banks still starting with the same amount of initial assets, parameter A.

Qualitatively the results remain broadly the same. However, two points deserve mentioning. First, expected systemic risk (lower panel) as well as bank 1's contribution to it (upper panel) are lower on Figure 3.9. For some structures, such as structure 32 which is at the low end of expected systemic risk, the decrease of expected systemic risk (from 0.87 on Figure 3.6 to 0.49 on Figure 3.9) and bank 1's contribution to it (from 0.29 on Figure 3.6 to 0.17 on Figure 3.9) are sizeable. For other structures, such as for example structure 61 which is at the high end of expected systemic risk, the effect is relatively small (expected systemic risk decreases from 0.99 on Figure 3.6 to 0.94 on Figure 3.9 and bank 1's contribution to it from 0.33 on Figure 3.6 to 0.31 on Figure 3.9.).

Second, the ordering of structures along the x-axis can be affected, providing further evidence that the firesales channel impacts expected systemic risk arising through different interlinkage structures to different extents. Shock transmission via direct interlinkages takes only place if a debtor bank is hit by a shock which is strong enough to turn the bank's net-value negative because the direct interlinkage channel only gets contagious once the debtor bank's equity has been completely extinguished. The analysis of Sub-Section 3.3.2 has already provided evidence that the firesales channel increases the impact of shocks, as, for example, a high value for the parameter for price responsiveness, ξ, causes the whole financial system to default at even tiny shocks. This feature indirectly also impacts the effect of interlinkages and can thus affect expected systemic risk as well as banks' contribution to it in some structures.

Consider, for example, expected systemic risk and bank 1's contribution to it in structures 19 and 25 (Tables 3.9 and 3.10, respectively) on Figures 3.6 and 3.9. Both structures yield the same expected systemic risk on the same figure (0.96 on Figure 3.6 and 0.79 on Figure 3.9.). However, comparing bank 1's contributions to expected systemic risk (upper panel) on Figure 3.6 with the firesales channel being active, bank 1 contributes less to expected systemic risk in structure 25 (0.32) than in structure 19 (0.33). By contrast, with the firesales channel shut down, on Figure 3.9 bank 1 contributes relatively more to expected systemic risk in structure 25 (0.30) than in structure 19 (0.25).

This change of order comes up because of the interaction between the interlinkage and firesales channels as well as the mean shock size banks are subject to. The underlying mechanism can best be clarified via first of all investigating the risk-channels through which bank 1 contributes to expected systemic risk. Taking into perspective only the interlinkage channel, bank 1 can contribute more to expected systemic risk in structure 25 than in structure 19.[24] Furthermore, in structure 25 bank 1 constitutes a larger proportion of the financial system (0.37) and has more non-liquid assets (0.92) than in structure 19 (0.33 and 0.8, respectively). Depending on the shock scenario, bank 1 can contribute more to systemic risk in structure 25 than in structure 19 in all three channels.

This is reflected on Figure 3.9 where bank 1 contributes more to expected systemic risk in structure 25 than in structure 19. Note that when the firesales channel is shut down, the interconnection channel is generally weak in the baseline specification and only plays a minor role in banks' contribution to expected systemic risk.[25] The result that bank 1 contributes more to expected systemic risk in structure 25 than in structure 19 on Figure 3.9 thus seems to be primarily driven by the larger size of bank 1 in structure 25.

However, as outlined, on Figure 3.6 bank 1 contributes slightly more to expected systemic risk in structure 19 than in structure 25. The change of order between the two structures when the firesales channel is active – rendering shocks more severe – comes up because in the former structure shocks which are close to the mean of the shock distribution cause bank 1 to contribute more to expected systemic risk than they do in structure 25.[26]

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[24] As can be seen on Tables 3.9 and 3.10, in structure 25 bank 3 has net-exposure to bank 1 and bank 2 has net exposure to bank 3 while in structure 19 bank 2 has net-exposure to bank 1 and bank 1 has net exposure to bank 3. This means that in structure 19 bank 1 can directly emit a shock to bank 2 and/or transmit a shock from bank 3 to bank 2. In structure 25, however, bank 1 can directly emit a shock to bank 3 which can then transmit the shock even further to bank 2. *Ceteris paribus*, in the model a bank X that emits a shock to another bank Y which can transmit the shock further to a third bank Z contributes more to systemic risk than a bank X which can directly emit a shock to another bank Y but also transmit a shock from another bank Z to bank Y.

[25] Banks that have borrowed from other banks to invest into non-liquid assets are relatively safe with the firesales channel shut down because non-liquid assets are equivalent to liquid assets.

[26] With the firesales channel intact shocks to banks in the financial system generally

Since shocks close to the mean receive a higher probability weight in the computation of the contribution to expected systemic risk than shocks on the upper range of the interval of shocks analyzed, bank 1 contributes more to expected systemic risk via the interlinkage channel – which in this case outweighs its relatively smaller contribution from the other two channels – in structure 19 than in structure 25 on Figure 3.6.[27]

Shutting down the firesales channel also impacts differently on structures of the financial system as regards expected systemic risk (lower panels on Figures 3.6 and 3.9). For example, the second lowest expected systemic risk is found in structure 8 (0.88; Table 3.5) on Figure 3.6. This structure is relatively safe because only banks 1 and 3 which have cross-exposure but no net-exposure to each other are interlinked. This offers them the potential to self-insure against shocks via netting. However, with the firesales channel shut down (Figure 3.9), the second lowest level of expected systemic risk can be found in structure 29 (0.62; Table 3.12). This change of order comes up because the firesales channel impacts the interlinkage channel to different extents in different structures: In structure 29 bank 2 has net exposure to bank 3 which is leveraged and holds more non-liquid assets than the other banks. However, with the firesales channel shut down, bank 3 gets extremely safe because the non-liquid assets are equivalent to liquid assets, so it rarely transmits a shock to bank 2 via the interlinkage channel. This shock buffer lowers systemic risk more than the self-insurance provided by the cross-exposure

get more impact, increasing also the influence of the interconnection channel. Taking into account the mean size of shocks to the system, a further aspect comes into play: in case of a big shock, that is, a shock on the upper range of the shocks considered, to bank 1, its net-value turns immediately negative and so it cannot recover via netting its counterparty exposure. In case of a medium shock, that is, a shock close to the mean of the shock distribution, to bank 1, however, it eventually improves its capital ratio via netting its counterparty exposure because the shock has not sufficient impact to turn bank 1's net-value negative. Since bank 1 can net more counterparty exposure in structure 25 (0.3) than in structure 19 (0.15) it has less chances to recover via netting in the latter structure and is thus more likely to emit a shock to a bank that has exposure to it.

[27]Note that this interpretation is corroborated by the fact that summing up all contributions to expected systemic risk by bank 1 with equal weights, that is, relaxing the assumption that shocks near the mean have a higher probability and all other parameters set as in the baseline specification, results, as expected, in bank 1 contributing more to expected systemic risk in structure 25 than in structure 19.

between banks 1 and 3 in structure 8. In addition, in the latter structure all banks hold the same amount of non-liquid assets, so banks that theoretically can emit shocks via interbank lendings have not a particularly large shock buffer from non-liquid assets when the firesales channel is shut down.

