VAR models on the relation between stock prices and the macroeconomy

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Abstract

This dissertation consists of three essays, which study the relation between stock prices and the macroeconomy using vector autoregressions (VARs). The first essay focuses on the link between stock prices and the current account. I find that stock markets provide a channel, in addition to the traditional exchange rate channel, through which external balance for a country with a current account imbalance can be restored. The second essay explores the transmission of U.S. stock price shocks to real activity and prices in G-7 countries. I achieve identification by imposing a small number of sign restrictions on impulse responses, while controlling for monetary policy, business cycle and government spending shocks. The results suggest that stock price movements are important for fluctuations in G-7 real activity and prices, but do not qualify as demand side business cycle shocks. The third essay investigates the impact of monetary and technology shocks on the stock market. I find an important role for technology shocks, but not monetary shocks, in explaining variations in real stock prices. The identification method is flexible enough to study the effects of technology news shocks. The responses are consistent with the idea that news on technology improvements have an immediate impact on stock prices.

Keywords: stock prices, current account fluctuations, monetary policy, technology shocks, news, international transmission, VARs, identification with sign restrictions

Zusammenfassung

Die vorliegende Dissertation besteht aus drei thematisch verwandten Aufsätzen, die den Zusammenhang zwischen Aktienpreisen und makroökonomischen Variablen mit Vektor Autoregressiven (VAR) Modellen untersuchen. Ich analysiere den Zusammenhang von Aktienpreisen und Leistungsbilanz (Kapitel 1), die Transmission amerikanischer Aktienpreisbewegungen zur Realwirtschaft und zu gesamtwirtschaftlichen Preisen in den G7 Ländern (Kapitel 2) und die Effekte geldpolitischer und technologischer Schocks auf den europäischen Aktienmarkt (Kapitel 3). Die drei Aufsätze folgen dem gleichen Prinzip. Ich erläutere zunächst die kontextrelevante VAR Methode, u.a. ein Panel VAR und ein Bayesianisches VAR mit Vorzeichenrestriktionen, bevor ich die empirischen Ergebnisse präsentiere und deren Relevanz sowie ihren Bezug zur bestehenden Literatur diskutiere.

Die verwandte Literatur besteht aus einer zunehmenden Anzahl VAR basierter Forschungsarbeiten, die Aktienpreisbewegungen zur Erklärung makroökonomischer Phänomene heranziehen. Zum Beispiel argumentieren Beaudry und Portier (2006), dass Aktienpreisbewegungen in erster Linie die veränderten Erwartungen von Markteilnehmern in bezug auf zukünftige Produktivitätsentwicklungen widerspiegeln. Letztere wiederum sind ihrer Meinung nach ein bedeutender Einflussfaktor des amerikanischen Wirtschaftszyklusses. Des Weiteren halten Fratzscher et al. (2007) Veränderungen in der relativen Aktienmarktkapitalisierung zugunsten der Vereinigten Staaten für eine mögliche Ursache des amerikanischen Leistungsbilanzungleichgewichts. Zu einem vergleichbaren Ergebnis kommen Fratzscher und Straub (2009) in bezug auf die G7 Länder. Sie sind der Meinung, dass Aktienpreisbewegungen einen beachtlichen Effekt auf die Außenhandelsbilanzen haben. Ebenso erwähnenswert ist die Arbeit von Assenmacher-Wesche und Gerlach (2008), die sich der Interaktion von Aktienpreisen, Realwirtschaft und Konsumentenpreisen in industrialierten Ländern widmet und eine signifikante Transmission von Aktienpreisbewegungen zu letzteren findet.

Trotz der Größe und Bedeutung heutiger Aktienmärkte sowie der Beachtung, welche diese in der empirischen Finanzmarktforschung erfahren haben, ist die Liste der Autoren, die sich mit der Interaktion von Aktienpreisen und makroökonomischen Variablen in VAR Modellen beschäftigen, vergleichsweise kurz. Ich werde in meinen drei Aufsätzen veranschaulichen, dass VAR Modelle nützliche Instrumente sind, um sowohl die Bedeutung von Aktienpreisbewegungen als Ursache makroökonomischer Schwankungen zu analysieren, als auch deren Funktion als Transmissionkanal ökonomischer Schocks, wie z.B. Technologie-Schocks, zu untersuchen. So widmet sich der erste Aufsatz der Bedeutung von Aktienpreis- und Wechselkursbewegungen sowie geldpolitischer Schocks für Schwankungen in der Leistungsbilanz. Während ein Großteil der bestehenden Literatur auf einige wenige Länder fokussiert, erstreckt sich meine Studie auf ein Panel von 17 industrialisierten Ländern. Die Analyse basiert auf einem Panel VAR Modell, welches das reale BIP, Konsumentenpreise, kurz- und langfristige Zinsen, Aktienpreise, Wechselkurse und die Leistungsbilanz als Variablen enhält. Ich finde keinen nennenswerten Einfluss geldpolitischer Schocks auf die Leistungsbilanz. Dieses Ergebnis steht im Widerspruch zu empirischen Befunden für die Vereinigten Staaten, kann aber auf das Verhalten des Wechselkurses, welcher den Effekt des geldpolitischen Schocks insbesondere für kleine offene Volkswirtschaften ausgleicht, zurückgeführt werden.

Im Gegensatz dazu haben Aktienpreis- und Wechselkursbewegungen einen nennenswerten Einfluss auf die Leistungsbilanz. Ein Anstieg der Aktienpreise von 10% hat eine Verschlechterung der Leistungsbilanz um 0,3 Prozentpunkte zur Folge, während eine Aufwertung der heimischen Währung in gleicher Größenordnung einen negativen Effekt von 0,4 Prozentpunkten hat. Der Effekt des Aktienpreis-Schocks baut sich erst im Zeitverlauf auf und erreicht sein Maximum nach 9 bis 11 Quartalen. Abhängig von der gewählten Identifizierungsmethode erreicht der Wechselkurs-Schock seinen maximalen Effekt entweder nach 7 bis 11 Quartalen oder innerhalb der ersten halben Jahres. Der letztere Befund steht somit im Widerspruch zum Mundell-Fleming-Dornbusch Modell, welches impliziert, dass sich die Leistungsbilanz nach einer Aufwertung der heimischen Währung zunächst verbessert bevor sie sich im Zeitablauf verschlechtert. Ein solcher "J-Kurven Effekt" kann häufig im Zusammenhang mit VAR Modellen einzelner Länder beobachtet werden, widerspricht jedoch der Intuition. Berücksichtigt man aber, dass es mir der Panel Ansatz ermöglicht, die Impulsantwortfunktionen im Vergleich zu Modellen mit nur einem Land präziser zu berechnen, so vermute ich, dass die Ergebnisse der bestehenden VAR Literatur in erster Linie auf überparametrisierte und somit unpräzise berechnete Modelle zurückzuführen sind.

Des Weiteren erklären Aktienpreis und Wechselkurs-Schocks sowohl über mittlere als auch längere Prognosezeiträume einen beachtlichen Teil der Schwankungen in der Leistungsbilanz. Dies gilt vor allem im Vergleich zu anderen Schocks, wie z.B. geldpolitischen Schocks. Die Analyse lässt mich vermuten, dass Aktienpreis und Wechselkurs-Schocks in etwa gleichbedeutend für Veränderungen in der Leistungsbilanz sind. Somit finde ich einen Transmissionsmechanismus, neben dem traditionellen Wechselkursmechanismus, durch den das Außenhandelsgleichgewicht für eine Volkswirtschaft mit einem Leistungsbilanzungleichgewicht wieder hergestellt werden kann. Unter Berücksichtigung dessen, dass Aktienpreisbewegungen von 10% (oder mehr) eher die Regel als die Ausnahme sind, ist dieses Ergebnis von ökonomischer Relevanz. Ich vermute, dass Aktienpreisbewegungen durch folgenden Transmissionsmechanismus Einfluss auf die Leistungsbilanz ausüben. Fallen Aktienpreise über einen längeren Zeitraum, so hat dies einen Rückgang der realwirtschaftlichen Aktivität aufgrund von Wohlstands- und Bilanzeffekten auf Privatkonsum und Privatinvestitionen zur Folge. Dieser wiederum reduziert die Nachfrage nach Importen und verbessert die Leistungsbilanz. Der erste Aufsatz bietet jedoch keine vollständige Analyse dieses Aktienpreiskanals und daher widme ich mich diesem in meinem zweiten Aufsatz. Im Besonderen analysiere ich mit Hilfe eines Mehrländer VAR Ansatzes die Interaktion von Aktienpreisbewegungen und realwirtschaftlicher Aktivität in einem internationalen Kontext.

Der zweite Aufsatz untersucht die Transmission von Preisbewegungen amerikanischer Aktien zur Realwirtschaft und zu gesamtwirtschaftlichen Preisen in den G7 Ländern in den Jahren 1974-2005. Ich identifiziere Aktienpreis-Schocks indem ich den Vorzeichen der Impulsantwortfunktionen einige wenige Restriktionen auferlege und gleichzeitig für die Effekte von geldund fiskalpolitischen sowie Wirtschaftsyzklus-Schocks kontrolliere. Im Vergleich zu verwandten Studien beruht dieser Ansatz weder auf potentiell unplausiblen Kurzfristrestriktionen noch ist er dogmatisch das Wesen von Aktienpreis-Schocks betreffend. Der Aufsatz ist eine Anwendung der neuen Mehrländer VAR Methode von Canova und Ciccarelli (2009). Ich bevorzuge das Mehrländer VAR gegenüber herkömmlichen Panel VAR Methoden, da es einige vorteilhafte Eigenschaften aufweist. So erlaubt es mir, Abhängigkeiten zwischen Ländern oder Parameterheterogenität zu berücksichtigen. Des Weiteren ist das Mehrländer VAR auch auf relativ kurze Zeitreihen anwendbar.

Die Ergebnisse deuten darauf hin, dass amerikanische Aktienpreis-Schocks eine nicht zu vernachlässigende Größe sind wenn es um die Analyse von Schwankungen in der realwirtschaftlichen Aktivität und den gesamtwirtschaftlichen Preisen in G7 Ländern geht. So erklären sie zwischen 9% und 40% der Schwankungen in der realwirtschaftlichen Aktivität der Vereinigten Staaten und zwischen 12% und 16% für die restlichen G7 Länder. Des Weiteren sind für alle G7 Länder zwischen 10% und 21% der Schwankungen des BIP Deflators die Folge von Aktienpreis-Schocks. Ihr Beitrag ist jedoch geringer als der hervorgerufen durch Wirtschaftsyzklus-Schocks. Dieses Ergebnis zusammen mit der Erkenntnis, dass Aktienpreis-Schocks keine gleichgerichtete Bewegung von realwirtschaftlicher Aktivität und gesamtwirtschaflichen Preisen induzieren, lässt mich urteilen, dass Aktienpreis-Schocks nicht als nachfrageorientierte Wirtschaftszyklus-Schocks bezeichnet werden können. Ich schlussfolgere auch, dass Aktienpreisbewegungen nur teilweise das Result von Aktienpreis-Schocks sind als vielmehr die Folge anderer Schocks. Dies führt mich zu meinem dritten Aufsatz. Der dritte Aufsatz untersucht die Ursachen von Schwankungen im europäischen Aktienmarkt mit einem Bayesianisches VAR Modell für den Zeitraum 1987-2005. Die Schätzperiode beinhaltet die Jahre 1995-2003 als der Aktienmarkt eine ausgeprägte Auf- und Abschwungphase durchlief. Im Rahmen des VAR Modells berücksichtige ich geldpolitische und technologische Schocks als potentielle Ursachen für Schwankungen im Aktienmarkt. Die Ergebnisse deuten an, dass Technologie-Schocks aber nicht geldpolitische Schocks eine wichtige Rolle bei der Erklärung von Aktienmarktbewegungen spielen. Technologie-Schocks eklären etwa 22% der Schwankungen im Aktienmarkt während der Erklärungsgehalt von geldpolitischen Schocks bei unter 5% liegt. Insbesondere während des Auf- und Abschwungs der Jahre 1995-2003 sind Technologie-Schocks für nahezu alle Schwankungen verantwortlich. Ich finde auch einen signifikanten Effekt von Neuigkeiten über technologische Innovationen auf den Aktienmarkt. Abschließend zeige ich, dass die Ergebnisse robust gegenüber der Berücksichtigung von fiskalpolitischen Schocks und Ölpreis-Schocks sind.

Contents

Introduction

1	Cros	oss-country evidence on the relation between stock pr	ices and the current account	4						
	1.1			4						
	1.2	07		6						
		1.2.1 Panel VAR model		6						
		1.2.2 Identification		9						
	1.3	The results		11						
		1.3.1 Unit root tests		11						
		1.3.2 Dynamic responses to monetary policy shock	5	12						
		1.3.3 Dynamic responses to stock price shocks		14						
		1.3.4 Dynamic responses to exchange rate shocks		15						
		1.3.5 Forecast error variance decomposition		16						
		1.3.6 Robustness		18						
	1.4	Conclusion		19						
2	Exp	ploring the international transmission of U.S. stock p	ice movements	21						
	2.1 Introduction									
	2.2	2 The multicountry VAR and identification		22						
		2.2.1 The model		22						
		2.2.2 Implementing sign restrictions		24						
	2.3	The empirical setup		25						
	2.4	International comovements of the variables		27						
	2.5	Impulse responses		30						
		2.5.1 U.S. monetary policy shocks		33						
		2.5.2 U.S. business cycle shocks		35						
		2.5.3 U.S. stock price shocks		37						
		2.5.4 U.S. government spending shocks		40						
	2.6	0 1 0		41						
	2.7	1		45						
3	Do 1	o monetary and technology shocks move euro area sto	ek prices?	46						
	3.1		•	46						
	3.2			48						

1

		3.2.1	Bayesian VAR model	48					
		3.2.2	Identifying sign restrictions	49					
	3.3	The re	esults	51					
		3.3.1	Dynamic responses to monetary and technology shocks	51					
		3.3.2	Explanatory power of the shocks	53					
		3.3.3	Are the estimated shocks plausible?	57					
		3.3.4	Dynamic responses to technology news shocks	58					
		3.3.5	Controlling for time-varying capacity utilization	59					
		3.3.6	Comparing the sign restrictions to short and long-run restrictions	61					
	3.4	Concl	usion	64					
A	Appendix to Chapter 1								
	A.1 The data								
	A.2	Error	bands	66					
B	Арр	endix	to Chapter 2	67					
	B.1	Transf	formation of the covariance matrix	67					
	B.2	The da	ata	67					
C	App	opendix to Chapter 3							
	C.1	The da	ata	68					
	C.2	Rotati	on matrices	69					
	C.3	Addit	ional tables and figures	69					
Re	eferer	nces		71					

List of Figures

1.1	Monetary policy shocks	13
1.2	Stock price shocks	14
1.3	Exchange rate shocks	15
1.4	Current account. Distribution of impulse responses	17
1.5	Current account. Distribution of size and location of peak deterioration or im-	
	provement	18
2.1	World and country indicators	27
2.2	Variable indicators	29
2.3	Estimated multicountry VAR shocks	32
2.4	Impulse responses to U.S. monetary policy shock for the United States	33
2.5	Impulse responses to U.S. monetary policy shock for the other G-7 countries	34
2.6	Impulse responses to U.S. business cycle shock for the United States	35
2.7	Impulse responses to U.S. business cycle shock for the other G-7 countries	36
2.8	Impulse responses to U.S. stock price shock for the United States	37
2.9	Impulse responses to U.S. stock price shock for the other G-7 countries	38
2.10	Impulse responses to U.S. government spending shock for the United States	39
2.11	Impulse responses to U.S. government spending shock for the other G-7 countries	40
3.1	Euro area stock market data	47
3.2	Monetary shocks	51
3.3	Technology shocks	52
3.4	Estimated monetary and technology shocks	53
3.5	Historical decomposition of euro area stock prices	54
3.6	Technology news shocks	59
3.7	TFP measures	60
3.8	Technology shocks when controlling for time-varying capacity utilization	61
3.9	Monetary shocks when fixing the initial TFP and real GDP response to zero \ldots	62
3.10	Technology shocks when requiring a large contribution to long-run TFP changes	63
C.1	Monetary shocks with responses under single draw restriction	70
C.2	Technology shocks with responses under single draw restriction	70

List of Tables

1.1	Augmented Dickey-Fuller unit root tests for the variables in levels	10
1.2	Augmented Dickey-Fuller unit root tests for the variables in differences	11
1.3	Forecast error variance decomposition of the current account variable	16
2.1	Sign restrictions on impulse responses	26
2.2	Correlation between the world and country indicators	28
2.3	Correlation between the variable indicators	30
2.4	Average R^2 for regression of variables on indicator series	31
2.5	Forecast error variance decomposition for the United States	42
2.6	Forecast error variance decomposition for the other G-7 countries	43
3.1	Sign restrictions on impulse responses	50
3.2	Historical business cycle variance decomposition	55
3.3	Forecast error variance decomposition	56
3.4	Granger causality tests	57
C.1	Granger causality tests with oil price	69

Introduction

This dissertation consists of three essays, which study the relation between stock prices and the macroeconomy using vector autoregressive (VAR) models. In particular, I investigate the link between stock prices and the current account (Chapter 1), the transmission of U.S. stock price movements to real activity and prices in G-7 countries (Chapter 2), and the impact of monetary and technology shocks on the euro area stock market (Chapter 3). All three essays follow the same principle. First, I introduce a VAR method, ranging from panel and multicountry VARs to a Bayesian VAR. I use existing methods to address topics of economic relevance, but also extend methods, particularly with respect to the identification of economic shocks. Second, I provide empirical results and discuss their relevance and relation to the existing literature.

In fact, there is an increasing number of VAR-based studies that stress the role of stock prices in explaining macroeconomic developments. For example, Beaudry and Portier (2006) argue that shocks to stock prices reflect changes in agents' expectations about future total factor productivity and are an important driver of U.S. business cycles. Fratzscher et al. (2007) point to stock market wealth as an explanation for U.S. external imbalances, while in an extension to the G-7 countries, Fratzscher and Straub (2009) find that shocks to stock returns have sizeable effects on external accounts. Furthermore, Assenmacher-Wesche and Gerlach (2008) study the relationships between stock prices, real activity and prices in industrialized countries and find a significant transmission of stock price shocks to the latter.

Despite the size and importance of today's stock markets and the attention they received in the empirical finance literature, the list of authors studying the interaction between stock prices and the macroeconomy in a VAR context is surprisingly short. However, I show in three essays that VARs are useful to evaluate both the role of stock prices in explaining fluctuations in macroeconomic variables and their importance in the transmission of economic shocks.

The first essay explores the role of shocks to monetary policy, stock prices and exchange rates in explaining current account fluctuations. While a considerable fraction of the existing literature focuses on individual countries, I extend the analysis to a set of 17 industrialized economies. Based on a panel VAR model using data on real GDP, consumer prices, short and long-term interest rates, stock prices, exchange rates and the current account, I find a small role for monetary policy shocks. This finding does not square with the empirical evidence for the United States, but can be attributed to the behavior of the exchange rate, which mitigates the effects of monetary policy shocks, in particular for small open economies.

In contrast, shocks to stock prices and exchange rates have a significant impact on the current account. While a 10% increase in stock prices leads to a deterioration of the current account of 0.3%, an appreciation of the exchange rate of similar magnitude depresses the current account by 0.4%. The effect of stock price shocks on the current account builds up gradually over time and reaches its maximum after around 9-11 quarters. Depending on the identification scheme, exchange rate shocks exert their maximal influence either after 7-11 quarters or within two quarters after the shock. The latter response of the current account to exchange rate shocks is hence inconsistent with the prediction of the Mundell-Fleming-Dornbusch model. In this model, the current account improves on impact following an exchange rate appreciation, before falling over time. Such a 'J-curve effect' is frequently observed in single country VAR models, but counterintuitive. Given that the panel set-up allows me to estimate the impulse responses more precisely as compared to single country VARs, it seems plausible that the findings of the existing VAR literature are the result of overparametrized and hence imprecisely estimated models.

Furthermore, stock price and exchange rate shocks explain a notable fraction of the variation of the current account at medium and long-term forecast horizons as compared to others shocks, in particular monetary policy shocks. The analysis suggests that stock price and exchange rate shocks are about equally important in explaining current account fluctuations. Hence I find a channel, in addition to the traditional exchange rate channel, through which external balance for an OECD country with a current account imbalance can be restored. Given that stock price movements of 10% (or more) are the norm rather than the exception, the results are of economic relevance.

Where does the impact of stock price shocks on the current account position come from? It seems likely that an extended period of falling stock prices leads to a contraction in real activity through wealth effects on consumption and balance sheet effects on investment, which in turn should reduce the demand for imports and improve the current account. The first essay, how-ever, does not provide a full description of this stock market channel and I aim at filling this gap in the second. Particularly, I focus on the interaction between stock prices movements and real activity in an international context. For that purpose, I move beyond conventional panel VAR techniques and use a multicountry VAR instead.

The second essay investigates the transmission of U.S. stock price movements to real activity and prices in G-7 countries in the period 1974-2005. I achieve identification by imposing a small number of sign restrictions on impulse responses, while controlling for monetary policy, business cycle and government spending shocks. In contrast to related studies, the approach does neither rely on potentially implausible short-run restrictions nor is it dogmatic with respect to the nature of stock price shocks. The essay is an application of the novel multicountry VAR methodology of Canova and Ciccarelli (2009), which I prefer to conventional panel VAR approaches since it has a number of appealing features. Among others, it allows for cross-country lagged interdependencies, heterogeneous dynamics and time series of moderate length.

I find that U.S. stock price movements are important for fluctuations in G-7 real activity and prices even when controlling for others shocks. They explain between 9% and 40% of the variation in real activity for the United States and 12% to 16% for the other G-7 countries. Moreover, between 10% and 21% of the variation in the GDP deflator across G-7 countries is due to such shocks. However, these numbers are smaller than those for U.S. business cycle shocks. This finding, together with the observation that stock price shocks do not induce a positive comovement of real activity and prices, leads me to conclude that shocks to stock prices do not qualify as demand side business cycle shocks. In addition, I find that stock price movements are to a large extent due to shocks other than stock price shocks. This last observation leads me to the third essay.

The third essay focuses on the underlying sources of movements in the euro area stock market. I address this issue by estimating a Bayesian VAR model on 1987-2005 data. The sample period covers the 1995-2003 episode when the stock market experienced a pronounced boom-bust cycle. Within the VAR framework, I consider monetary and technology shocks as underlying disturbances. I find an important role for technology shocks, but not monetary shocks, in explaining variations in real stock prices. Over the sample period, more than 22% of the variation in stock prices can be attributed to technology shocks while monetary shocks explain less than 5%. Moreover, technology shocks are responsible for almost all variation in stock prices during the boom-bust cycle of 1995-2003. In addition, I find a significant response of stock prices to technology news shocks. And finally, I show that these findings are robust to the inclusion of additional disturbances, such as government spending or oil price shocks.

1 Cross-country evidence on the relation between stock prices and the current account

This chapter explores the relation between stock prices and the current account for 17 OECD countries in 1980-2007. I use a panel vector autoregression (VAR) to compare the effects of stock price shocks to those originating from monetary policy and exchange rates. While monetary policy shocks have little effects, shocks to stock prices and exchange rates have sizeable effects. A 10% contraction in stock prices improves the current account by 0.3% after two years. Hence I find a channel, in addition to the traditional exchange rate channel, through which external balance for an OECD country with a current account imbalance can be restored.

1.1 Introduction

The determinants of current account fluctuations have been discussed extensively in the academic literature in recent years. One reason is that the dispersion in current account positions has never been so large as today. This triggered worries that an unwinding of global imbalances could cause a severe global financial crisis. In the wake of the current financial crisis, it is even more important to understand the sources of these imbalances and the likely adjustment mechanisms. Particularly the role of stock prices is of interest and is thus the central issue of this chapter. The existing literature on the link between stock prices and the current account is small and concentrates on individual countries. In contrast, I extend the analysis to a broad set of OECD countries and compare the effects of stock price shocks to those originating from monetary policy and exchange rates.

Since the U.S. current account imbalance is so large, many authors focus on the U.S. in their analysis. While some point to low private savings in the U.S. as a main driver of this imbalance (see, e.g., Krugman, 2007), others investigate the role of public savings (see, e.g., Erceg et al., 2005; Corsetti and Müller, 2006, among others). From a simple accounting perspective, budget and current account deficits move in the same direction. Thus, the swing of the U.S. fiscal position from surplus to deficit during the Bush era may have accelerated the deterioration of the U.S. current account. However, the two aforementioned papers find little impact of fiscal shocks on the current account and reject what is known as the 'twin deficit' hypothesis. Moreover, Kim and Roubini (2008) find even evidence of a 'twin divergence', i.e., when fiscal accounts worsen, the current account improves and vice versa.

Another camp identifies productivity shocks as a main determinant of the current account (see, e.g., Bussière et al., 2005; Corsetti et al., 2006; Bems et al., 2007, among others). Country-

specific productivity shocks raise relative consumption as well as the price of nontradables and deteriorate the trade balance. Corsetti et al. (2006) find evidence that this effect is particularly persistent for the United States. A third strand focuses on the role exchange rates play in restoring external balance for countries with large external deficits (see, e.g., Obstfeld and Rogoff, 1995; Blanchard et al., 2005, among others). A common result of this literature is that a large and steady depreciation of the exchange rate is needed to rebalance the current account (see, e.g., Krugman, 2007).

Despite the vast literature on the sources of current account fluctuations, it is striking that only few authors discuss the contribution of stock price shocks to the emergence of global imbalances. Some notable and recent exceptions are Fratzscher et al. (2007), Barnett and Straub (2008) and Fratzscher and Straub (2009). The motivation is the following. While the U.S. reports remarkable current account deficits, many countries, particularly from emerging Asia and the Middle East, run current account surpluses of similar magnitude. Having recovered from the 1997-1998 Asian crisis, the demand for foreign exchange reserves was huge among Asian countries. Since the U.S. financial market is the largest and most liquid in the world, a dominant fraction of these reserves were invested in U.S. dollar denominated assets, particularly in U.S. government bonds. Furthermore, the surge in oil prices created large surpluses among the oilexporting countries that were in turn reinvested in U.S. bonds and equity. In addition, the lack of well functioning capital markets in the emerging world spurred the demand for U.S. assets. As Bernanke (2005) puts it, a 'saving glut' in Asia and among oil-exporting countries is a potential driver of the U.S. current account deficit.

Consequently, I expect that the (relative) attractiveness of a country's financial market is an important determinant of international capital flows. If a country experiences a favorable stock price shock more funds are allocated to the country, the exchange rate is likely to appreciate and the current account worsens. Furthermore, the increase in stock prices may impact on real activity through wealth effects on consumption and balance sheet effects on investment. Both raise the demand for imports and deteriorate the current account.

Of course, there is no clear structural interpretation of a stock price shock. Building on the assumption that stock prices are forward-looking and thus reflect people's expectations, a large body of the literature interprets shocks to them as shifts in expectations, and so do I. For example, people expect productivity to rise in the future or the share of a country's output in the world to increase (see Engel and Rogers, 2006). Alternatively, one may also think of stock price shocks in the form of rational bubbles (see Kraay and Ventura, 2005). Fratzscher et al. (2007) find that shocks to stock prices have large and persistent effects on the U.S. trade balance. Using a Bayesian VAR, they measure the impact of a 10% increase in stock prices to be 0.9% over 10-15 quarters and find this effect to be larger than that of the exchange rate. In a more recent study Fratzscher and Straub (2009) extend the analysis to the G-7 economies and obtain again evidence of a significant impact of stock price movements on the trade balance. However, the response of the trade balance to stock price shocks varies substantially across countries, suggesting that a strong response is probably unique to the United States.

This chapter contributes to the existing literature in the following way. Using a panel vector autoregression, I investigate the impact of monetary policy, stock price and exchange rate shocks on the current account. The panel set-up allows me to filter out country-specific effects and to study the average effects of the three shocks. The results suggest that both stock price and exchange rate shocks have a significant impact, while monetary policy shocks have little effects. Hence I find a channel, in addition to the traditional exchange rate channel, through which external balance for an OECD country with current account deficits can be restored. An extended period of falling stock prices is likely to reduce real activity through wealth and balance sheet effects as well as the demand for imports and thus improves the current account.

The rest of this chapter is organized as follows. Section 1.2 outlines the panel VAR model and the identification strategy. An impulse response analysis and a forecast error variance decomposition are presented in Section 1.3. Moreover, I provide robustness checks. Finally, Section 1.4 concludes.

1.2 Methodology

1.2.1 Panel VAR model

I use a panel VAR of the form:

$$Y_{it} = B_i(L) Y_{i,t-1} + C_i(L) D_t + u_{it},$$
(1.1)

where i = 1, 2, ..., N; t = 1, 2, ..., T; Y_{it} is a $G \times 1$ vector of endogenous variables for each country i, B_i are $G \times G$ matrices in the lag operator L, D_t is a $K \times 1$ vector which includes deterministic variables (e.g., a constant, a time trend or a dummy) or common exogenous variables (e.g., oil prices), C_i are $G \times K$ matrices in the lag operator L, and u_{it} is a $G \times 1$ vector of random disturbances with mean zero and country-specific variance σ_i^2 .