In summary, given the settings in the baseline specification with the firesales and size channels (partially) shut down, this sub-section yields four insights as regards the interlinkage channel. First, expected systemic risk and a bank's contribution to it tend to increase with the amount of interlinkages in the financial system. Second, cross-exposure gives banks the possibility to self-insure (via netting on the interbank market to increase the capital ratio) and thus can lower expected systemic risk and banks' contribution to it. Third, net-exposure increases expected systemic risk as well as the contribution to it from banks which are net borrowers. Fourth, the effect of the interlinkage channel on expected systemic risk and bank 1 's contribution to it depends on the magnitude of the shock to the financial system which is also impacted by the firesales channel. Since the interlinkage channel only becomes contagious at relatively large shocks, that is, those shocks which turn the net-value of banks negative, and the firesales channel amplifies the effect of shocks to the financial system, the effect of the interlinkage channel on expected systemic risk as well as banks' contribution to it increase with the extent of firesales in the financial system.

The next sub-section analyzes the effect of a bank's size on expected systemic risk.

3.3.4 The Effect of Banks' Size on Expected Systemic Risk

The effect of banks' size on expected systemic risk is isolated via shutting down the interlinkage and firesales channels. Using structure 32 (Table 3.14) in which no banks borrow from or lend to each other and the price responsiveness of the liquid asset, parameter ξ, set to zero, the amount of initial assets of bank 1 is increased over a range from 1 to 3, while the amount of initial assets of banks 2 and 3 remains set to 1 as in the baseline specification.

Figure 3.10 displays the effect of varying bank 1's initial assets on expected systemic risk (lower panel) as well as its contribution to it (upper panel) in structure 32. Controlling for the effect of the firesales and interlink-

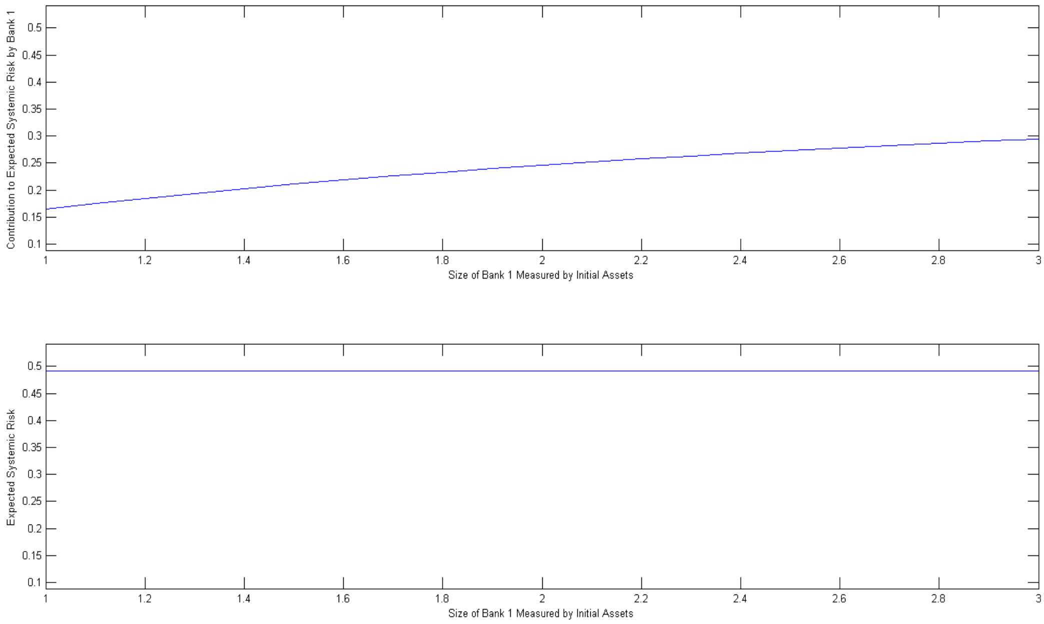


Figure 3.10: Effect of an Increase of Size on Expected Systemic Risk in Financial System Structure 32

age channels and increasing bank 1's size results in increasing its contribution to expected systemic risk (from 0.16 to 0.29). However, given the definition of systemic risk as well as the symmetry of the shock vectors and assigned probabilities which are used in the computation of expected systemic risk, the expected amount of systemic risk does not change (constantly at 0.49). This outcome is driven by the fact that in the weighted sum of systemic risk over all shock scenarios the changes in systemic risk resulting from increasing bank 1's size relatively to the other banks in the financial system exactly offset each other.

Increasing bank 1's size does not change its probability of default in any shock scenario but only increases its proportion in the financial system as measured by the sum of its assets and reduces the proportion of the remainder two banks by the same amount. When increasing bank 1's size, systemic risk thus increases in scenarios in which only bank 1 or bank 1 and one other bank default, decreases in scenarios in which only bank 2 or 3 or both default, and remains unchanged in scenarios where all banks or none of the banks default. For example, say in scenario A only bank 1 defaults while in scenario B banks 2 and 3 default with both scenarios having the same probabilities. Increasing the relative size of bank 1 in the financial system results in increasing systemic risk in scenario 1 and lowering it by the same amount in scenario 2. Expected systemic risk computed according to Equation (3.10) including both scenarios does not change. Note that the level of expected systemic risk can be affected of course if the distribution of shocks is not symmetric.

In summary, controlling for the effect of the interlinkage and firesales channels, increasing a bank's size with respect to the financial system increases the contribution to expected systemic risk from that bank and lowers the contribution of the remainder two banks by the same amount such that expected systemic risk remains unaffected.

The next sub-section investigates the effect of the capital requirement ratio on expected systemic risk.

3.3.5 The Effect of Capital Requirements on Expected Systemic Risk

In order to lower systemic risk in the financial system, several calls have been voiced to increase banks' capitalization. Since capital held in excess of liabilities is the main shock buffer before a bank starts emitting shocks via its interbank liabilities it is regarded to be one of the most effective tools in macro- and micro-prudential regulation. For example, under the proposed Basel III framework an essential strengthening of banks' capitalization is envisaged to make the financial system more resilient.[28]

In the following analysis the implications of different levels of banks' capital ratios on expected systemic risk will be analyzed with all remainder

[28] Bank for International Settlements (2010).

parameters set as in the baseline specification. Figure 3.11 displays expected systemic risk (lower panel) as well as bank 1's contribution to expected systemic risk (upper panel) when the required equity ratio in the financial system is varied over a range from 1% to 25%.

Expected systemic risk and bank 1 's contribution to it are displayed along the y-axis, the varying levels of required capital are displayed along the x-axis, and the interlinkage structures have been ordered along the z-axis according to their highest sum of expected systemic risk or contribution to it, that is, the integral over the x-axis for a given structure. For example, adding up all contributions to expected systemic risk from bank 1 over the range of analyzed required capital ratios, structures 12 and 64 (Tables 3.7 and 3.16, respectively) yield the highest values, which is the reason for these structures being farthest right on the upper panel.

As regards the ordering of financial system structures along the z-axis, results remain broadly the same with respect to figure 3.6. In the model increasing the parameter for the required capital ratio results in lowering expected systemic risk as well as bank 1's contribution to it. The lowest sum of contribution to expected systemic risk from bank 1 is achieved in structure 31 (Table 3.13). The highest expected systemic risk over all capital requirements analyzed is achieved in structures 10 and 61 (Tables 3.6 and 3.15, respectively). The lowest sum of expected systemic risk is obtained in structure 27 (Table 3.11), where at high levels of bank capitalization the self-insurance mechanism via cross-exposures becomes very effective, making it thus less risky than structure 32 (Table 3.14) which yields the lowest level of expected systemic risk on Figure 3.6.

The analysis in this sub-section provides evidence that increasing the capital requirement is an effective means to lower expected systemic risk and banks' contribution to it.

Overall, the results in this section show that our model reproduces the stylized facts which could be observed during the recent financial crisis. The main risk-channels which cause the emergence of systemic risk are interlinkages, firesales and the size of a bank with respect to the financial system. It has been shown that banks' capital requirements are an effective shock buffer

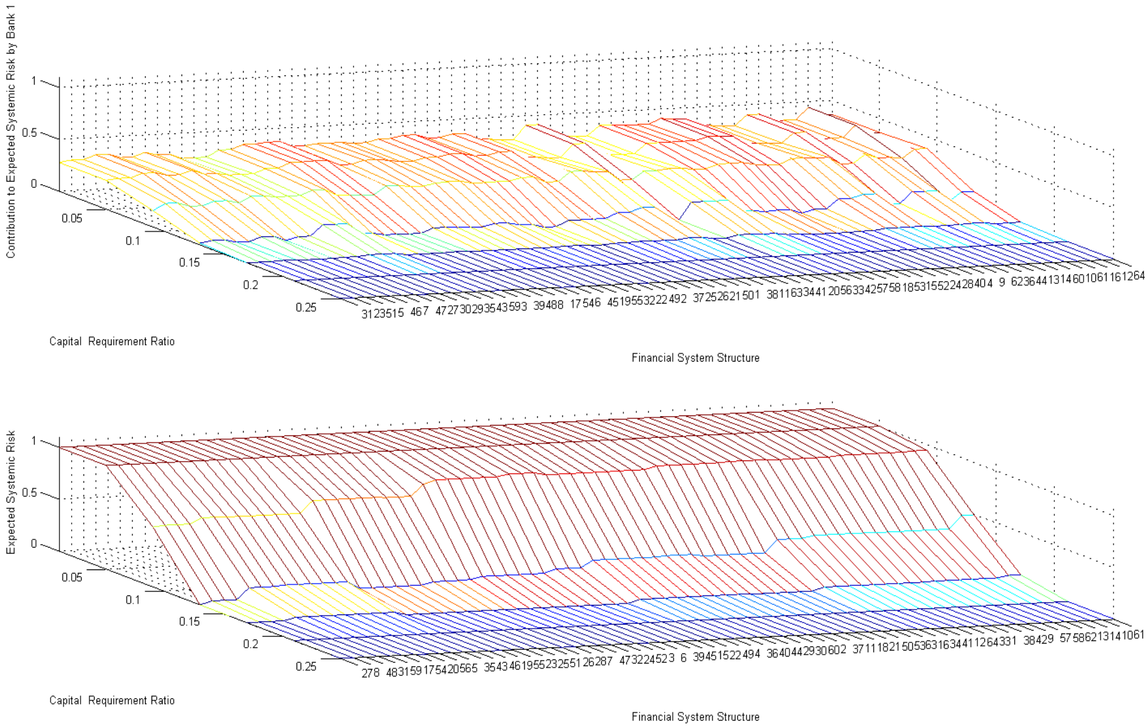


Figure 3.11: Effect of the Capital Requirement on Expected Systemic Risk

and can make the financial system more resilient to expected systemic risk as well as banks' contribution to it.

In the following section the model will be used to explore a systemic risk charge and fund which address systemic risk from a macroprudential perspective.

3.4 Developing a Systemic Risk Charge and Fund

A supervisor's approach to manage systemic risk should feature in particular three characteristics. First of all, it should address extreme shock scenarios, that is, shock events with an unusually high impact on the financial system. Systemic risk arises primarily through unexpectedly high losses which generally lead to firesales, contagion, and the default of individual institutions. To properly identify risk-channels and banks' contribution to expected systemic risk, these scenarios should cover a sufficient range of different shocks. Second, addressing systemic risk should not give wrong incentives, that is, it should not cause moral hazard[29] but, akin to a Pigouvian tax, incentivize financial institutions to lower their negative externality on the financial system which arises through their contribution to systemic risk. Third, the approach should envisage to preserve with a high probability even in strongly adverse scenarios a fraction of the financial system which is deemed necessary to prevent a financial shock from severely affecting the real economy.

It has been shown in the previous section that banks' contribution to systemic risk is driven by three risk-channels, (i) the extent of direct shock transmission through interbank liabilities which itself depends on the interlinkage structure and the amounts lent and borrowed, (ii) the extent of firesales which themselves depend on the amount of non-liquid asset holdings and the price responsiveness of the non-liquid asset, and (iii) banks' size relative to the financial system. If the supervisor wants to lower systemic risk, it is unlikely that he starts regulating all these dimensions involved in banks' contribution to expected systemic risk. However, it makes sense to use in particular one instrument, additional capital, to make the financial system more resilient to expected systemic risk. On the one hand, as has become clear in the previous section, this instrument has a high impact as shock buffer to lower expected systemic risk and, on the other hand, remaining administrative regulatory approaches such as, for example, forcing a bank to change its portfolio composition or counterparties, would be unfeasible in

[29] See Poole (2008) for a discussion of financial institutions, financial stability, and moral hazard.

reality.

Our model will be used to investigate a systemic risk management approach in which a systemic risk charge and systemic risk fund are determined within an SVaR concept.[30] As will become clear, the SVaR concept combines the previously outlined characteristics in a unified framework. The general idea is to charge banks according to their contribution to expected systemic risk. Banks which contribute more to expected systemic risk have to pay a higher risk charge than banks which contribute less. These payments are used to capitalize a systemic risk fund which is re-injected into the financial system in an optimal way to make it more resilient to systemic risk.

In the following, the approach to determine (i) the optimal amount of capital for the risk fund and (ii) the individual financial institution's contribution to it, as well as (iii) the optimal (macroprudential) capital amounts individual financial institutions are injected from the systemic risk fund to make the financial system more resilient to systemic risk will be outlined.

To set up the systemic risk charge and fund, the supervisor first of all defines a distribution of extreme shock scenarios deemed possible. Given our model, the supervisor will be able to compute the expected systemic risk as well as individual institutions' contribution to it associated with the stress scenarios. Next, the supervisor chooses an SVaR. The SVaR is defined as the proportion of the financial system which the supervisor is willing to accept to become insolvent in a given quantile of the shock distribution. For example, an SVaR could be defined as 'In 95% of all shock-scenarios systemic risk shall not exceed 0.37'. Given all shock scenarios the supervisor then computes the minimum (macroprudential) capital amounts which banks in the financial system need to be injected to fulfill this SVaR. The sum of these additional capital injections (which need not be the same across banks) constitutes the overall necessary amount of capital in the systemic risk fund.