I include seven endogenous variables for each country: real GDP, consumer prices, a nominal short-term interest rate, a nominal long-term interest rate, nominal stock prices, a real effective exchange rate, and a current account to GDP ratio. The estimation period is 1980Q1-2007Q4 and I provide a description of the data in Appendix A.1. The variables are expressed in logs, except the interest rate variables and the current account to GDP ratio, which are in percent. Since the current account is measured with respect to the 'rest of the world', I find it appropriate to incorporate all other endogenous variables in relative terms. I proceed in the following way. First, I construct bilateral trade weights for each country with all other countries in the panel and each period. Particulary, the weight that I attach to country j for country i in period t is:

$$\omega_{i,j,t} = \frac{imp_{i,j,t} + exp_{i,j,t}}{\sum_{j=1}^{N} (imp_{i,j,t} + exp_{i,j,t})},$$
(1.2)

where $imp_{i,j,t}$ is the amount of goods and services (in millions of U.S. dollars) that is imported by country *i* from country *j* in period *t*, $exp_{i,j,t}$ is the amount of goods and services that is exported by country *i* to country*j* in period *t* and $\sum_{j=1}^{N} (imp_{i,j,t} + exp_{i,j,t})$ is the total sum of imports and exports of country *i* with all other countries in period *t*. Obviously, $\omega_{i,j,t} = 0$ for i = j. Thus, $\omega_{i,j,t}$ captures the importance of country *j* for country *i* with respect to trade. Second, I calculate foreign variables for each country *i* as follows:

$$x_{it}^* = \sum_{j=1}^{N} \omega_{i,j,t} x_{jt}.$$
(1.3)

Using time-varying rather than fixed weights allows me to control for changing patterns in global trade. I proceed like this for (log) real GDP (y_{it}), (log) consumer prices (p_{it}), nominal short-term interest rates (r_{it}^s), nominal long-term interest rates (r_{it}^l) and (log) nominal stock prices (s_{it}). But not for the (log) real effective exchange rate ($REER_{it}$) and the current account to GDP ratio (ca_{it}) since both are already measured relative to major trading partners. Finally, I obtain relative variables by substracting foreign from domestic variables. Hence, the vector of endogenous variables becomes

$$Y_{it} = \begin{bmatrix} y_{it} - y_{it}^* & p_{it} - p_{it}^* & r_{it}^s - r_{it}^{s*} & r_{it}^l - r_{it}^{l*} & s_{it} - s_{it}^* & REER_{it} & ca_{it} \end{bmatrix}'.$$
 (1.4)

The construction of foreign variables is comparable to the procedure of Pesaran et al. (2004) or Dees et al. (2007) in a Global VAR context. Moreover, Fratzscher et al. (2007) follow a similar strategy for the U.S. and specify the variables relative to the rest of the world. However, they use weights based on global GDP shares rather than trade weights. Alternatively, I could include domestic and foreign variables separately. Given the number of variables, however, this procedure is computationally hardly feasible.

One purpose of this chapter is to evaluate the effects of monetary policy shocks on the current account and therefore I include all relevant channels through which monetary policy impacts on the economy. Monetary policy impacts on short and long-term interest rates and thus on the term structure. Furthermore, monetary policy is transmited to the economy through stock prices and exchange rates. I include nominal stock prices since I expect that movements in them have contributed to the development of global imbalances in the last three decades. Finally, I add the real effective exchange rate to capture the external competitiveness of the country under study.

The vector of common exogenous variables, D_t , includes the U.S. dollar price of oil, p_t^{oil} , and a constant for each country. The oil price is considered for several reasons. First, it is a well known shortcoming of VAR analyses that inflation expectations cannot be taken into account explicitly. Including oil or commodity prices helps to overcome this problem since both are correlated with inflation expectations. Second, some of the countries in the panel are net oil exporters (notably Canada, Norway and the UK) and are influenced by movements in the price of oil. Third, I do not control for cross-section dependence in the panel and expect that including an observed common factor reduces ineffiences that arise in this context.

Preliminary estimation of individual VAR models suggests that a lag order of four for the endogenous variables is optimal, using lag order selection criteria like AIC, SBC or likelihood ratio tests, and is thus set to four for all countries. Furthermore, the oil price enters contemporaneously and with one lag.

Following Swamy (1970) and Pesaran and Smith (1995), I assume that the B_i and C_i matrices vary across countries according to the following random coefficient model:

$$B_{pi} = B_p + \eta_{1,p,i}, \qquad C_{qi} = C_q + \eta_{2,q,i}, \tag{1.5}$$

where B_p and C_q are $G \times G$ and $G \times K$ constant matrices, $\eta_{1,p,i}$ and $\eta_{2,q,i}$ are $G \times G$ and $G \times K$ random matrices, and p and q are the respective lag orders. Furthermore, $\eta_{1,p,i}$ and $\eta_{2,q,i}$ are distributed independently of u_{it} with zero mean and constant covariance matrices Ω_{1p} and Ω_{2q} , i.e. $vec(\eta_{1,p,i}) \sim iid(0, \Omega_{1p})$ and $vec(\eta_{2,q,i}) \sim iid(0, \Omega_{2q})$.

As long as the time series dimension T is sufficiently large to run individual time series regressions, I can estimate the panel VAR in several ways: first, by stacking the data and using standard pooled estimators such as the random or fixed effects estimator; second, by estimating individual VARs for each country seperately and averaging the estimated coefficients across countries. The second approach is proposed by Pesaran and Smith (1995) and is known as the mean group estimator. Provided the panel is not only large with respect to time, but also homogeneous (i.e. $\eta_{1,p,i} = \eta_{2,q,i} = 0$ for all *i*), all estimators yield consistent and unbiased estimates of the coefficients for *N* being large as well. But if the coefficients differ across countries (i.e. $\eta_{1,p,i} \neq \eta_{2,q,i} \neq 0$ for some *i*), the random and fixed effects estimators give inconsistent and potentially misleading estimates of the coefficients (see Nickell, 1981). The mean group estimator, however, is consistent even in the presence of parameter heterogeneity for *N* and *T* being large. Since the cross-sectional and the time series dimension are both sufficiently large (N = 17 and T = 112) and some degree of parameter heterogeneity across countries seems likely, I prefer the mean group estimator and estimate the coefficient matrices as follows:

$$\hat{B}_p = \frac{1}{N} \sum_{i=1}^{N} \hat{B}_{pi}, \qquad \hat{C}_q = \frac{1}{N} \sum_{i=1}^{N} \hat{C}_{qi}, \qquad (1.6)$$

for $p = 1, 2, ..., p^{max}$ and $q = 0, 1, ..., q^{max}$. Pesaran and Smith (1995) show that the mean group estimator converges relatively fast and that \hat{B}_p and \hat{C}_q are appropriate measures of the average effects of $Y_{i,t-p}$ and D_{t-q} on Y_{it} .

Furthermore, I obtain all relevant statistics, such as impulse responses or a forecast error variance decomposition, accordingly, i.e., by averaging the respective numbers over all countries.

1.2.2 Identification

A common way of analyzing the dynamics of a panel VAR is to calculate impulse responses. I assume that the reduced form errors (u_{it}) are linked to the structural innovations (ϵ_{it}) in the following way:

$$u_{it} = A_i \epsilon_{it}. \tag{1.7}$$

To achieve identification, I impose the restriction that the A_i matrices are lower triangular. Such a recursive identification scheme is frequently employed in the literature and leaves it to me to specify the instantaneous causal ordering of the variables. In what follows, I assume that the variables in the system are ordered as in Y_{it} .

Monetary policy shocks raise the relative short-term interest rate $(r_{it}^s - r_{it}^{s*} > 0)$, but do not have any contemporaneous impact on either real GDP or consumer prices. Both variables respond with a lag of one quarter to changes in monetary policy. However, I allow the financial market variables (long-term interest rates, stock prices and exchange rates) to respond immediately to changes in short-term interest rates. Similar identification schemes are often used in the

	$y - y^*$	$p - p^*$	$r^s - r^{s*}$	$r^l - r^{l^*}$	$s - s^*$	REER	ca
Australia	-2.22	-2.72	-2.98	-3.61^{\dagger}	-3.42	-1.97	-3.86^{\dagger}
Austria	-1.70	-2.36	-3.66^{\dagger}	-2.97	-2.07	-1.74	-2.10
Belgium	-2.34	-3.04	-2.24	-2.55	-2.71	-2.63	-0.89
Canada	-1.71	-4.00^{\dagger}	-3.06	-3.27	-0.55	-0.92	-1.66
France	-2.59	-4.30^{\dagger}	-2.72	-1.59	-2.37	-2.54	-0.72
Germany	-1.46	-2.74	-2.80	-1.27	-2.69	-2.35	-1.07
Italy	-0.87	-3.12	-3.22	-3.00	-2.68	-2.32	-1.73
Japan	-1.81	-2.71	-4.20^{\dagger}	-2.87	-2.25	-1.36	-2.58
Korea	-1.52	-2.31	-2.11	-2.67	-1.83	-2.26	-3.26
Netherlands	-2.82	-2.03	-2.73	-3.01	-1.82	-1.89	-2.67
New Zealand	-2.10	-2.47	-2.21	-2.27	-2.28	-2.69	-2.38
Norway	-2.11	-2.51	-3.29	-2.69	-1.68	-2.23	-3.40
Spain	-1.41	-4.43^{\dagger}	-4.71^{\dagger}	-3.24	-2.76	-2.06	-1.84
Sweden	-0.86	-1.25	-2.83	-2.54	-4.06^{\dagger}	-2.84	-1.44
Switzerland	0.27	-2.07	-1.17	-1.83	-1.91	-2.42	-3.49^{\dagger}
UK	-2.42	-0.77	-2.60	-2.61	-1.74	-2.79	-2.50
U.S.	-2.22	-3.75^{\dagger}	-3.49^{\dagger}	-2.65	-1.67	-2.61	-1.90

Table 1.1: Augmented Dickey-Fuller unit root tests for the variables in levels

Notes: ADF tests include a constant and a trend. A [†] denotes significance at the 5 percent level.

analysis of monetary policy transmission in an open economy context (see, e.g., Eichenbaum and Evans, 1995; Grilli and Roubini, 1996, among others).

Stock price shocks are associated with an increase in relative stock prices ($s_{it} - s_{it}^* > 0$). Again, real GDP and consumer prices respond with a lag. Furthermore, it seems likely that monetary policy takes changes in stock prices into account since they potentially influence real GDP and consumer prices. However, I do not expect that monetary policy reacts instantaneously to changes in stock prices but only if they rise or fall for a longer period of time. The same argument applies to the exchange rate. Hence, both variables are ordered after real GDP, consumer prices and the short-term interest rate.

Within the block of financial market variables an appropriate ordering is, however, unclear. But it turns out that the impulse responses are robust to alternative ordering schemes. Therefore, I order the financial market variables as follows: first, long-term interest rates; second, stock prices; and third, the real effective exchange rate. Furthermore, exchange rate shocks raise the real effective exchange rate ($REER_{it} > 0$).

	$y - y^*$	$p - p^*$	$r^s - r^{s*}$	$r^l - r^{l^*}$	$s - s^*$	REER	ca
Australia	-4.44^{\dagger}	-3.30^{\dagger}	-4.50^{\dagger}	-3.90^{\dagger}	-4.68^{\dagger}	-3.62^{\dagger}	-4.70^{\dagger}
Austria	-4.83^{\dagger}	-3.92^{\dagger}	-5.15^{\dagger}	-4.90^{\dagger}	-3.67^{\dagger}	-4.69^{\dagger}	-5.79^{\dagger}
Belgium	-5.75^{\dagger}	-4.65^{\dagger}	-6.86^{\dagger}	-5.08^{\dagger}	-6.30^{\dagger}	-3.80^{\dagger}	-6.43^{\dagger}
Canada	-4.47^{\dagger}	-2.81	-5.05^{\dagger}	-4.74^{\dagger}	-5.28^{\dagger}	-3.12^{\dagger}	-6.64^{\dagger}
France	-3.67^{\dagger}	-1.97	-5.18^{\dagger}	-4.60^{\dagger}	-5.82^{\dagger}	-4.15^{\dagger}	-5.28^{\dagger}
Germany	-3.55^{\dagger}	-2.13	-4.46^{\dagger}	-4.92^{\dagger}	-4.73^{\dagger}	-5.45^{\dagger}	-4.42^{\dagger}
Italy	-4.90^{\dagger}	-2.12	-4.65^{\dagger}	-4.77^{\dagger}	-7.06^{\dagger}	-4.62^{\dagger}	-4.96^{\dagger}
Japan	-3.78^{\dagger}	-3.93^{\dagger}	-5.86^{\dagger}	-6.31^{\dagger}	-4.08^{\dagger}	-4.02^{\dagger}	-4.62^{\dagger}
Korea	-4.48^{\dagger}	-5.31^{\dagger}	-5.45^{\dagger}	-5.83^{\dagger}	-4.95^{\dagger}	-4.55^{\dagger}	-4.68^{\dagger}
Netherlands	-3.62^{\dagger}	-2.02^{\dagger}	-4.88^{\dagger}	-3.71^{\dagger}	-3.50^{\dagger}	-4.56^{\dagger}	-5.98^{\dagger}
New Zealand	-5.52^{\dagger}	-2.87	-5.45^{\dagger}	-4.98^{\dagger}	-4.54^{\dagger}	-4.06^{\dagger}	-5.80^{\dagger}
Norway	-3.77^{\dagger}	-2.71	-4.90^{\dagger}	-4.12^{\dagger}	-5.10^{\dagger}	-5.96^{\dagger}	-4.76^{\dagger}
Spain	-4.37^{\dagger}	-2.37	-5.94^{\dagger}	-6.53^{\dagger}	-4.54^{\dagger}	-3.87^{\dagger}	-3.62^{\dagger}
Śweden	-3.71^{\dagger}	-2.85	-6.16^{\dagger}	-6.49^{\dagger}	-4.55^{\dagger}	-4.49^{\dagger}	-6.35^{\dagger}
Switzerland	-5.23^{\dagger}	-3.73^{\dagger}	-6.99^{\dagger}	-5.09^{\dagger}	-3.76^{\dagger}	-4.96^{\dagger}	-4.72^{\dagger}
UK	-3.41^{\dagger}	-3.43^{\dagger}	-6.04^{\dagger}	-5.91^{\dagger}	-5.52^{\dagger}	-5.22^{\dagger}	-5.86^{\dagger}
U.S.	-4.38^{\dagger}	-3.02^{\dagger}	-3.04^{\dagger}	-4.92^{\dagger}	-4.58^{\dagger}	-3.40^{\dagger}	-3.78^{\dagger}

Table 1.2: Augmented Dickey-Fuller unit root tests for the variables in differences

Notes: ADF tests include a constant only. A † denotes significance at the 5 percent level.

Finally, I order the current account to GDP ratio last, imposing the restriction that the current account responds immediately to changes in other variables, but these react only with a lag to changes in the current account. This seems plausible since the current account is nothing else than the accumulation of foreign assets or debt (if one abstracts from valuation effects) and I do not expect that variables react to changes in the stock of net foreign assets within the period.

1.3 The results

1.3.1 Unit root tests

Before presenting the main results in the next sections, I explore the integrating properties of the variables in the panel VAR. I have to decide whether estimating the model in levels or first differences, which depends on the order of integration of the variables. Table 1.1 shows the results of augmented Dickey-Fuller (ADF) unit root tests for the endogenous variables in level specification. The ADF regressions contain a constant and a time trend. I set the lag order for the first differences equal to five. I report similar test results for the endogenous variables in first differences in Table 1.2. In this case the ADF regressions include a constant only and the lag length is four. The results are insensitive to variations in the lag length.

Overall, there is strong evidence that nearly all of the variables in the panel are integrated of order one. In fact, for most of the countries the null of a unit root in the level cannot be rejected at a 5 percent significance level for any variable. In contrast, the test statistics for the endogenous variables in first differences are, with only a few exceptions, highly significant. Consequently, I conclude that the endogenous variables are I(1). I draw the same conclusion for the oil price. In this case the test results are -0.48 (level) and -5.53 (first difference), respectively. Thus, it would be a valid strategy to estimate the panel VAR in first differences. However, differencing the variables destroys cointegrating relationships in the model. Therefore, I estimate the panel VAR in levels, taking any cointegrating relationships implicitly into account. Indeed, Johansen cointegration tests indicate that there is evidence of at least one cointegrating vector, implying that the individual country models can be estimated in levels.

1.3.2 Dynamic responses to monetary policy shocks

Figure 1.1 shows the responses of real GDP, consumer prices, short-term interest rates, long-term interest rates, stock prices, the exchange rate and the current account to one standard error monetary policy shocks, corresponding to an increase in the short-term interest rate of about 50 basis points. I report the responses when the VAR coefficients are fixed at their ordinary least squares (OLS) point estimates, together with a 90 percent confidence interval. I construct error bands using a non-parametric bootstrap that I describe in Appendix A.2. The figure shows the responses at each horizon between 0 and 28 quarters after the shock.