The fund is capitalized via charging financial institutions according to their contribution to systemic risk. Equation (3.13) displays the systemic

[30] The following SVaR approach features some of the characteristics of the VaR concept which is a well established measure in risk management used on the level of individual banks. The VaR indicates for a given portfolio the loss it will not exceed in a specified time horizon with a given probability. See, for example, Jorion (2006).

risk charge, H, for the i'th bank.

$$H_i = \Psi \cdot \frac{\phi_i^E}{\sum_j^3 \phi_j^E}. \tag{3.13}$$

where $i \in j$, Ψ is the amount of capital to be collected for the entire systemic risk fund, and ϕ_i^E designates the contribution to expected systemic risk by bank i as measured by the Shapley value. After collecting all individual charges in the fund,[31] the money is re-injected into 'neuralgic' financial institutions, that is, those institutions which increase the financial system's resilience most, as additional capital which they are required to hold as liquid assets. The additional capital can be injected on top of the required capital from microprudential regulation in the form of preferred stock such that its function as an additional shock-buffer only emerges after other shareholders' equity has been extinguished.

As will become clear in the following, requiring banks to hold this macroprudential capital in addition to the microprudential capital requirement, the risk fund primarily addresses systemic risk arising through the interlinkage channel. The other two risk channels are only indirectly affected. The size channel is not directly affected because the additional capital is not included in computing banks' proportion of the financial system. Furthermore, banks default if they cannot fulfill both the macro- and microprudential capital requirement, that is, a default does not get more unlikely through additional capital. The firesales channel is also not directly affected because of a same argument. Since banks have to maintain the higher capitalization their market behaviour as regards sales of non-liquid assets does not change. However, both channels are indirectly affected as, for example, a reduced impact from the interlinkage channel because of a higher capitalization can prevent a shock from being spread further via that channel to a bank with a sizeable amount of non-liquid assets on the balance sheet. The firesales channel is thus indirectly dampened via less shock transmission through the interlinkage channel.[32]

[31] Note that at this point it is assumed that banks can pay these charges from profits, for example, by deferring dividend payments.

[32] The firesales and size channels could be addressed via 'triggering' in case a systemic

An important feature of the SVaR concept is that individually all banks can default. If none of the banks' sizes exceeds the proportion of the financial system that is accepted to break down under the SVaR, then, depending on which scenario realizes, all three banks are threatened with insolvency. This reduces the risk of moral hazard from the systemic risk fund.

In the following, the outlined systemic risk charge and fund will be computed for the baseline specification of the financial system developed in the previous section. The structure of the financial system analyzed is structure 19 (see Appendix 3.A as well as Table 3.9 in Appendix 3.B at the end of this chapter). The shocks are modeled as outlined in Section 3.2.

The supervisor's SVaR is defined as 'In at least 95% of possible shock scenarios, not more than 37% of the financial system shall default'. The following exercise consists of finding the minimum additional capital amounts that need to be injected into financial institutions to fulfill this SVaR. Since in structure 19 the biggest bank constitutes 37% of the financial system (measured by the size of their balance sheets, banks 1 to 3 constitute, in rounded values, 33%, 29%, and 37% of the financial system, respectively), theoretically each bank can default with the SVaR still being fulfilled if the other two banks remain solvent in a given shock scenario.

The loss function, ϵ, which is minimized to compute the optimal amount of additional capital that needs to be injected to fullfill the SVaR is given by Equation 3.14.

$$\epsilon = \sum_{i}^{3} \tau_i + \sum_{w}^{L} o_w(\tau), \tag{3.14}$$

where τ_i is the additional amount of capital injected into financial institu-

shock emerges either (i) reduced required capital ratios, if the additional (macroprudential) capital had been injected as preferred stock, or, (ii) the conversion of debt into equity, in case the additional (macroprudential) capital had been injected in the form of Contingent Convertible Bonds (CoCos). (For a review on the advantages and disadvantages of contingent capital see Pazarbasioglu, Zhou, Leslé, and Moore (2011).) However, any threshold value, be it triggered by a market based measure or by a supervisory authority, can lead to perverse incentives and cause moral hazard. Investigating the effect of such triggers in our model would be interesting to pursue but is beyond the scope of this chapter and thus not addressed.

tion i. o_w is the systemic risk in scenario w, with L the number of scenarios that exceed the accepted proportion of systemic risk after exclusion of the percentage amount of scenarios the supervisor allows to attain or exceed the maximum systemic risk. For example, consider the supervisor sets up 100 scenarios, with each scenario assigned a different probability. According to the SVaR, in 95% of all scenarios the proportion of insolvent banks with respect to the financial system shall not exceed 0.37. Say, in case the supervisor injects no additional capital at all, that is $\sum_i^3 \tau_i = 0$, the sum of probabilities of scenarios resulting in excess of a systemic risk of 0.37 is 25%. Inspecting Equation (3.14), ϵ then consists of the sum of systemic risk resulting in all scenarios exceeding the SVaR, excluding those scenarios in excess of the SVaR which add up to the highest expected systemic risk based on 5% of the shock scenarios.[33]

Note that minimizing Equation (3.14) to find out the necessary additional capital and the financial institutions in which additional capital needs to be injected requires a non-standard optimization technique because the objective function can have multiple local minima. The simulated annealing approach,[34] a probabilistic metaheuristic optimization procedure, is used to find the optimal solution for Equation (3.14). A parallelized variant of the optimization algorithm is outlined in Appendix 3.C at the end of this chapter.

Table 3.2 displays the optimal results from the systemic risk fund exercise. The first three rows display the banks' weighted Shapley values, that is, their contribution to expected systemic risk, resulting from the set of all shocks. Note that these Shapley values are calculated following Equation (3.12) on the basis of the financial system without any capital injections from the systemic risk fund. Rows four to six display the resulting optimal capital risk

[33] In Equation (3.14) probabilities are not used to weight the scenarios. However, excluding the 5% of scenarios in excess of the SVaR which result in the highest expected value yields the lowest value of the loss function. In any case, in the exercise, all shock scenarios included in the second term of equation (3.14) consist of at least the systemic risk value arising through the insolvency of two banks which exceeds the first term of Equation (3.14). The supervisor has thus a strong incentive to make sure the SVaR is not exceeded in any of the scenarios representing 95% of the shock distribution.

[34] See Kirkpatrick, Gelatt, and Vecchi (1983).

Contribution to Expected Systemic Risk of Bank 1	0.3289
Contribution to Expected Systemic Risk of Bank 2	0.3017
Contribution to Expected Systemic Risk of Bank 3	0.3246
Contribution of Bank 1 to Systemic Risk Fund	0.0472
Contribution of Bank 2 to Systemic Risk Fund	0.0433
Contribution of Bank 3 to Systemic Risk Fund	0.0465
Amount of Capital Injected to Bank 1 from Systemic Risk Fund	0.0494
Amount of Capital Injected to Bank 2 from Systemic Risk Fund	0.0350
Amount of Capital Injected to Bank 3 from Systemic Risk Fund	0.0526

Table 3.2: Results of the Systemic Risk Fund Exercise in Financial System Structure 19

charge – which depends on the necessary size of the systemic risk fund as well as banks' individual contributions to expected systemic risk – for each bank. These values are computed following Equation (3.13) where Ψ is obtained by minimizing Equation (3.14) and summing up the optimal individual capital injections. Rows seven to nine which are also obtained from the minimization of Equation (3.14) display the optimal amount of capital injected from the systemic risk fund into the respective banks to fulfill the SVaR.