As you can see, the effect on the short-term interest rate settles at around zero after two and a half years. Long-term interest rates rise immediately, however, the initial impact is only one third of that of the short-term interest rate. Long-term interest rates fall thereafter and the response is zero after two and a half years. Real GDP contracts significantly following monetary policy shocks and reaches its trough after two years, before it recovers. Consumer prices rise on impact, displaying a 'price puzzle', but start to fall after around two years. Including oil prices does not help to overcome the 'price puzzle' in my context, presumably the result of the sample period chosen or the fact that I include them as exogenous, not endogenous, variable. Furthermore, stock prices fall sharply in response to a monetary policy tightening, but recover quickly. The trough is reached after four quarters. Furthermore, the response of the exchange rate, which is defined in such a way that an increase means an appreciation, exhibits a puzzle as well. The domestic currency depreciates on impact and it takes nearly one year until the effect

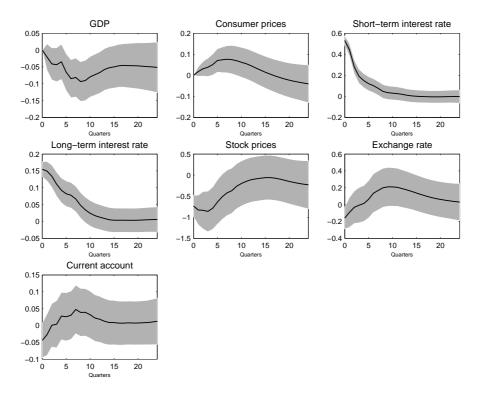


Figure 1.1: Monetary policy shocks

Notes: I show the responses when the VAR coefficients are fixed at their OLS point estimates, together with a 90 percent confidence interval. Entries are percent.

turns positive. But since consumer prices are used to construct the exchange rate, and consumer prices show a 'price puzzle', it is not suprising that the 'price puzzle' is evident in the response of the exchange rate as well. Overall, these findings are compatible with those of a large body of the monetary VAR literature.

The response of the current account is ambiguous. It is slightly negative on impact, but quickly changes sign and is above the initial level after seven quarters. After about three years it settles at around zero. Moreover, the response is never significantly different from zero. Consequently, it seems implausible that loose monetary policies contribute to current account deficits. While an expansionary monetary policy shock raises domestic demand and deteriorates net exports, it also depreciates the domestic currency and improves net exports. The results of the impulse response analysis suggest that the overall effect on net exports, or more exactly the current account, is about zero.

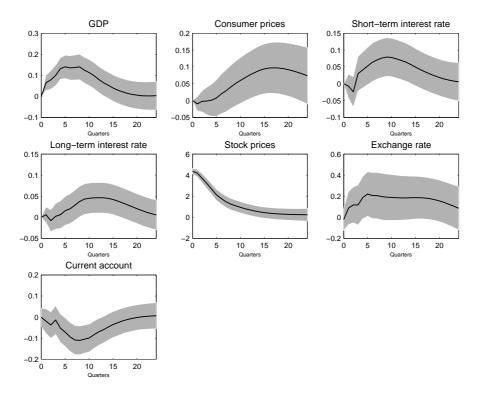


Figure 1.2: Stock price shocks

Notes: See Figure 1.1

1.3.3 Dynamic responses to stock price shocks

Figure 1.2 shows the responses to one standard error shocks that raise relative stock prices by more than 4% initially. As we can see, the rise in stock prices is followed by a significant and long lasting increase in both real GDP and consumer prices, suggesting the presence of wealth and balance sheet effects on consumption and investment, respectively. Moreover, I can distinguish between stock price shocks and technology disturbances. While the former induce a positive correlation between real GDP and consumer prices, the latter are typically associated with a negative correlation. This distinction between stock price and technology shocks is important since I expect that technology innovations are a potential source for movements in stock prices.

Furthermore, in response to the increase in real GDP and rising consumer prices, the monetary policy authority is tightening. Short-term interest rates display a hump-shaped pattern, consistent with the idea that monetary policy follows a Taylor-type feedback rule when setting short-term interest rates. In addition, long-term interest rates react positively as well. The effect on the exchange rate is, however, unclear. While the point estimate suggests that the domes-

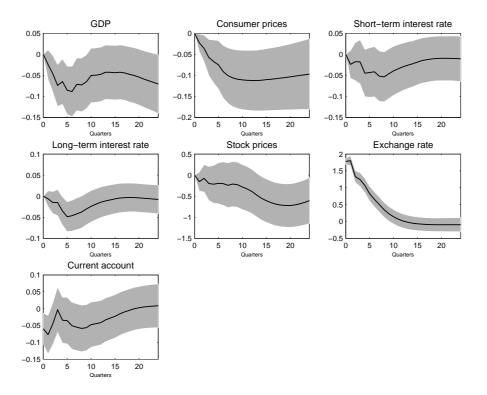


Figure 1.3: Exchange rate shocks

Notes: See Figure 1.1

tic currency appreciates, the uncertainty surrounding the impulse response is high. Finally, the current account worsens immediately (though not significantly) and reaches a trough after eight quarters. Thereafter, the current account improves and external balance is restored after around five years. The maximum impact of the 4% (a 10 %) increase in stock prices on the current account is -0.12% (-0.3%). Hence, the impact of stock price shocks on the current account is not only statistically but also economically significant, given that stock price movements of 10% (or more) are the norm rather than the exception. Moreover, the results are compatible with these in Fratzscher and Straub (2009), who report responses of the trade balance to stock price shocks (of size 10%) between -1.02% (for Germany) and 0.28% (for the UK) after eight quarters.

1.3.4 Dynamic responses to exchange rate shocks

I show the responses to one standard error innovations in the exchange rate in Figure 1.3. The exchange rate appreciates by 1.8% on impact, falls thereafter and finally settles around zero after 12 quarters. The appreciation is associated with a loss of external competitiveness and

Horizon	$y - y^*$	$p - p^*$	$r^s - r^{s*}$	$r^l - r^{l^*}$	$s - s^*$	REER	ca
4	6	2	5	3	3	4	77
8	6	3	6	5	7	7	65
12	7	5	7	6	10	9	57
16	9	6	7	6	12	11	50
20	11	7	7	6	14	11	43
24	13	8	7	6	16	12	38

Table 1.3: Forecast error variance decomposition of the current account variable

Notes: Entries are percent. I fix the VAR coefficients at their OLS point estimates.

net exports are likely to fall. Thus, real GDP contracts significantly following exchange rate shocks. Furthermore, the appreciation lowers import prices and as a consequence consumer prices fall. Consumer prices reach a through after around eight quarters. Monetary policy authorities respond to the fall in real GDP and consumer prices by lowering short-term interest rates, while long-term interest rates match the behavior of short-term interest rates nearly one-to-one. In addition, stock prices fall immediately and are well below their initial level after five years, reflecting the contraction in real GDP.

The current account falls sharply in response to the appreciation. It reaches a trough right in the first quarter after the shock and then improves. However, the response is negative for the next five years. The effect of exchange rate shocks on the current account is strong, significant and long lasting. A 10% increase in the exchange rate depresses the current account by 0.4%, more than the impact of stock price shocks of similar magnitude.

1.3.5 Forecast error variance decomposition

The forecast error variance decomposition shows the proportion of the unanticipated changes of a variable that can be attributed to own innovations and to innovations to other variables in the system. Table 1.3 shows the variance decomposition of the current account. I fix the VAR coefficients at their OLS point estimates and identify monetary policy, stock price and exchange rate shocks in the same recursive way as before. Moreover, I report the contribution of the structural innovations up to 24 quarters following the shock.

For instance, 77% of the 4-step ahead forecast error variance of the current account is due to own innovations. This number decreases considerably over time and is 38% after six years. Moreover, innovations in consumer prices and long-term interest rates contribute less than 8%

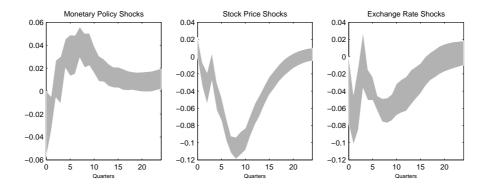


Figure 1.4: Current account. Distribution of impulse responses

Notes: I show the distribution (shaded area) of responses to monetary policy, stock price and exchange rate shocks based on 5,040 different recursive identification schemes. I fix the VAR coefficients at their OLS point estimates.

over all forecast horizons. 13% of the forecast error variance of the current account is accounted for by innovations in real GDP. Givent that I do not attach any structural interpretation to these shocks, the numbers are difficult to interpret.

For any forecast horizon, monetary policy shocks contribute less than 8%. This is compatible with the results of the impulse response analysis. Monetary policy shocks are thus not a main source of fluctuations in the current account. This is in contrast to the findings of Barnett and Straub (2008) who identify the U.S. Federal funds rate as a main source of the variability in the U.S. current account. They estimate the contribution of monetary policy shocks to the forecast error variance to be 62% at low forecast horizons and 41% at a seven year forecast horizon. Furthermore, Fratzscher et al. (2007) find also evidence that monetary policy exerts influence. However, their numbers are considerably smaller and comparable to those stemming from my panel VAR.

The results are different for innovations in stock prices and the exchange rate. For longterm forecasts, 16% and 12% of the forecast error variance is accounted for by stock price and exchange rate innovations, respectively. Thus, both variables contribute substantially to the forecast error variance of the current account and their joint contribution is nearly as large as the contribution of all other variables together (not taking own innovations into account). Fratzscher et al. (2007) instead report a much smaller impact of the exchange rate on the U.S. trade balance. Only a small fraction of the variability can be attributed to exchange rate shocks at long-term forecast horizons. Exchange rate movements appear less important for the U.S. than for other countries. This is not surprising since the U.S. is a large and rather closed econ-

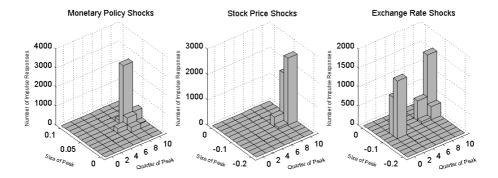


Figure 1.5: Current account. Distribution of size and location of peak deterioration or improvement

Notes: I show the distribution of size (in percent) and location (in quarters) of peak deterioration or improvement, conditional on monetary policy, stock price and exchange rate shocks and based on 5,040 different recursive identification schemes. I fix the VAR coefficients at their OLS point estimates.

omy. However, most countries in my panel are small, open and thus sensitive to exchange rate movements. But the results reconcile with the notion that stock prices explain a considerable part of current account fluctuations. Though the effect is smaller than typically found for the U.S., it is nevertheless notable.

1.3.6 Robustness

As a robustness check, I evaluate how sensitive the results are to variations in identification. In particular, I estimate the 7-variable panel VAR and construct impulse response using all 5,040 possible Cholesky orderings. Since I am interested in identification uncertainty, but not sampling uncertainty, I fix the VAR coefficients at their OLS point estimates. As a result of this exercise, I obtain a distribution of impulse responses for the current account variable. The procedure is agnostic with respect to the appropriate ordering of the variables and thus conservative in measuring identification uncertainty.

Figure 1.4 shows the responses of the current account to monetary policy, stock price and exchange rate shocks, respectively. The top of the shaded area represents the maximum response for each quarter and the lower end corresponds to the minimum. As you can see, the shape of the response is the same as when using the benchmark identification scheme, while the uncertainty surrounding the point estimates is moderate, suggesting that the results are independent of the restrictions imposed on the covariance matrix. In fact, the covariance matrix is nearly diagonal and thus different identification schemes inevitably lead to similar results. Furthermore, Figure 1.5 delivers the joint distribution of the peak and its altitude for the current account. Following monetary policy shocks, the current account improves by 0.05% after 7-9 quarters, confirming that monetary policy shocks have at best a moderate impact on the current account. In contrast, stock price shocks have sizeable effects. Following stock price shocks, the current account worsens by more than 0.1% after 9-11 quarters. The distribution is sharply peaked, which leads to the conclusion that this results holds regardless of the identification scheme employed. As you can see, the results are different for exchange rate shocks. There is considerable mass on an early and strong as well as on a late and somewhat milder deterioration. This is the result of the w-shaped response of the current account to exchange rate shocks. Depending on whether one allows the current account to respond instantaneously or not, the peak deterioration is either 0.1% after 1-2 quarters or 0.08% after 7-11 quarters.

I conclude that the responses of the current account to both monetary policy and stock price shocks are robust to different identification schemes. With respect to exchange rate shocks, I find that the location of the peak deterioration is sensitive to changes in identification, but not the size of the peak.

1.4 Conclusion

In this chapter, I examine the role of shocks to monetary policy, stock prices and exchange rates in explaining current account fluctuations. While a considerable fraction of the existing literature focuses on individual countries, I extend the analysis to a set of 17 industrialized economies. Based on a panel VAR model using data on real GDP, consumer prices, short and long-term interest rates, stock prices, exchange rates and the current account, I find a small role for monetary policy shocks. This finding does not square with the empirical evidence for the U.S., but can be attributed to the behavior of the exchange rate, which mitigates the effects of monetary policy shocks, in particular for small open economies.

In contrast, shocks to stock prices and exchange rates have a significant impact on the current account. While a 10% increase in stock prices leads to a deterioration of the current account of 0.3%, an appreciation of the exchange rate of similar magnitude depresses the current account by 0.4%. The effect of stock price shocks on the current account builds up gradually over time and reaches its maximum after around 9-11 quarters. Depending on the identification scheme, exchange rate shocks exert their maximal influence either after 7-11 quarters or within two quarters after the shock. The latter response of the current account to exchange rate shocks is hence inconsistent with the prediction of the Mundell-Fleming-Dornbusch model. In this model, the current account improves on impact following an exchange rate appreciation, before falling over time. Such a 'J-curve effect' is frequently observed in single country VAR models, but counterintuitive. Given that the panel set-up allows me to estimate the impulse responses more precisely as compared to single country VARs, it seems plausible that the findings of the existing VAR literature are the result of overparametrized and hence imprecisely estimated models. And finally, stock price and exchange rate shocks explain a notable fraction of the variation of the current account at medium and long-term forecast horizons as compared to others shocks, in particular monetary policy shocks.

The analysis suggests that stock price and exchange rate shocks are about equally important in explaining current account fluctuations. Thus I find a channel, in addition to the traditional exchange rate channel, through which external balance for an OECD country with a current account imbalance can be restored. I demonstrate the economic relevance of this stock price channel with an example. According to the numbers reported above, a stock market underperformance of 100% improves the current account by about 3%. Such a large underperformance is not unusual if the country under study is in a crisis situation. Moreover, the adjustment needs not to happen immediately but may take several years. Take Japan as an example. While the Japanese stock market lost about half of its value during the 1990s, the U.S. market soared by more than 400% at the same time, providing an explanation for the current account surpluses in Japan and the deficits in the United States. Thus, even for countries with large current account deficits stock price movements are a potential driver of the adjustment process.

2 Exploring the international transmission of U.S. stock price movements

I investigate the transmission of U.S. stock price shocks to real activity and prices in G-7 countries using a multicountry vector autoregressive (VAR) model. I achieve identification by imposing a small number of sign restrictions on impulse responses, while controlling for monetary policy, business cycle and government spending shocks. The results suggest that (a) stock price movements are important for fluctuations in G-7 real activity and prices, but do not qualify as demand side business cycle shocks, and (b) the transmission is similar across G-7 countries.

2.1 Introduction

There is an increasing number of VAR-based studies that stress the role of stock prices in explaining macroeconomic developments. For example, Beaudry and Portier (2006) argue that shocks to stock prices reflect changes in agents' expectations about future total factor productivity and are an important driver of U.S. business cycles. Fratzscher et al. (2007) point to stock market wealth as an explanation for U.S. external imbalances, while in an extension to the G-7 countries, Fratzscher and Straub (2009) find that shocks to stock returns have sizeable effects on external accounts. Furthermore, Assenmacher-Wesche and Gerlach (2008) study the relationship between stock prices, real activity and prices in industrialized countries and find a significant transmission of stock price shocks to the latter.

The main challenge in identifying stock price shocks is to disentangle movements in stock prices that are due to the business cycle or to other shocks and those that are exogenous, a difficulty the existing literature largely ignores. One camp uses sign restrictions on impulse responses and treats shocks to stock prices as demand side business cycle shocks, assuming that stock prices impact on real activity and prices (see, e.g., Fratzscher et al., 2007; Fratzscher and Straub, 2009). Another camp imposes zero restrictions on impulse matrices and rules out a contemporaneous effect of stock prices on real activity, prices and interest rates (see, e.g., Assenmacher-Wesche and Gerlach, 2008). Both approaches are debatable. The first one is dogmatic regarding the nature of stock price shocks, the second imposes short-run restrictions that are likely to be violated in reality. A counterexample is the immediate monetary policy response to the stock market crash in October 1987.

In this chapter, I identify shocks to U.S. stock prices using a small number of sign restrictions on impulse responses, while controlling for monetary policy, business cycle and government spending shocks. The approach allows me to filter out the effects of these shocks on stock prices and is agnostic with respect to the nature of stock price shocks. The procedure shares similarities with the identification scheme of Mountford and Uhlig (2005) in the context of fiscal policy shocks. Furthermore, consistent with the aforementioned studies, I take an international perspective. I use a multicountry VAR for the G-7 countries as described in Canova and Ciccarelli (2009). The approach is novel and has been used so far to construct indicators of world and national business cycles (see Canova et al., 2007) or to investigate the propagation of monetary and technology shocks between the U.S. and the euro area (see Caivano, 2006). I prefer the multicountry VAR to other panel data approaches since it allows for cross-country lagged interdependencies and heterogeneous dynamics. Both features are often neglected in the literature but likely to be present in my context. Furthermore, the multicountry VAR methodology can be applied to panel data where the cross-sectional dimension is short and the time series is of moderate length only. In addition, a factor structure keeps estimation simple.

I find that stock price shocks are important for fluctuations in G-7 real activity and prices even when controlling for other shocks. However, such shocks do not qualify as demand side business cycle shocks since they do not induce a positive comovement of real activity and prices. Moreover, the transmission appears to be similar across G-7 countries.

The rest of this chapter is organized as follows. Section 2.2 outlines the multicountry VAR and the identification strategy with sign restrictions. Section 2.3 describes the empirical implementation. In Section 2.4, I discuss the preferred specification of the multicountry VAR and document its empirical properties. Section 2.5 presents an impulse responses analysis. Section 2.6 presents a forecast error variance decomposition. Finally, Section 2.7 concludes.

2.2 The multicountry VAR and identification

2.2.1 The model

Consider the multicountry VAR:

$$y_{it} = \sum_{j=1}^{p} B_{ij} Y_{t-j} + c_i + u_{it},$$
(2.1)

where i = 1, 2, ..., N; t = 1, 2, ..., T; y_{it} is a $G \times 1$ vector of variables for country i, B_{ij} is a $G \times NG$ coefficient matrix for lag j, $Y_t = (y'_{1t}, y'_{2t}, ..., y'_{Nt})'$ is a $NG \times 1$ vector containing the variables for all N countries, c_i is a constant, and u_{it} is a $G \times 1$ vector of random disturbances.

Grouping coefficients for country *i* yields a $NGp + 1 \times G$ matrix $\delta_i = (B_{i1}, B_{i2}, ..., B_{ip}, c_i)'$. Furthermore, let $\delta = vec(\delta_1, \delta_2, ..., \delta_N)$ be the $NGk \times 1$ vector of all coefficients, where k = NGp + 1 is the number of coefficients in each equation. In most applications, *k* is larger than the number of observations T and the multicountry VAR cannot be estimated without imposing restrictions. I follow Canova and Ciccarelli (2009) and assume that the coefficient vector can be factored as

$$\delta = \sum_{f=1}^{F} \Xi_f \theta_f, \tag{2.2}$$

where $F \ll k$ is the number of factors, the Ξ_f 's are conformable matrices and the θ_f 's are factor loadings. Thus the dimensionality is reduced significantly. Rather than a large number of coefficients, only a small number of factor loadings has to be estimated. The choice of the factors is application and sample dependent. Factors may cover variations that are common across countries and variables or are specific to a particular country, variable or lag. In contrast to Canova and Ciccarelli (2009), I do not let the θ 's vary over time or allow for idiosyncratic components.

Let $X_{it} = (Y'_{t-1}, Y'_{t-2}, ..., Y'_{t-p}, 1)'$ be the $k \times 1$ matrix of regressors for country *i* and define $X_t = I_{NG} \otimes X'_{it}, \Xi = (\Xi_1, \Xi_2, ..., \Xi_F)$ and $\theta = (\theta'_1, \theta'_2, ..., \theta'_F)'$. The multicountry VAR can be rewritten as

$$Y_t = X_t \delta + u_t$$

= $X_t \Xi \theta + u_t$
= $\chi_t \theta + u_t$, (2.3)

where $\chi_t = X_t \Xi$ and $u_t = (u'_{1t}, u'_{2t}, ..., u'_{Nt})'$.

For illustration, I consider N = G = 2, p = 1 and F = 3. Then $\Xi = (\Xi_1, \Xi_2, \Xi_3)$ and $\theta = (\theta_1, \theta'_2, \theta'_3)'$. Here θ_1 is a scalar (a common factor), $\theta_2 = (\theta_{21}, \theta_{22})'$ is a 2×1 vector of country specific factors and $\theta_3 = (\theta_{31}, \theta_{32})$ is a 2×1 vector of variable specific factors. Let $i_1 = (1, 1, 1, 1, 0)'$, $i_2 = (1, 1, 0, 0, 0)'$, $i_3 = (0, 0, 1, 1, 0)'$, $i_4 = (1, 0, 1, 0, 0)'$ and $i_5 = (0, 1, 0, 1, 0)'$, then

$$\Xi_{1} = \begin{pmatrix} i_{1} \\ i_{1} \\ i_{1} \\ i_{1} \\ i_{1} \end{pmatrix}_{20 \times 1}, \quad \Xi_{2} = \begin{pmatrix} i_{2} & i_{3} \\ i_{2} & i_{3} \\ i_{2} & i_{3} \\ i_{2} & i_{3} \end{pmatrix}_{20 \times 2}, \quad \Xi_{3} = \begin{pmatrix} i_{4} & i_{5} \\ i_{4} & i_{5} \\ i_{4} & i_{5} \\ i_{4} & i_{5} \end{pmatrix}_{20 \times 2}, \quad (2.4)$$

implying that the first equation of the reparametrized multicountry VAR reads as

$$y_{11,t} = \theta_1 \chi_{1t} + \theta_{21} \chi_{2t} + \theta_{22} \chi_{3t} + \theta_{31} \chi_{4t} + \theta_{32} \chi_{5t} + u_{11,t},$$
(2.5)

where $\chi_{1t} = \sum_i \sum_g \sum_j y_{ig,t-j} + 1$, $\chi_{2t} = \sum_g \sum_j y_{1g,t-j}$, $\chi_{3t} = \sum_g \sum_j y_{2g,t-j}$, $\chi_{4t} = \sum_i \sum_j y_{i1,t-j}$ and $\chi_{5t} = \sum_i \sum_j y_{i2,t-j}$.

The overparametrized multicountry VAR is transformed into a parsimonious seemingly unrelated regression (SUR) model with observable linear combinations of the right hand side variables of the VAR as regressors. χ_{1t} contains information for all countries and variables, χ_2 (χ_3) contains information specific to country 1 (2) and χ_4 (χ_5) contains information specific to variable 1 (2). Pooling data in such a way removes both cross-section and time series noise and is expected to lead to more stable estimates of δ . Moreover, I allow the θ 's to be different across equations and estimate the SUR model sequentially by ordinary least squares (OLS). Finally, I use the estimated factor loadings to recover the coefficient vector δ .

2.2.2 Implementing sign restrictions

Given the dimensionality of the model, an exact identification is not possible. But I can identify a subset of shocks for the U.S. and study their transmission. Suppose the U.S. is ordered first and the reduced form errors are expressed as linear combinations of the shocks: $u_{1t} = P_1\epsilon_{1t}$, with P_1 being a $G \times G$ matrix and ϵ_{1t} a $G \times 1$ vector of orthogonal shocks with covariance matrix $\Sigma_{\epsilon_1} = E(\epsilon_{1t}\epsilon'_{1t}) = I_G$. The model for the U.S. is thus given by

$$y_{1t} = \sum_{j=1}^{p} B_{1j} Y_{t-j} + c_1 + P_1 \epsilon_{1t}.$$
(2.6)

The restriction on P_1 so far is: $\Sigma_{u_1} = E(u_{1t}u'_{1t}) = E(P_1\epsilon_{1t}\epsilon'_{1t}P'_1) = P_1\Sigma_{\epsilon_1}P'_1 = P_1P'_1$. In order to achieve exact identification within the U.S. model $\frac{G(G-1)}{2}$ additional restrictions have to be imposed on P_1 . A frequently used strategy is to assume a recursive ordering of the variables in y_{1t} , thus demanding P_1 to be lower triangular. This can be achieved by means of a Cholesky decomposition of Σ_{u_1} .

I follow a different approach and identify shocks by imposing restrictions on the sign of impulse responses. This approach is developed inter alia by Faust (1998), Canova and De Nicoló (2002), Uhlig (2005) and Rubio-Ramírez et al. (2005) and is motivated as follows. Suppose there does exist an orthonormal $G \times G$ matrix Q such that QQ' = Q'Q = I. Then $u_{1t} = P_1QQ'\epsilon_{1t}$ is an admissible decomposition and $\epsilon_{1t}^* = Q'\epsilon_{1t}$ is a new set of shocks with the property that $\Sigma_{\epsilon_1^*} = E\left(\epsilon_{1t}^*\epsilon_{1t}^{*'}\right) = E\left(Q'\epsilon_{1t}\epsilon_{1t}'Q\right) = I$. Thus, ϵ_{1t}^* has the same covariance matrix as ϵ_{1t} but is associated with a different impulse matrix $P_1^* = P_1Q$. This ability to create a large number of candidate impulses makes the sign restriction approach advantageous compared to recursive identification schemes. In recursive systems the number of possible factorizations is quickly exhausted and the factorization that produces responses that are consistent with a priori beliefs is chosen. But in many cases counterintuitive results cannot be avoided. The 'price puzzle' is an example. However, the sign restrictions approach allows me to consider a large number of decompositions and to avoid counterintuitive results. And instead of imposing informal shortrun restrictions, I explicitly state which restrictions I use.

I apply the following algorithm. First, I calculate a lower triangular factor of Σ_{u_1} , labeled P_1 , using a Cholesky decomposition. The results, however, are invariant to the ordering of the variables as Uhlig (2005) shows. The Cholesky decomposition is only a computational tool and I could alternatively use an eigenvalue-eigenvector decomposition of Σ_{u_1} . Second, I draw a $G \times G$ random matrix W from a multivariate standard normal distribution and apply the QR decomposition to W, such that W = QR and QQ' = Q'Q = I. Rubio-Ramírez et al. (2005) show that this Q matrix has the required uniform distribution. Third, I construct an impulse matrix P_1Q and calculate the associated responses. If all the restrictions are fulfilled, I keep the draw. Otherwise, I discard it. I consider a large number of candidate Q's and draw inference from those draws that are kept.

This strategy allows me to identify up to *G* shocks for the United States. Moreover, I let the remaining variables react according to a transformed covariance matrix. I transform $\Sigma_u = E(u_t u'_t)$ in such a way that the identification of U.S. shocks is invariant to the ordering of the countries and variables in the model. Dees et al. (2007) apply a similar transformation in the context of a Global VAR. I provide details in Appendix B.1.

2.3 The empirical setup

I estimate the multicountry VAR on quarterly data for the years 1974-2005, covering a period of largely flexible exchange rates and rising financial globalization. The estimation period is limited by the availability of fiscal data. I provide a summary of the data sources in Appendix B.2. I include nine variables for each of the G-7 countries: the government budget (primary balance in percent of GDP), real government spending (real government consumption plus investment), real GDP, real private consumption, real private investment, the GDP deflator, a nominal short-term interest rate, a monetary aggregate, and nominal stock prices. I consider the government budget and real government spending to identify government spending shocks, while I use interest rates and monetary aggregates to identify monetary policy shocks. Moreover, real GDP, real private consumption, real private investment, the GDP deflator and nominal stock prices are the variables of interest.

	(Contractionary shocks	to	
	U.S. Mon. Policy	U.S. Business Cycle	U.S. Stock Prices	U.S. Gov. Spend.
Gov. Budget		_		+
Gov. Spend.				_
GDP		_		
Consumptior	ı	_		
Investment		_		
GDP Deflator				
Money (M1)	_			
Interest Rate	+			
Stock Prices			_	

Table 2.1: Sign restrictions on impulse responses

Notes: The horizon is four quarters.

Government budget outcomes and interest rates enter the model in levels, but I consider the remaining variables in annualized quarterly growth rates, even though this may result in a slight misspecification of the model since I cannot exploit the informational content of cointegrating relationships in this case. But I want to ensure that all variables are expressed in the same unit of measurement, i.e. in percent, and that their variability is comparable before I construct averages. Otherwise averages could be dominated by a particular variable. Therefore, I normalize all series by substracting the mean and by dividing by their respective standard deviation. Finally, I set the lag length to two. Since in the SUR model regressors are averages over the lags of the variables, the results are robust to variations in the lag length.

Table 2.1 summarizes the sign restrictions. I impose restrictions for four quarters on the level of U.S. variables. I consider a horizon of one year to avoid only transitory movements in variables and thus spurious identification of shocks. Moreover, the horizon is consistent with related studies (see, e.g. Mountford and Uhlig, 2005; Scholl and Uhlig, 2008; Peersman and Straub, 2009, among others). Furthermore, I require that all the restrictions are satisfied simultaneously. This ensures orthogonality of shocks and allows me to filter out the effects of monetary policy, business cycle and government spending shocks on stock prices.