Three points are worth mentioning. First of all, banks' contribution to expected systemic risk is driven by the three risk-channels outlined before, size, firesales, and interlinkages. In particular note that the higher contribution to expected systemic risk of bank 1 with respect to bank 3 in this structure has already been analyzed in Sub-Section 3.3.3 in the context of investigating the effect of interlinkages on expected systemic risk.[35] Bank 2 contributes least to expected systemic risk because the other banks have no net-exposure to it, it holds the smallest amount of non-liquid assets, and constitutes the smallest proportion of the financial system. This is reflected in the contributions to expected systemic risk and the banks' contribution to the systemic risk fund on Table 3.2. Bank 1 contributes slightly more to

[35]Given the symmetry of all structures, the contribution of bank 1 to expected systemic risk in structure 25 is the same as the contribution of bank 3 to expected systemic risk in structure 19. Sub-Section 3.3.3 clarified why in the baseline specification displayed on Figure 3.6 the contribution to systemic risk by bank 1 (upper panel) is larger in structure 19 than in structure 25.

expected systemic risk and thus has to pay the highest charge, followed by banks 3 and 2, respectively.

Second, the optimal size of the systemic risk fund (0.14), obtained when summing up rows 7 to 9 on Table 3.2 represents 3.5% of system-wide assets. Calculating for each shock the difference between the net-value of the financial system, that is, the sum of all banks' net-values, with and without pre-injecting the capital from the systemic risk fund into the banks, and summing up these differences weighted with the shock probabilities shows that in expectation the financial system would have to be injected ex-post an additional capital of about 4.1% in relation to system wide assets if the same outcome as with pre-injecting the capital amounts was desired. This expected size of an ex-post bail-out exceeds the size of the fund that is immediately re-injected into the financial system to fulfill the supervisor's SVaR.[36] This second result is driven by pre-emptively nipping the contagious effects of financial shocks in the bud, in particular knock-on defaults via the interlinkage channel and resulting firesales of non-liquid assets when the systemic risk fund is immediately injected into the financial system.

Third, the optimal amounts of additional capital injected from the systemic risk fund do not fully reflect the ranking which emerges in banks contribution to expected systemic risk. Although bank 1 contributes more to expected systemic risk than bank 3, it is optimal to inject more capital into bank 3 to fulfill the SVaR.[37] Taking a systemic perspective, the optimal macroprudential capitalizations thus need not necesarily reflect banks' contribution to systemic risk in a proportional way. This result is mainly driven by using different probability weights when computing banks' contribution

[36]Note that the size of an ex-post bail-out fund gets even larger if one does not take the expected difference over all scenarios, but the largest difference that results in the 95% of scenarios in which the SVaR must be fulfilled.

[37]Note that this result is robust to controlling for scenarios in which more than 37% of the financial system default, that is, the 5% of scenarios which are accepted under the outlined SVaR to exceed the highest proportion the supervisor is willing to accept as insolvent in the system. Calculating the contribution to expected systemic risk without additional capital injections only for the 95% of scenarios in which 62% (due to rounding, the three banks' proportions add up to 0.99) or more of the banking system remains solvent with the optimal injections from the systemic risk fund, results in the same order of contribution to expected systemic risk as displayed on Table 3.2.

to expected systemic risk, however, following the definition of the SVaR, equally weighting 95% of the shock scenarios for computing banks' optimal additional capital injections.[38]

Note that qualitatively, the same result emerges, however more robust to distributional assumptions about the shock scenarios, when taking into consideration that additional capital injections affect the channels of contribution to expected systemic risk to different extents. As outlined before, increasing a bank's capitalization does not directly affect its contribution to expected systemic risk via the size and firesales channels. The main impact of additional capital is lowering expected systemic risk emerging via the interlinkage channel. To make this point clear consider, for example, a slight modification of the baseline specification which consists of strongly increasing the size of one of the financial institutions while making the remainder two financial institutions highly interlinked in the financial system. Increasing bank 1's initial assets, parameter A, to 2, leaving all remainder parameter values as in the baseline specification, and taking financial system structure 60 results in the desired setting. Table 3.3 displays the financial system as well as the banks' proportions in the outlined set up.

	Bank 1	Bank 2	Bank 3	NLA	LA	Proportion
Bank 1		0.30	0.30	1.12	0.28	0.44
Bank 2	0		0	1.04	0.26	0.28
Bank 3	0	0		1.04	0.26	0.28
ROW	1.86	0.92	0.92			

Table 3.3: Financial System Structure 60 with Parameter A increased to 2 for bank 1

As can be seen, bank 1 constitutes the largest proportion of the financial system (44%) while banks 2 and 3 both constitute a relatively little propor-

[38]The probability weights play no role in the 95% of scenarios in which the supervisor insures that 62% or more of the financial system remain solvent. In these scenarios the supervisor only tries to find the minimum amount of capital which ensures that at most one bank defaults. As has been outlined in Sub-Section 3.3.3, without giving different weights to the shock scenarios, bank 1 contributes more to expected systemic risk in structure 25 than in structure 19. Given the symmetry of all structures, the contribution of bank 1 to expected systemic risk in structure 25 is the same as the contribution of bank 3 in structure 19.

Contribution to Expected Systemic Risk of Bank 1	0.4693
Contribution to Expected Systemic Risk of Bank 2	0.2610
Contribution to Expected Systemic Risk of Bank 3	0.2610
Contribution of Bank 1 to Systemic Risk Fund	0.0731
Contribution of Bank 2 to Systemic Risk Fund	0.0407
Contribution of Bank 3 to Systemic Risk Fund	0.0407
Amount of Capital Injected to Bank 1 from Systemic Risk Fund	0.0000
Amount of Capital Injected to Bank 2 from Systemic Risk Fund	0.0772
Amount of Capital Injected to Bank 3 from Systemic Risk Fund	0.0772

Table 3.4: Results of the Systemic Risk Fund Exercise in Financial System Structure 60

tion (28%, each). Furthermore, bank 1 holds the largest amount of non-liquid assets (1.12) while banks 2 and 3 hold a relatively small amount (1.04, each). With regards to interlinkages, bank 1 has net-exposure both to banks 2 and 3. In this setting bank 1 contributes most to expected systemic risk via the size and firesales channels and banks 2 and 3 contribute most to expected systemic risk via the interlinkage channel.

Defining the SVaR as 'In 95% of all shock-scenarios systemic risk shall not exceed 0.44' and repeating the systemic risk fund exercise, Table 3.4 displays the optimal results for the financial system outlined on Table 3.3.

Again, there is no correspondence between a bank's systemic risk charge and the capital that is optimally injected into it. Though bank 1 contributes most to expected systemic risk and thus pays the highest charge for the systemic risk fund, from a financial stability perspective it is optimal to inject this capital into banks 2 and 3, only. As outlined before, this outcome results from the fact that the contribution to expected systemic risk is driven by three different risk-channels which are affected to a different extent by the supervisor's instrument to lower expected systemic risk, additional capital injections. Since the contribution of bank 1 is only driven by the firesales and size channels which are not directly addressed in the model by additional capital, the SVaR is optimally attained via injecting all additional capital into banks 2 and 3 which contribute most to expected systemic risk via the interlinkage channel.[39]

Overall, the SVaR analysis shows that linking a bank's macroprudential capital requirements directly to its contribution to systemic risk, as, for example, suggested in Acharya, Pedersen, Philippon, and Richardson (2009),[40] is not necessarily an optimal and consistent policy approach when taking a systemic risk management perspective. Following the results in our framework, linking banks' macroprudential capital requirements directly to their contribution to expected systemic risk can be inconsistent or inefficient if, as is likely the case, the drivers of expected systemic risk are differently affected by additional macroprudential capital requirements. This result becomes more intuitive when pointing out that a variant of the Tinbergen rule applies in our setting. The Tinbergen rule implies that consistent economic policy requires the number of policy instruments to at least equal the number of policy targets.[41] In our systemic risk management approach a consistent and *efficient* economic policy calls for the same requirement because there are two policy targets which the supervisor tries to achieve. First of all, a numerical value with respect to expected systemic risk, the SVaR, and, second, to incentivize banks to lower their contribution to expected systemic risk via an appropriate risk charge. Though ultimately related, both targets can become distinct when the risk-channels through which banks contribute to expected systemic risk are affected by the instrument to achieve systemic stability, additional capital, to a different extent.