Monetary policy shocks raise interest rates, while monetary aggregates and the GDP deflator fall. Hence, I avoid 'price or liquidity puzzles' by construction. Contractionary business cycle shocks depress real GDP, real private consumption and real private investment. I impose no

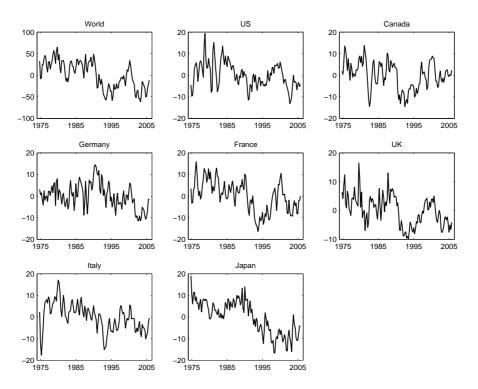


Figure 2.1: World and country indicators

restriction on the response of the GDP deflator and thus control for both supply and demand side shocks. But I require that the government budget deteriorates in response to contractionary business cycle shocks since important budget components, such as tax revenues or transfer payments, are heavily influenced by the state of the economy. Shocks to stock prices contract stock prices, while I do not restrict the response of any other variable. Thus, I am agnostic about the nature of such shocks. This distincts the approach from those in the related literature. I test the hypothesis that stock price shocks impact on real activity and the GDP deflator rather than assuming it. Finally, government spending shocks lower government spending and improve the government budget, assuming that the fiscal authority does not fully compensate for the reduction in spending by lowering taxes or increasing transfer payments.

2.4 International comovements of the variables

Before presenting impulse responses and a forecast error variance decomposition in the next two sections, I explore the country and variable-specific factor or indicator series. Given that the multicountry VAR methodology is novel and only few applications are available, it seems appropriate to check for its plausibility. Moreover, I want to investigate whether all the indicator

	World	U.S.	Canada	Germany	France	UK	Italy	Japan
World	1.00							
U.S.	0.69	1.00						
Canada	0.65	0.44	1.00					
Germany	0.53	0.27	0.02	1.00				
France	0.86	0.52	0.51	0.33	1.00			
UK	0.76	0.39	0.57	0.28	0.66	1.00		
Italy	0.78	0.58	0.43	0.32	0.71	0.46	1.00	
Japan	0.68	0.26	0.25	0.46	0.48	0.45	0.36	1.00

Table 2.2: Correlation between the world and country indicators

series are necessary to model the data. Since the series are correlated by construction, it seems likely that I can leave out some when estimating the model.

Figure 2.1 shows the world and country indicators. The country indicators average across variables and lags and mirror important episodes for the countries under study. For example, the troughs in the U.S. indicator series coincide with the recessions that hit the U.S. during the sample period: one in the mid 1970s, the double dip recession in the early 1980s, the recession in 1991, and finally that of 2001. Moreover, the peak in the German indicator in the early 1990s marks the reunification boom, while the collapse of the European Monetary System (EMS) in 1992 is particularly evident for the UK and Italy. Furthermore, the weak economic performance in Japan during the 1990s which was accompanied by deflationary pressures results in a substantial decline of the indicator over this period.

Though some of these events are specific to a country or region, a casual comparison of the plots leads me to conclude that the indicators share similarities. This is confirmed by Table 2.2 which shows evidence of a positive comovement of the country indicators. Not surprisingly, they also tend to comove positively with the world indicator suggesting that country-specific events are of temporary importance.

Figure 2.2 shows the variable indicators which average across countries and lags. Some notable developments are readily apparent. The GDP and investment series, and to a lesser extent consumption, track the severe contractions in the mid 1970s and early 1980s, the U.S. recessions in 1991 and 2001, and the European one in 1992. The indicator series for the GDP deflator and interest rates decline over time, reflecting global disinflation. The series for government spending appears to be stable over time, except for the mid 1990s when government spending is weak

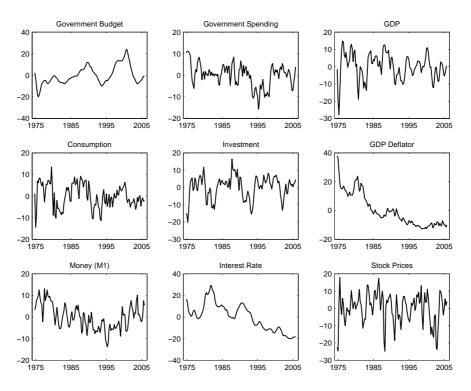


Figure 2.2: Variable indicators

for a couple of years and government budgets experienced rapid improvements, probably the result of fiscal consolidation in Europe following the Maastricht treaty in 1992. Moreover, monetary aggregates decline steadily until the mid 1990s but rise thereafter. Finally, stock prices appear to be noisy even after taking averages across countries and time. The years 1974 (first oil shock), 1987 (stock market crash) and 2001 (U.S. recession) are associated with negative returns.

I report the correlation between the variable indicators in Table 2.3. Overall, correlations are lower for variable than for country indicators. A few exceptions are worth mentioning. GDP, consumption and investment show a positive comovement. Furthermore, the GDP deflator and interest rates tend to be positively correlated as well, while the government budget and the GDP deflator display a negative correlation.

I conclude, while it is desirable to have all of the variable indicators in the model, there is probably no need to include the full set of country indicators once the world indicator has been added to the model. A bulk of the variation in the data can presumably be explained by common movements and adding country indicators leads to multicollinearity. Thus, I do not consider a specification where all are included but experiment with the following possibilities. First, I run regressions for each of the 63 series and include a world, nine variable but no country indicator. Second, I perform the same regressions but add an U.S. country indicator for all countries since

	Gov. Budget	Gov. Spend.	GDP	Cons.	Invest.	GDP Defl.	Money (M1)	Int. Rate	Stock Prices
Gov. Budget	1.00								
Gov. Spending	g - 0.03	1.00							
GDP	0.15	-0.04	1.00						
Consumption	0.09	0.19	0.77	1.00					
Investment	0.30	-0.17	0.85	0.65	1.00				
GDP Deflator	-0.47	0.40	-0.09	-0.03	-0.29	1.00			
Money (M1)	-0.35	0.52	0.06	0.28	-0.01	0.41	1.00		
Interest Rate	-0.27	0.25	-0.14	-0.15	-0.31	0.74	-0.01	1.00	
Stock Prices	-0.06	-0.16	0.20	0.31	0.26	-0.07	0.16	0.00	1.00

Table 2.3: Correlation between the variable indicators

the U.S. was the single largest member of the world economy during the sample period. Third, I replace the U.S. by a country indicator for the same country as the left hand side variable.

Table 2.4 reports the average fraction of the variance that is explained by the respective set of indicators, i.e. the average R^2 . The upper panel shows the average across all countries and variables, the middle panel reports for each country the average across variables and the lower panel for each variable the average across countries. Several findings are of interest. First, about 40% of the variance across variables and countries is explained by the indicators. Second, the average R^2 is similar across countries, but not across variables. While movements in some variables are explained well (government budget, GDP deflator and interest rates), those in others are not (particularly stock prices), reflecting different degrees of persistence. Third, adding country indicators to the model raises the R^2 by little. Consequently, I feel comfortable with the idea not to add all of the country indicators. However, I prefer to have the own country indicator included since it allows me to discriminate between developments specific to a country and those to the world.

2.5 Impulse responses

In this section, I present the impulse responses following shocks to U.S. monetary policy, the business cycle, stock prices and government spending. I estimate the multicountry VAR, fix coefficients at their OLS point estimates and draw one million *Q* matrices, leaving me with 289 responses that are consistent with the set of identifying restrictions. The acceptance ratio is low

	Own Country Indicator	U.S. Country Indicator	No Country Indicator
All	0.40	0.40	0.39
U.S.	0.43	0.43	0.42
Canada	0.43	0.42	0.41
Germany	0.31	0.30	0.30
France	0.45	0.45	0.44
UK	0.38	0.39	0.37
Italy	0.46	0.46	0.45
Japan	0.36	0.35	0.34
Gov. Budget	0.81	0.79	0.77
Gov. Spending	0.21	0.21	0.20
GDP	0.27	0.28	0.26
Consumption	0.15	0.15	0.14
Investment	0.26	0.26	0.25
GDP Deflator	0.69	0.70	0.68
Money (M1)	0.25	0.25	0.24
Interest Rate	0.88	0.88	0.87
Stock Prices	0.10	0.11	0.10

Table 2.4: Average R^2 for regression of variables on indicator series

Notes: Table shows the average fraction of the variance that is explained by the indicator series, i.e. the average R^2 . The upper panel reports the averages across all countries and variables, the middle panel shows for each country the averages across variables and the lower panel for each variable the averages across countries. 'No Country Indicator' means that each variable is regressed on a world, all variable but not on a country indicator. 'U.S. Country Indicator' indicates that the U.S. country indicator is included in all regressions. 'Own Country Indicator' means that the country indicator added to the right hand side of the regression refers to the same country as the left hand side variable.

compared to related studies for two reasons. First, I identify four shocks simultaneously. And second, identification in a multicountry VAR is more difficult than in a standard VAR.

A common practice is to report the median of the posterior distribution, often in combination with percentile bands providing a measure of the range of responses. However, the distribution is across models and the median is not generated by a single model, i.e. by a single Q matrix. Thus, draws from the posterior distribution are not orthogonal, which is particularly problematic if multiple shocks are identified. In order to overcome this problem, I follow Fry and Pagan (2007) and choose a Q matrix that produces responses, which are as close as possible to the median. This preserves the consensus view that the median is an informative statistic,

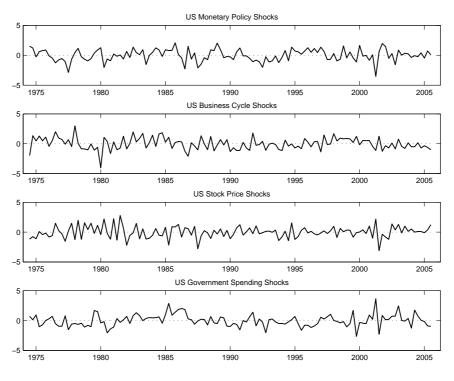


Figure 2.3: Estimated multicountry VAR shocks

Notes: Entries are percent.

while orthogonality is retained. I normalize all responses by dividing by the standard deviation across all accepted draws and choose that *Q*, which minimizes the sum of squared deviations from the median over all accepted draws, variables and time horizons:

$$Q_{s}^{\star} = argmin \sum_{i=1}^{4} \sum_{j=1}^{63} \sum_{k=0}^{24} \left(\frac{\phi_{ijk} \left(Q_{s} \right) - med\left(\phi_{ijk} \right)}{std\left(\phi_{ijk} \right)} \right)^{2}$$
(2.7)

where $\phi_{ijk}(Q_s)$ is the response of variable j = 1, ..., 63 to shock i = 1, ..., 4 at horizon k = 0, ..., 24 generated by model s = 1, ..., 289.

The set of admissible models is thus reduced from 289 to 1 and I construct impulse responses and multicountry VAR shocks (this section) as well as a forecast error variance decomposition (next section) on the basis of the selected model. In order to summarize the information, I average statistics for Canada, Germany, France, UK, Italy and Japan and present results for this panel of countries and the United States.

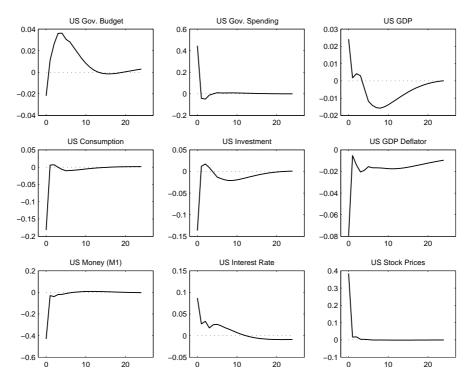


Figure 2.4: Impulse responses to U.S. monetary policy shock for the United States Notes: Entries are deviations from baseline in percent; horizontal axis denotes quarters after the shock.

2.5.1 U.S. monetary policy shocks

I show the estimated U.S. monetary policy shocks in the first panel of Figure 2.3. The stance of monetary policy in the United States is loose in the mid and late 1970s, but tight around 1980 following the appointment of Paul Volcker as chairman of the Federal Reserve. Moreover, the series displays negative innovations in 1987 and 2001, indicating an accomodative role of U.S. monetary policy in response to the U.S. stock market crash and the terrorist attacks on 9/11, respectively. Furthermore, the unexpected tightening around 1994-95 coincides with U.S. bond market turbulences. Overall, the estimated shocks mirror important U.S. monetary episodes, suggesting that the series is plausible.

Figures 2.4 and 2.5 show the impulse responses following a shock to U.S. monetary policy for the United States and the panel of other G-7 countries, respectively. I report the responses at each horizon between 0 and 24 quarters after the shock. Consider first the transmission within the United States. By construction, the shock has a positive effect on the interest rate, but a negative impact on the monetary aggregate and the GDP deflator for a year throughout. As a

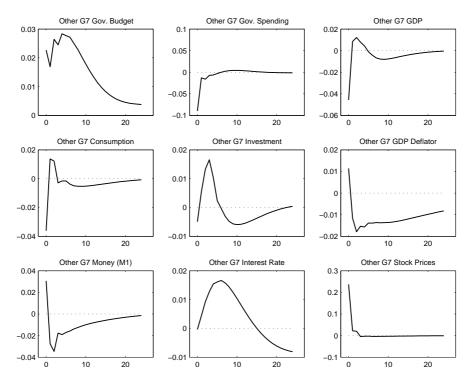


Figure 2.5: Impulse responses to U.S. monetary policy shock for the other G-7 countries Notes: See Figure 2.4

consequence, real consumption and real investment contract on impact and are below their initial level for most of the following six years. Similarly, real GDP falls after the monetary policy shock, but displays a less intuitive postive response in the short-run. Surprisingly, the government budget improves in the years after the shock even though real activity is contracting. I presume that U.S. monetary and fiscal policy were somewhat coordinated over the sample period and that the monetary tightening is accompanied by an increase in taxes. Furthermore, stock prices rise in response to the monetary policy shock which is counterintuitive. However, I simultaneously identify an orthogonal shock that depresses stock prices for four quarters by construction and hence stock prices have the tendency to rise in response to other shocks. Overall, the responses settle around zero within a reasonable period of time, suggesting that the model is stable.

With respect to the transmission to the panel of other G-7 countries, I find that the U.S. monetary policy shock produces foreign responses that are similar to those for the United States. The main differences are in the effects on interest rates and government spending. While U.S. interest rates rise on impact and decline steadily thereafter, the positive effect on foreign inter-

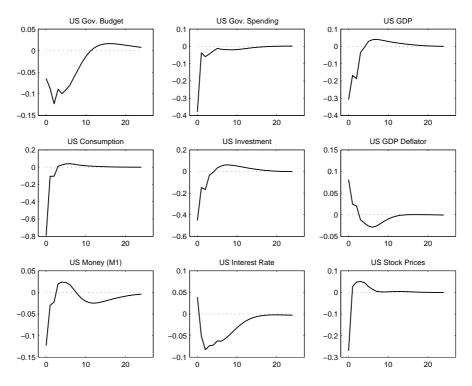


Figure 2.6: Impulse responses to U.S. business cycle shock for the United States

Notes: See Figure 2.4

est rates builds up gradually over time, resulting in a hump-shaped response. Moreover, U.S government spending increases after the U.S. monetary policy shock, but foreign government spending is below its initial level for about a year after the shock.

2.5.2 U.S. business cycle shocks

The second panel of Figure 2.3 shows the estimated U.S. business cycle shocks. Negative innovations coincide with the 1973-75 and 1980 NBER recession dates, while that of 1981-82 is not picked up. Moreover, the contraction of 1990-91 is apparent, but the mild recession of 2001 is not different from other shocks. Furthermore, the series shows a number of positive innovations in the early and mid 1980s and late 1990s, reflecting the recovery after the double dip recession and the 'new economy boom', respectively. In addition, the business cycle series is less volatile after 1985, consistent with the idea of a 'great moderation'. In sum, the estimated series is a plausible description of the cyclical behavior of the U.S. economy over the sample period.