The solution to the dilemma in the SVaR concept is to use two instru-

[39]Note that the result is robust to relaxing the distributional assumptions such that all scenarios emerge with the same probabilities. Furthermore, it is robust to controlling for scenarios in which more than 44% of the financial system default, that is the 5% of scenarios which are accepted under the outlined SVaR to exceed the highest proportion the supervisor is willing to accept as insolvent in the system. Calculating the contribution to expected systemic risk without additional capital injections only for the 95% of scenarios in which 56% or more of the banking system remain solvent with the optimal injections from the systemic risk fund, results in the same order of contribution to expected systemic risk as displayed on Table 3.4.

[40]The authors propose, *inter alia*, that "[c]apital requirements could be set as a function of a financial firm's marginal expected shortfall" (p. 8) which is their measure for a bank's contribution to systemic risk. See also V. Acharya and M. Richardson (2009).

[41]See J. Tinbergen (1952).

ments, a levy to fulfill the incentive requirement[42] and a capital injection to guarantee systemic stability. Though a proper incentive requirement should foster the target of financial stability, it is possible that both targets cannot be achieved by only one instrument in an efficient or in a consistent way if the risk-channels are unequally affected by the single instrument. Merging the two instruments in case the risk-channels are indeed affected differently by additional capital injections can result in not properly incentivizing financial institutions to lower their contribution to expected systemic risk[43] or in requiring a systemic risk fund with a larger amount than the one implied by the optimal SVaR approach[44] which then results in a sub-optimal capital allocation.

The next section concludes.

[42]Note that the incentive requirement implied by the SVaR is only fulfilled if financial institutions are aware of how they can lower their contribution to systemic risk. This however potentially depends in part on the decisions taken by other banks. In the model and SVaR approach the incentive requirement is only fulfilled to the extent that banks which contribute more to systemic risk face a higher risk charge. It still needs to be investigated, desireably in richer framework where banks do not only try to fulfill a capital requirement but also maximize their profit, whether a trade-off between maximizing profit and paying an adequate risk charge for the resulting contribution to systemic risk is feasible.

[43]This is the case if each bank is only charged the optimal amount of capital it will be required to hold as additional (macroprudential) capital. In the example on Table 3.4 this would be achieved via setting the contributions of banks to the systemic risk fund, rows 4 to 6, to the respective values displayed in rows 7 to 9. The SVaR would be optimally fulfilled, however, the incentive requirement not. Hence the policy approach would be inconsistent.

[44]This is the case if the incentive requirement is fulfilled, that is, banks are charged according to their contribution to systemic risk while fulfilling the SVaR, however, not in an optimal way. With respect to the example on Table 3.4 this is achieved via including the additional restriction in the optimization procedure that the amount injected into a bank must be equal to the amount charged from that bank. In the example, this restriction leads to a higher sum of necessary capital injections, that is, in a sub-optimal capital allocation with respect to not including the restriction.

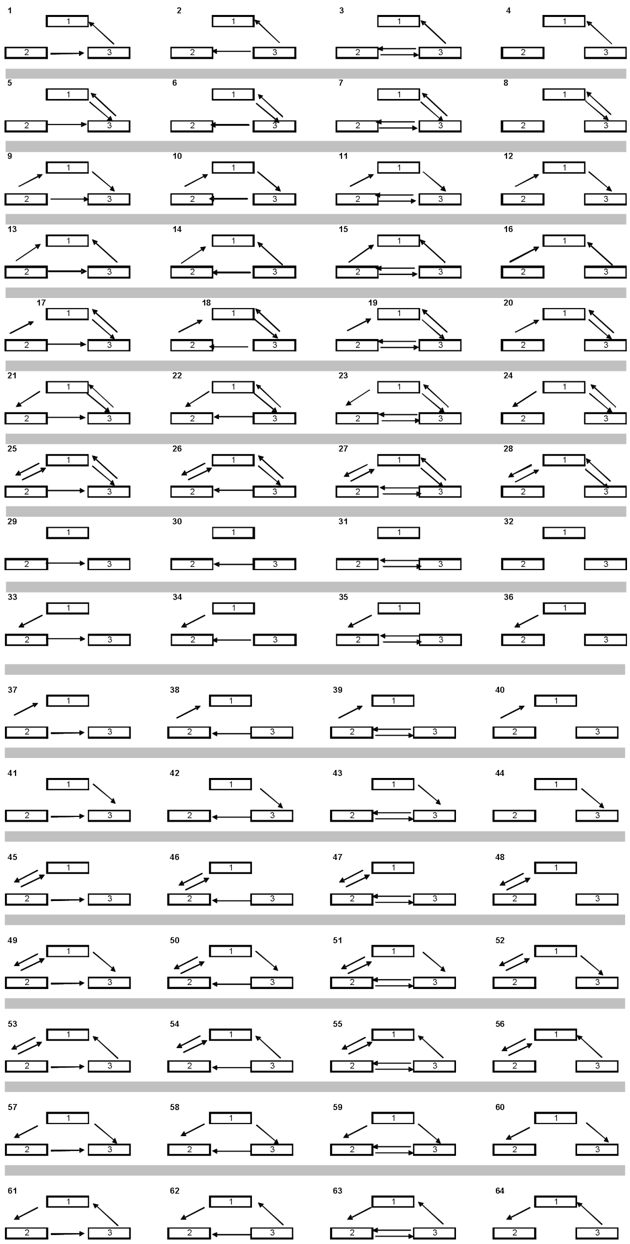
3.5 Conclusion

In this chapter a model that allows to replicate the main stylized facts of systemic risk which came up during the recent financial crisis has been developed. In our model, the three main risk-channels through which systemic risk arises are banks' size, their interlinkages, and firesales of non-liquid assets. Furthermore, a proposed systemic risk charge and fund are designed within an SVaR approach which allows to make the financial system more resilient to systemic risk and charges banks according to their contribution to expected systemic risk. This systemic risk management concept allows to simultaneously determine the necessary capital of a systemic risk fund, banks optimal (macroprudential) capitalization, and risk charge in a unified framework which is consistent and efficient.

Among numerous insights into the complex processes arising in an interdependent financial network two key results are of particular importance. First of all, keeping additional (macroprudential) capital obtained from charging banks according to their contribution to expected systemic risk in the financial system to make it more resilient to extremely adverse shock scenarios is likely to come at a lower cost than bailing out banks ex-post. The reason for this outcome is that re-injecting capital into 'neuralgic' points of the financial system helps nipping crisis developments and contagion effects in the bud before they can unfold their mischief. Besides the argument that a systemic risk fund which is not injected into the financial system but kept centralized in a 'government chest' sparks political interest to divert its intended use after a longer period with no systemic events, the result of our systemic risk fund analysis provides further evidence as to why it is better to keep macroprudential capital which is levied via a risk charge in the financial system.