I show the impulse responses to a contractionary U.S. business cycle shock for the United States in Figure 2.6. By construction, real GDP, real consumption and real investment fall after

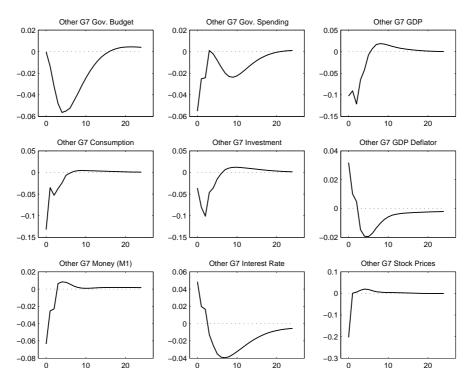


Figure 2.7: Impulse responses to U.S. business cycle shock for the other G-7 countries Notes: See Figure 2.4

the shock and the government budget deteriorates. The effect on the budget, but not on real activity, is persistent even after removing the restriction. Fiscal balance is restored not until three years after the shock. However, real activity variables are expressed in quarterly growth rates and not in levels, hence it is not surprising that their responses return to their initial level soon after removing the restriction.

What are those shocks? So far, business cycle shocks induce a positive comovement of real activity and the government budget, while I impose no restriction on the response of the GDP deflator, consistent with both supply and demand side shocks. Thus, the response of the GDP deflator provides an answer. As you can see, real activity and the GDP deflator are negatively correlated for years after the shock, suggesting that the shock is a supply side shock. Possible candidates are technology or oil price shocks. However, I am not interested in the exact nature of such shocks since the main purpose of identifying business cycle shocks is to control for their effect on stock prices.

In fact, stock prices are adversely affected by the contractionary business cycle shock on impact. However, they recover soon after. Most of the adjustment takes place within a few

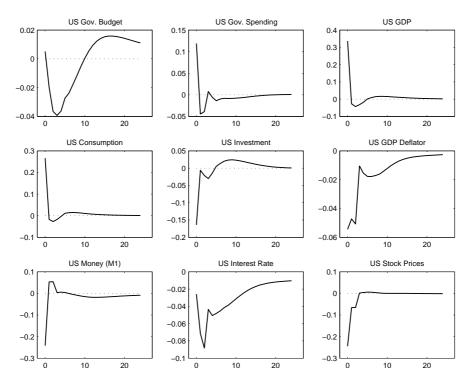


Figure 2.8: Impulse responses to U.S. stock price shock for the United States Notes: See Figure 2.4

quarters, consistent with the idea that stock prices incorporate news on the state of the business cycle in a short period of time. Furthermore, government spending and interest rates fall after the shock, suggesting an accomodative role for U.S. monetary policy, but not U.S. fiscal policy, in dealing with the contraction in real activity.

Finally, we can see from Figure 2.7 that the U.S. business cycle shock induces adjustments within the other G-7 countries that are similar to those for the United States. Though foreign real activity variables display slightly delayed responses, the results support the view that real activity across G-7 countries is highly synchronized (see, e.g., Canova et al., 2007, among others).

2.5.3 U.S. stock price shocks

I show the estimated U.S. stock price shocks in the third panel of Figure 2.3. The series is volatile in the late 1970s and early 1980s and less volatile during the pronounced bull market 1982-2000. In particular, the 1995-2000 stock market boom is associated with a decline in volatility, consistent with the idea that stock returns and volatility are negatively correlated. Furthermore, the series displays negative innovations to U.S. stock prices in 1987 (the U.S. stock market crash)

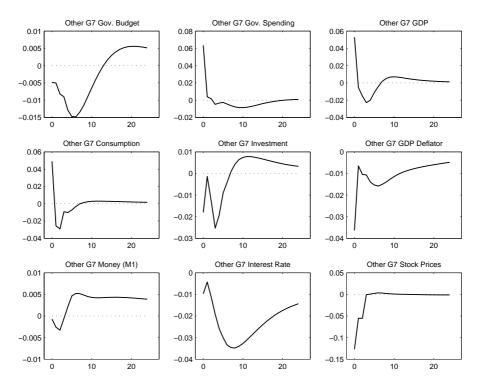


Figure 2.9: Impulse responses to U.S. stock price shock for the other G-7 countries Notes: See Figure 2.4

and 2001-03 (the U.S. bear market). In sum, the estimated shocks reflect important U.S. stock market events and appear to be plausible.

Figure 2.8 shows the impulse responses to an U.S. stock price shock for the United States. The stock price shock is orthogonal to the monetary policy shock, the business cycle shock and the government spending shock and stock prices decline for a year. However, I do not restrict the response of any other variable. As you can see from Figure 2.8, the response for stock prices immediately returns to zero once I remove the restriction, reflecting the low persistence of stock returns. Furthermore, the shock has a clear implication for the GDP deflator. The GDP deflator falls on impact and is below its initial level for the following six years. In contrast, I do not obtain a clear-cut result regarding the effect on real activity. While real investment falls on impact, real GDP and real consumption display positive responses. Thereafter, all three variables contract for a few quarters before returning to their initial level. A possible explanation for the improvement of real GDP in the short-run is that both U.S. monetary and fiscal policy are accomodative in response to the stock price shock. Government spending increases on impact, while the government budget and interest rates are both falling over time.

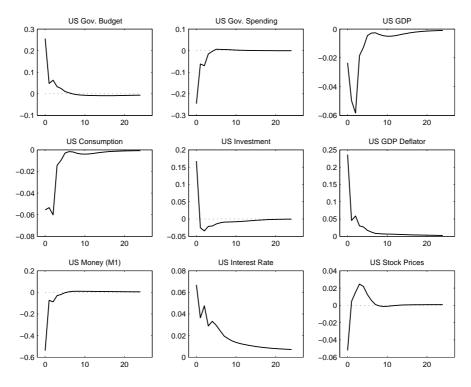


Figure 2.10: Impulse responses to U.S. government spending shock for the United States Notes: See Figure 2.4

I conclude that the U.S. stock price shock does not qualify as a demand side business cycle shock as often argued in the literature (see, e.g., Fratzscher et al., 2007, among others). There is at best weak evidence of a positive comovement of stock prices, real GDP, real consumption, real investment and the GDP deflator. Given that the business cyle shock of the previous section turns out to be a supply side shock, a positive comovement would be possible even when requiring orthogonaliy between stock price and business cycle shocks.

Are the sign restrictions confusing shocks? Seems unlikely since I control for monetary policy, business cycle and government spending shocks when identifying shocks to stock prices. Of course, there are other candidates that may be relevant in this context, such as investment-efficiency shocks. As for the stock price shock in Figure 2.8, investment-efficiency shocks lead to a negative correlation between consumption and investment. However, investment-efficiency shocks are also associated with a positive correlation between real GDP and investment, which is not the case for the stock price shock. Thus, it seems unlikely that the stock price shock is an investment-efficiency shock.

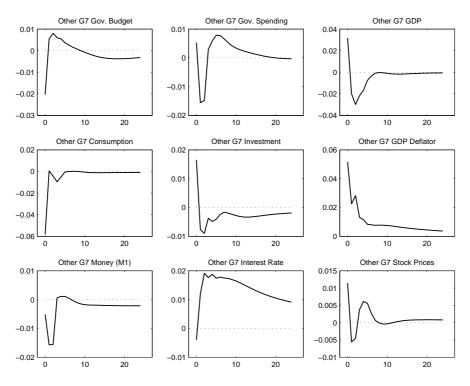


Figure 2.11: Impulse responses to U.S. government spending shock for the other G-7 countries

Notes: See Figure 2.4

As you can see from Figure 2.9, the U.S. stock price shock produces responses for the other G-7 countries that are similar to those for the United States. In particular, the shock is instantaneously incorporated in foreign stock prices, reflecting the close linkages between international stock markets. However, it seems that the negative effect of the decline in stock prices on real activity is larger over the medium-term for the other G-7 countries as compared to the United States.

2.5.4 U.S. government spending shocks

I show the estimated U.S. government spending shocks in the last panel of Figure 2.3. Overall, breaks in the series appear to be correlated with changes in the presidential terms. The estimated government spending shocks are negative on average in the late 1970s and early 1980s, indicating a restrictive fiscal policy during the presidencies of Gerald Ford and Jimmy Carter. In contrast, the Reagan era 1981-89 is associated with a series of positive shocks. In particular, U.S. fiscal policy is expansionary at the beginning of his second term in 1985, thanks to tax reduc-

tions and increased military defense spending. However, U.S. fiscal policy becomes restrictive after the election in 1989 and the presidencies of George Bush senior and Bill Clinton coincide with a number of negative shocks. Finally, the series is volatile during the first term of George Bush junior 2001-05, while the peaks in 2001 and 2003 indicate the military build ups associated with the wars in Afghanistan and Iraq, respectively. Of course, I cannot rule out that some of the estimated shocks reflect permanent changes in the conduct of U.S. fiscal policy rather than unsystematic fluctuations.

Figure 2.10 shows the impulse responses to an U.S. government spending shock for the United States. Such a shock reduces real government spending for one year while the government budget is restricted to improve. It also reduces real GDP and real consumption. Both variables fall on impact and are below their initial level for the following six years. In contrast, real investment rises on impact before falling over time, consistent with the textbook view of a crowding-in effect of the fiscal tightening. The positive effect on real investment seems to come from a reduction in real interest rates. Though both the interest rate and the GDP deflator rise after the shock, the GDP deflator increases stronger, suggesting a fall in real interest rates. The negative correlation between real government spending on the one hand and the GDP deflator as well as the interest rate on the other hand is less intuitive. However, such a finding is not uncommon in the fiscal policy literature (see, e.g., Mountford and Uhlig, 2005, among others). Finally, stock prices fall on impact, reflecting the contraction in real activity but recover thereafter.

I end this section by presenting the impulse responses for the other G-7 countries in Figure 2.11. It appears that the U.S. government spending shock is not directly transmitted to foreign fiscal policy variables. Both government spending and the budget display responses that are different to those of their U.S. counterparts. While the government budget has the tendency to fall rather than to improve over time, government spending is above its initial level after a year. However, the remaining variables follow their U.S. counterparts closely. Thus, the U.S. government spending shock contracts foreign real GDP and real consumption over the medium-term, while real investment is crowded in on impact, but falls thereafter. In addition, foreign interest rates and the GDP deflator increase.

2.6 Forecast error variance decomposition

In this section, I present a forecast error variance decomposition and assess how much of the variation in the variables can be accounted for by shocks to U.S. stock prices as compared to monetary policy, business cycle and government spending shocks. I report the numbers for the

	V	ariability due to shock	: to	
	U.S. Mon. Policy	U.S. Business Cycle	U.S. Stock Prices	U.S. Gov. Spend.
Gov. Budget	4	43	6	47
Gov. Spending	46	35	4	16
GDP	1	57	40	2
Consumption	4	85	10	1
Investment	6	76	9	9
GDP Deflator	12	11	10	66
Money (M1)	32	4	12	52
Interest Rate	13	40	33	14
Stock Prices	49	27	23	1

Table 2.5: Forecast error variance decomposition for the United States

Notes: I show the contribution in percent after 24 quarters.

United States in Table 2.5 and those for the panel of other G-7 countries in Table 2.6. Both tables show the variance shares at forecast horizons of 24 quarters. I consider long-term forecast horizons for two reasons. First, the identification uncertainty is large at the short-end and not all of the variables display on-impact responses that are plausible. Calculating variance shares at long-term forecast horizons avoids that the results are dominated by potentially implausible short-term forecasts. Second, I am interested in the long-term predictive ability of stock price shocks for fluctuations in real activity variables and the GDP deflator rather than in their role at business cycle frequencies. Furthermore, I do not compute the total variance of the 24-step ahead forecast error but only that part which is explained by the four shocks. Given the dimensionality of the model, this seems reasonable. Consequently, the variance shares exactly sum to 100 percent even though the model is only partially identified.

With respect to the United States, I find that government spending and monetary policy shocks have no explanatory power for movements in real GDP, real consumption and real investment. Both shocks explain less than 10% of the variation in real activity at a 6-year horizon. Thus, monetary policy shocks have either little real effects in the long-run or their size is too small to be important in relation to other shocks. In contrast, monetary policy shocks have large effects on the monetary aggregate, stock prices and government spending, while government spending shocks account for a substantial fraction of the variation in the GDP deflator and the monetary aggregate. But given that government spending shocks explain 66% of the variation

	V	ariability due to shock	: to	
	U.S. Mon. Policy	U.S. Business Cycle	U.S. Stock Prices	U.S. Gov. Spend.
Gov. Budget	15	51	15	19
Gov. Spending	g 23	44	25	8
GDP	7	63	12	17
Consumption	8	48	13	31
Investment	9	62	16	14
GDP Deflator	22	28	21	29
Money (M1)	27	32	22	19
Interest Rate	9	42	36	13
Stock Prices	43	34	21	2

Table 2.6: Forecast error variance decomposition for the other G-7 countries

Notes: I show the contribution in percent after 24 quarters.

in the GDP deflator and monetary policy shocks account for 46% of the variation in government spending, it seems likely that the identification scheme cannot exactly disentangle both shocks. As already mentioned, a possible explanation is that U.S. monetary and fiscal policy were coordinated over the sample period. However, I am not too concerned about this drawback since I am not interested in monetary policy and government spending shocks per se but consider them to filter out their impact on stock prices.

Not surprisingly, U.S. business cycle shocks explain the largest fraction of the variation in real GDP, real consumption and real investment. Between 57% and 85% of the variation in real activity is due to such shocks. Moreover, about half of the movements in the government budget are explained by changes in the business cycle and the other half by exogenous innovations to fiscal policy. In addition, business cycle shocks account for 40% of the variation in the interest rate, supporting the view that the largest fraction of the variation in interest rates is due to the endogenous part of monetary policy, i.e. the systematic response to shocks other than monetary policy shocks.

How much of the variation in U.S. variables cannot be attributed to shocks to U.S monetary policy, the business cycle and government spending and is thus due to U.S. stock price shocks? As you can see, only 23% of the variation in stock prices is due to own innovations, supporting my idea that controlling for other shocks is important when studying the transmission of stock price movements. Moreover, about one third of the variation in the interest rate, but less than

10% of the variation in government spending and the budget is due to stock price shocks, suggesting an active role for the monetary authority, but not fiscal authority, in dealing with stock price movements. The effects of U.S. stock price shocks on real activity and the GDP deflator are less clear-cut. While stock price shocks explain 40% of the variation in real GDP, their impact on real consumption, real investment and the GDP deflator is small. Given that real consumption and real investment make up a large fraction of real GDP, the impact of stock price shocks on real GDP must hence come from elsewhere, presumably through the trade balance.

With respect to the transmission of U.S. shocks to other G-7 countries, I find that U.S. business cycle shocks account for the largest fraction of the variation across all foreign variables. Business cycle shocks explain between 28% of the variation in case of the GDP deflator and 63% for real GDP, reflecting an international business cycle. Since U.S. monetary policy shocks have little effects on U.S. real activity, it is not surprising that their impact on foreign real activity is small, explaining less than 10% of the variation in foreign real GDP, real consumption and real investment. In contrast, about a quarter of the variation in the GDP deflator and monetary aggregates and nearly half of the variation in foreign stock prices is due to U.S. monetary policy shocks. The latter result suggests that U.S. monetary policy is an important factor for movements in international stock prices.