Second, using the model to analyze the proposed systemic risk charge and fund provides evidence that there is not necessarily a correspondence between a bank's contribution to systemic risk – which determines its risk charge – and the capital that is optimally injected into it to make the financial system more resilient to systemic risk. If the drivers of systemic risk are affected by additional (macroprudential) capital to different extents one is well advised to carefully distinguish between a bank's contribution to systemic risk as a determinant of its risk charge and the amount of capital injected into it to make the financial system more resilient. Increasing a bank's capital is an efficient administrative instrument to lower systemic risk and banks' contribution to it. However, not distinguishing between a bank's risk charge and its macroprudential capitalization can result in inconsistent or inefficient economic policy.

Appendix 3.A: Structures of the Financial Network Matrix[45]



[45]An arrow from a bank to another bank symbolizes that this bank has exposure to the other bank through interbank lending.

Appendix 3.B: Structures Referred to in the Analysis

The structures of the financial system outlined in the following tables have been referred to in the analysis of Sections 3.3 and 3.4. The entries in the tables are generated along the parameter settings in the baseline specification. The left part of each table is built up as outlined on Figure 3.2, and the right side outlines the respective bank's proportion in the financial system as measured by the amounts of its assets relative to system-wide assets.

	Bank 1	Bank 2	Bank 3	NLA	LA	Proportion
Bank 1		0	0.3	0.80	0.20	0.36
Bank 2	0		0	0.80	0.20	0.28
Bank 3	0.3	0		0.80	0.20	0.36
ROW	0.912	0.936	0.912			

Table 3.5: Financial System Structure 8

	Bank 1	Bank 2	Bank 3	NLA	LA	Proportion
Bank 1		0	0.3	0.80	0.20	0.33
Bank 2	0.3		0	0.80	0.20	0.33
Bank 3	0	0.3		0.80	0.20	0.33
ROW	0.912	0.912	0.912			

Table 3.6: Financial System Structure 10

	Bank 1	Bank 2	Bank 3	NLA	LA	Proportion
Bank 1		0	0.3	0.8	0.2	0.36
Bank 2	0.3		0	0.56	0.14	0.28
Bank 3	0	0		1.04	0.26	0.36
ROW	0.912	0.9312	0.9168			

Table 3.7: Financial System Structure 12

	Bank 1	Bank 2	Bank 3	NLA	LA	Proportion
Bank 1		0	0	1.28	0.32	0.44
Bank 2	0.3		0	0.56	0.14	0.28
Bank 3	0.3	0		0.56	0.14	0.28
ROW	0.8976	0.9312	0.9312			

Table 3.8: Financial System Structure 16

	Bank 1	Bank 2	Bank 3	NLA	LA	Proportion
Bank 1		0	0.3	0.8	0.2	0.33
Bank 2	0.15		0.15	0.68	0.17	0.29
Bank 3	0.15	0.15		0.92	0.23	0.37
ROW	0.912	0.9216	0.9024			

Table 3.9: Financial System Structure 19

	Bank 1	Bank 2	Bank 3	NLA	LA	Proportion
Bank 1		0.15	0.15	0.92	0.23	0.37
Bank 2	0.15		0.15	0.68	0.17	0.29
Bank 3	0.3	0		0.8	0.2	0.33
ROW	0.9024	0.9216	0.912			

Table 3.10: Financial System Structure 25

	Bank 1	Bank 2	Bank 3	NLA	LA	Proportion
Bank 1		0.15	0.15	0.80	0.20	0.33
Bank 2	0.15		0.15	0.80	0.20	0.33
Bank 3	0.15	0.15		0.80	0.20	0.33
ROW	0.912	0.912	0.912			

Table 3.11: Financial System Structure 27

	Bank 1	Bank 2	Bank 3	NLA	LA	Proportion
Bank 1		0	0	0.8	0.2	0.30
Bank 2	0		0.3	0.56	0.14	0.30
Bank 3	0	0		1.04	0.26	0.39
ROW	0.936	0.9312	0.9168			

Table 3.12: Financial System Structure 29

	Bank 1	Bank 2	Bank 3	NLA	LA	Proportion
Bank 1		0	0	0.80	0.20	0.28
Bank 2	0		0.3	0.80	0.20	0.36
Bank 3	0	0.3		0.80	0.20	0.36
ROW	0.936	0.912	0.912			

Table 3.13: Financial System Structure 31

	Bank 1	Bank 2	Bank 3	NLA	LA	Proportion
Bank 1		0	0	0.80	0.20	0.33
Bank 2	0		0	0.80	0.20	0.33
Bank 3	0	0		0.80	0.20	0.33
ROW	0.936	0.936	0.936			

Table 3.14: Financial System Structure 32

	Bank 1	Bank 2	Bank 3	NLA	LA	Proportion
Bank 1		0.3	0	0.80	0.20	0.33
Bank 2	0		0.3	0.80	0.20	0.33
Bank 3	0.3	0		0.80	0.20	0.33
ROW	0.912	0.912	0.912			

Table 3.15: Financial System Structure 61

	Bank 1	Bank 2	Bank 3	NLA	LA	Proportion
Bank 1		0.3	0	0.8	0.20	0.36
Bank 2	0		0	1.04	0.26	0.36
Bank 3	0.3	0		0.56	0.14	0.28
ROW	0.912	0.9168	0.9312			

Table 3.16: Financial System Structure 64

Appendix 3.C: A Parallelized Simulating Annealing Algorithm

To minimize the loss-function outlined in Section 3.4 (Equation (3.14)) the simulated annealing algorithm is used. The algorithm has been developed by Kirkpatrick, Gelatt, and Vecchi (1983) and is a heuristic optimization procedure to approximate the global minimum of a complex function that has multiple local minima.[46] It has been inspired from the annealing process in metallurgy where a slow cooling down of metal insures that atoms have enough time to form stable crystals without defects.

To minimize a function with the simulated annealing algorithm, new function values are generated along random changes to the control parameters in a Markov chain. New solutions that lead to improvements, that is, decreasing values, in the function are always accepted as new element in the Markov chain, whereas new solutions that lead to an increase in the function value are only accepted with a certain probability. This acceptance probability is influenced by a temperature used in the algorithm. At high temperature values the acceptance probability is high, and at low temperatures this probability is small. The optimization procedure consists of numerous sub-optimizations along Markov chains. After each Markov chain the temperature is gradually lowered which decreases the initially high probability of 'uphill-moves' – thus preventing the optimization routine to get 'trapped' in local minima. The final solution is found when the system has 'frozen', that is, when for the length of one Markov chain no new solutions are accepted. Figure 3.12 displays the simulated annealing algorithm.

In the following, a variant of simulated annealing developed for our application is outlined. It uses parallel Markov chains as well as an automatic adjustment of the stepsize and temperature to increase accuracy and the chance that the global minimum is found.

Following Parks (1990) new solutions are generated following Equation 3.15

$$\boldsymbol{\rho}_{i+1} = \boldsymbol{\rho}_i + \boldsymbol{D} \cdot \boldsymbol{u}, \tag{3.15}$$

[46] The following outline also draws strongly upon Parks (2010).

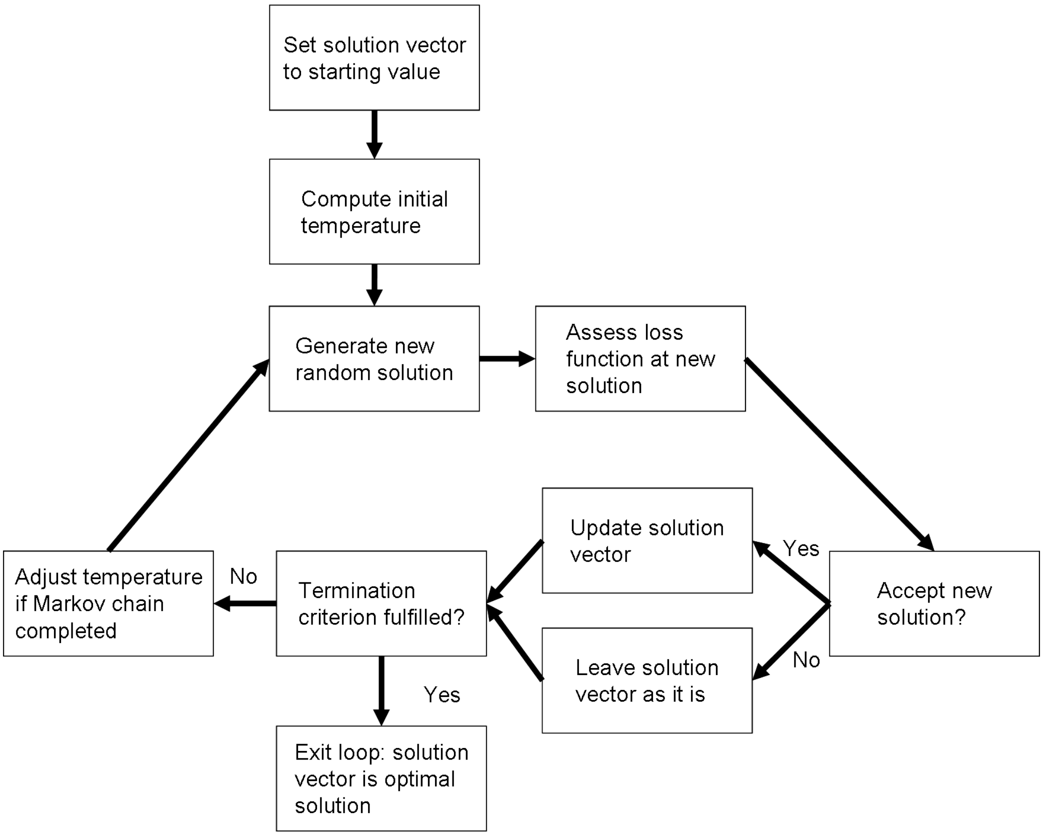


Figure 3.12: Simulated Annealing Algorithm

where $\boldsymbol{\rho}$ is the vector of control variables, $\boldsymbol{D}$ is a diagonal matrix scaling the stepsize of changes to the control variables, and $\boldsymbol{u}$ is a vector of uniformly distributed numbers on the interval (-1,1). $\boldsymbol{D}$ is updated after a successful draw as $\boldsymbol{D}^* = (1-\pi)\boldsymbol{D} + \pi\omega\boldsymbol{R}$, where $0 < \pi < 1$ is a parameter that controls how fast $\boldsymbol{D}$ is updated, ω is a scaling parameter, and $\boldsymbol{R}$ is a diagonal matrix containing the absolute value of successfully implemented steps, that is $\boldsymbol{R} = |\boldsymbol{D}\boldsymbol{u}|$. Following Parks (2010), the values of π and ω are set to 0.1 and 2.1, respectively.

Since the stepsize is flexibly adjusting to the functions' topography, the acceptance probability for uphill movements, that is increasing function values, needs to take this into account and is calculated following Equation 3.16

$$prob = exp\left(-\frac{\delta f^+}{T\bar{d}}\right), \tag{3.16}$$

where $\bar{d}$ is the average step size, that is, $\bar{d} = \sum_k |D_{kk}u_k|$, and δf^+ is the increase in the loss function at the updated vector of control variables.

Following Kirkpatrick, Gelatt, and Vecchi (1983) the initial temperature is set such that the average probability of a function increase equals 0.8. The initial temperature, T_0, can be found via an initial search with the initial stepsize set to 1, with all function changes being accepted, and then applying Equation 3.17

$$T_0 = -\frac{\delta\bar{f}^+}{ln(0.8)}, \tag{3.17}$$

where $\delta\bar{f}^+$ is the average positive change in the loss function during the initial search's Markov chain.

The maximum length of one Markov chain is set such that the search, given the initial step size theoretically can pace several times through the whole search space deemed realistical for the problem at hand, which in this application is set to be a cube with side length $2*A$, with A the inital assets of banks in the model.[47] In this application, with the initial maximum stepsize set to 1, the length of the Markov chain is set to fifty times the searchspace's volume divided by the initial maximum stepsize, that is $(2 \cdot A)^3 \cdot 50 = 400$. Clearly, the length of the Markov chain is a relatively arbitrary parameter. Setting its length too short can result in the system freezing prematurely, that is, getting stuck in a local optimum. Setting it too long can result in unnecessarily long computation time. In practice, the adequacy of the length of the Markov chain for the function to be minimized can be evaluated via taking out several optimizations with different starting values to cross-check whether they lead to the same optimal solution, also when taking random starting values.[48]

[47]Note that the algorithm theoretically can explore far beyond this limit since the stepsize is adjusting freely to the necessary length. As robustness check totally unrealistic starting values of up to $1000 \cdot A$ have been chosen, always resulting in the same optimal solution, though eventually taking a long time to compute.

[48]Note that no matter which length the Markov chain is assigned, it is very unlikely to end up at exactly the same solution in each optimization given the heuristic nature of

After a Markov chain of new random solutions has been completed the temperature is adjusted following an adaptive approach from Huang, Romeo, and Sangiovanni-Vincentelli (1986) where the temperature is decremented following Equation 3.18

$$T_{k+1} = \iota_k \cdot T_k, \tag{3.18}$$

and ι_k is given by Equation 3.19

$$\iota_k = max\left\{0.5, exp\left(-\frac{0.7 \cdot T_k}{\sigma_k}\right)\right\}, \tag{3.19}$$

where σ_k is the standard deviation of the loss function values that have been accepted during the Markov chain at temperature T_k. Note that the Markov chain is interrupted before its maximal length has been reached if the number of accepted random draws along the Markov chain equals 60% of the length of the Markov chain.

After the temperature has been decreased or at the beginning of the optimization procedure, the actual optimal value as well as stepsize and temperature are given to q parallel Markovian processes, where q is the number of CPUs used for parallel computing. Each process then optimizes the Markov chain along the lines outlined above until it is completed or interrupted because the number of accepted draws attained 60%. Next, the best solution as well as the according temperature and stepsize of these sub-optimizations from the parallel Markov chains are taken as new best value for the parallel optimization and given again as input to q parallel Markovian processes.

The algorithm terminates when the number of accepted changes in the entire optimal Markov chain is zero.

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the algorithm. However, same solutions can be characterized as being in the same close neighborhood.

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