Furthermore, I do not obtain evidence of a fiscal policy coordination among G-7 countries. U.S. government spending shocks account for a mere 8% of the variation in foreign government spending at a 6-year forecast horizon. Moreover, their effect on foreign government budgets is moderate, explaining less than 20% of the variation. Of course, I cannot rule out some degree of policy coordination at short-term horizons or over the business cycle.

Overall, U.S. stock price shocks have a moderate impact on foreign variables, explaining between 13% and 36% of the variation. Consistent with the findings for the United States, only 21% of the variation in foreing stock prices is due to U.S. stock price shocks, U.S. monetary policy and business cycle shocks are more relevant. Moreover, I find that 36% of the variation in foreign interest rates is explained by U.S. stock price shocks. As for the United States, this number suggests a strong response of monetary policy to stock price movements. In addition, I obtain evidence of a notable effect of U.S. stock price shocks on foreign government spending and the budget, suggesting a more active role for fiscal policy in the other G-7 countries in dealing with stock price movements as compared to the United States. Finally, U.S. stock price shocks explain between 12% and 16% of the variation in foreign real activity, while 21% of the variation in the GDP deflator are due to such shocks. These numbers are larger than those for U.S. monetary policy shocks, but smaller than for U.S. business cycle shocks.

2.7 Conclusion

This chapter examines the transmission of U.S. stock price movements to real activity and prices in G-7 countries in the period 1974-2005. I achieve identification by imposing a small number of sign restrictions on impulse responses, while controlling for monetary policy, business cycle and government spending shocks. In contrast to related studies, the approach does neither rely on potentially implausible short-run restrictions nor is it dogmatic with respect to the nature of stock price shocks. The chapter is an application of the novel multicountry VAR methodology of Canova and Ciccarelli (2009). I prefer the multicountry VAR to conventional panel data approaches since it has a number of appealing features. Among others, it allows for cross-country lagged interdependencies, heterogeneous dynamics and time series of moderate length.

The results are as follows. U.S. stock price movements are important for fluctuations in G-7 real activity and prices, even when controlling for others shocks. They explain between 9% and 40% of the variation in real activity for the United States and 12% to 16% for the other G-7 countries. Moreover, between 10% and 21% of the variation in the GDP deflator across G-7 countries is due to such shocks. However, these numbers are smaller than those for U.S. business cycle shocks. This finding, together with the observation that stock price shocks do not induce a positive comovement of real activity and prices, leads me to conclude that shocks to stock prices do not qualify as demand side business cycle shocks. Furthermore, the transmission of U.S. monetary policy, business cycle, stock price and government spending shocks is similar across the United States and the other G-7 countries.

Finally, I want to acknowledge a limitation and point to a direction for future research. In this paper, I leave the responses of many variables agnostically open and use the rule of Fry and Pagan (2007) to narrow down the set of admissible models. Alternatively, I could combine the sign restrictions with bounds restrictions on the magnitude of certain elasticities, such as the government spending multiplier. Kilian and Murphy (2009) propose such a procedure in the context of oil market VARs to reduce the number of models. I would expect that imposing additional restrictions reduces the overall identification uncertainty and the number of counter-intuitive on-impact responses.

3 Do monetary and technology shocks move euro area stock prices?

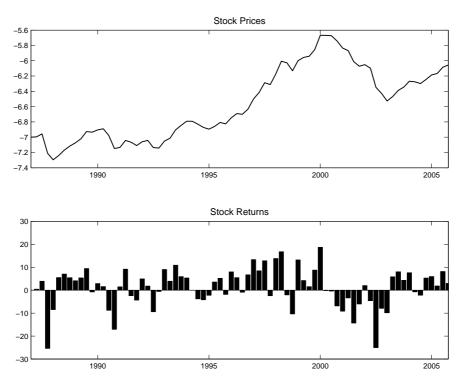
I use a Bayesian vector autoregressive (VAR) model to investigate the impact of monetary and technology shocks on the euro area stock market in 1987-2005. I find an important role for technology shocks, but not monetary shocks, in explaining variations in real stock prices. The identification method is flexible enough to study the effects of technology news shocks. The responses are consistent with the idea that news on technology improvements have an immediate impact on stock prices. These findings are robust to several modelling choices, including the productivity measure, omitted variables, and the identifying restrictions.

3.1 Introduction

The objective of this chapter is to understand the underlying sources of movements in the euro area stock market. I address this issue by estimating a Bayesian VAR model on 1987-2005 data. The sample period covers the 1995-2003 episode when the stock market experienced a pronounced boom-bust cycle (see Figure 3.1). Stock prices tripled between 1995 and 2000, showing double-digit returns each year. The boom ended in early 2000 and stock prices declined thereafter by 60% until 2003.

Within the VAR framework, I consider monetary and technology shocks as underlying disturbances. I find an important role for technology shocks, but not monetary shocks, in explaining variations in real stock prices. Over the sample period, more than 22% of the variation in stock prices can be attributed to technology shocks while monetary shocks explain less than 5%. Moreover, technology shocks are responsible for almost all variation in stock prices during the boom-bust cycle of 1995-2003. In addition, I find a significant response of stock prices to technology news shocks. Finally, I show that these findings are robust to the inclusion of additional disturbances, such as government spending or oil price shocks.

To identify monetary and technology shocks, I use sign restrictions on impulse responses as in Canova and De Nicoló (2002) or Uhlig (2005). I prefer this approach to the long-run restriction method of Galí (1999), which builds on the assumption that technology shocks are the only source of long-run variations in productivity. First, Uhlig (2004) convincingly argues that there exist other shocks that may influence productivity in the long-run, such as permanent changes in capital income taxation or social attitudes to the workplace. And second, the sign restriction method is flexible enough to study the effects of technology news shocks on stock prices. Technology news shocks have only a delayed impact on productivity and are identified by Beaudry





Notes: All entries are log levels (upper panel) or percent (lower panel).

and Portier (2006) as being an important determinant of U.S. stock price movements. Furthermore, I can incorporate additional short or long-run restrictions into the framework.

Following Beaudry and Portier (2006), I interpret technology shocks as being the exogenous component of total factor productivity (hereafter 'productivity'). Technology improvements either raise productivity immediately or with a lag of a few quarters. This delayed impact is motivated by technology diffusion models, in which firms need some time to adjust productive capacity, i.e. have to hire skilled workers and buy new machines. The most important aspect in such models is that the new technological opportunities are anticipated by economic agents and immediately incorporated into forward looking variables, in particular stock prices. This results from the assumption that the current stock market value equals the discounted stream of expected firm profits which in turn are a function of future production possibilities.

I incorporate monetary shocks into the analysis since it is not a priori clear to me why they should not have effects on real stock prices. Monetary shocks are changes in the stance of monetary policy that cannot be explained by a policy rule, i.e. the endogenous response of the policy interest rate to movements in real activity and inflation. Examples include the response to the stock market crash in 1987, the collapse of the Long-Term Capital Management hedge funds or the terrorist attacks on 9/11. Given the evidence of the monetary VAR literature that monetary disturbances influence the business cycle, they may have (temporary) effects on the discount factor or firm profits, and hence on the stock market. Moreover, the stock market boom of 1995-2000 was accompanied by falling nominal and real interest rates, raising the question if loose monetary policy has contributed to a stock market bubble. In addition, the end of the boom in 2000 coincided with a monetary tightening.

The rest of this chapter is organized as follows. Section 3.2 outlines the Bayesian VAR and the identification strategy with sign restrictions. Section 3.3 reports the results, including an impulse response analysis and a forecast error variance as well as a historical decomposition. Moreover, I assess the plausibility of the estimated shocks and provide robustness checks. Finally, Section 3.4 concludes.

3.2 The empirical setup

3.2.1 Bayesian VAR model

A VAR is given by

$$Y_t = A_1 Y_{t-1} + \dots + A_p Y_{t-p} + u_t, ag{3.1}$$

where Y_t is a $G \times 1$ vector of variables, A_i is a $G \times G$ coefficient matrix for lags $i = 1, ..., p, u_t$ is a $G \times 1$ vector of residuals with covariance matrix Σ , and data are available for t = 1, ..., T. Given the vector of structural shocks ϵ_t , the residual vector can be written as $u_t = B\epsilon_t$, where $E[\epsilon_t \epsilon'_t] = I$ and thus $\Sigma = E[u_t u'_t] = BB'$.

The vector Y_t contains an index for total factor productivity (tfp_t) , real GDP in per capita terms (y_t) , the GDP deflator (p_t) , a nominal short-term interest rate (i_t) , a monetary aggregate (m_t) , and real stock prices in per capita terms (s_t) . I consider all variables in log levels, except the interest rate, which is expressed in percent. By doing the analysis in levels, I allow for implicit cointegrating relationships between the variables. I do not include a constant or time trend and set the lag length to four.

I estimate the VAR on quarterly data for the period 1987-2005 and provide a summary of the data sources in Appendix C.1. For stock prices, I use the Dow Jones EURO STOXX Net Return index (which includes dividends), deflated by the GDP deflator and transformed in per capita terms by dividing by the civilian labor force. The index is available from STOXX Limited and was introduced in 1987, which determines the sample period. To obtain quarterly data, I average daily figures. Data on real GDP, the GDP deflator, the interest rate and the civilian

labor force come from the Area-wide Model (AWM) database. I use the civilian labor force to transform real GDP into per capita terms. Moreover, monetary data (M1) are from the OECD Main Economic Indicators (MEI) database.

To construct the productivity index, I obtain data on the capital stock (K_t) from the AWM database and on annual total hours worked (H_t) from the EU KLEMS Growth and Productivity Accounts. The EU KLEMS database is updated until 2005, which limits my sample period. Moreover, I use the interpolation method of Fernández (1981) to obtain quarterly figures on hours, using real GDP and total employment as indicator series. The latter series is from the AWM database. Furthermore, the EU KLEMS database provides data on labor and capital compensation, which I use to calculate an average labor share ($\bar{\alpha} = 0.66$) for the sample period. Finally, I construct a measure of (log) total factor productivity as $tfp_t = log (GDP_t/H_t^{\bar{\alpha}}K_t^{1-\bar{\alpha}})$, where GDP_t denotes real GDP.

For estimation and inference, I employ a Bayesian approach. In particular, I use a weak Normal-Wishart prior for (A, Σ) as in Uhlig (2005), while shocks are identified per sign restrictions following Canova and De Nicoló (2002). I take a joint draw from (A, Σ) and derive an orthogonal decomposition of $\Sigma = BB' = PDP'$ using the eigenvalue-eigenvector decomposition. *P* is a matrix of eigenvectors, *D* is a diagonal matrix with eigenvalues on the main diagonal and $B = PD^{1/2}$. Given that for any orthonormal matrix *Q*, i.e. QQ' = I, $\Sigma = BQQ'B' = \hat{B}\hat{B}'$ is an admissible decomposition, I can construct a large number of candidate impulse matrices \hat{B} . I generate orthonormal matrices using the multiple of the basic set of Givens matrices as $Q = \prod_{m,n} Q_{m,n}(\theta)$ with $Q_{m,n}(\theta)$ being G(G-1)/2 = 15 bivariate rotation matrices of different elements of the VAR: $\theta = \theta_1, ..., \theta_{15}$, the rows m, n are rotated by the angle θ_i . I provide an example for $Q_{m,n}(\theta)$ in Appendix C.2. To exhaust the range of possible decompositions, I do not use a grid search method as in Canova and De Nicoló (2002) but follow Peersman (2005) and draw the parameters θ_i from a uniform distribution on the interval $[0, \pi]$. Finally, I calculate the associated responses for each candidate draw and keep it if all the restrictions are satisfied. Otherwise, I discard it. Based on the draws kept, I calculate the statistics of interest.

3.2.2 Identifying sign restrictions

Sign restrictions on impulse responses are frequently used to identify monetary shocks in VAR models and widely accepted (see, e.g., Faust, 1998; Canova and De Nicoló, 2002; Uhlig, 2005; Scholl and Uhlig, 2008, among others). These authors impose a small number of uncontroversial restrictions on the sign of impulse responses for selected variables, while being agnostic with respect to the responses of others. This procedure allows them to rule out 'price or liquidity

Shocks	Variables	Horizon in quarters
Monetary	$p_{t+j} \le 0, i_{t+j} \ge 0, m_{t+j} \le 0$	j = 0,, 2
Technology	$tfp_{t+j} \ge 0$	j = 0,, 7
Technology news	$tfp_{t+j} = 0$ $tfp_{t+j} \ge 0$	j = 0, 1 j = 2,, 9

Table 3.1: Sign restrictions on impulse responses

Notes: Horizon 0 denotes the initial response. p = GDP deflator; i = interest rate; m = monetary aggregate; tfp = total factor productivity.

puzzles' by construction. Consistent with this literature, I impose that a positive interest rate shock has a negative effect on the monetary aggregate and the GDP deflator. I do not restrict the response of real stock prices to leave the question at hand open. Furthermore, I set the horizon for the sign restrictions equal to three, i.e. the restrictions are binding on impact and for the following two quarters. This horizon is within the range used in related studies and rules out short-lived deviations from a policy rule.

Furthermore, I identify two technology shocks. A technology shock that immediately impacts on productivity. And a technology news shock where the effect of the technology improvement on productivity is delayed by two quarters. The results are robust to variations in this time period. Contrary to other sign restrictions approaches (see, e.g., Dedola and Neri, 2007; Peersman and Straub, 2009, among others), I do not restrict the response of any other variable. In particular, I do not require a positive response of real GDP. Given that Basu et al. (2006) obtain evidence in favor of a contractionary effect of technology improvements in the short-run, this appears reasonable. I set the horizon over which productivity has to respond positively equal to eight quarters, consistent with the conventional wisdom that technology improvements have persistent effects on productivity.

Table 3.1 summarizes the sign restrictions. I impose all restrictions either as \leq or \geq , while I implement a zero restriction as 'approximate equality constraint' following Kilian and Murphy (2009). That is, the restriction does not have to hold literally, but the response has to be at least close to zero. In particular, I accept a draw if the response is within the interval +/- 0.00005. Furthermore, I identify a monetary and in addition either a technology or technology news shock at the same time to ensure orthogonality between them.

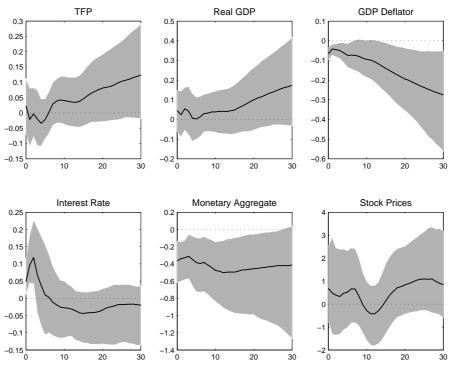


Figure 3.2: Monetary shocks

Notes: I show the median response, together with the area between the 16th and 84th percentiles. Entries are percent; horizontal axis denotes quarters after the shock.

3.3 The results

3.3.1 Dynamic responses to monetary and technology shocks

I show the responses to monetary as well as technology shocks in Figures 3.2 and 3.3, respectively. In both cases, the figure plots the median of the posterior distribution, together with the area between the 16th and 84th percentiles, calculated at each horizon between 0 and 30 quarters after the shock. I construct 250,000 candidate responses, leaving me with about 1,500 draws that satisfy the restrictions. An acceptance ratio of 0.6% is compatible with related studies.

By construction, the monetary aggregate and the GDP deflator fall in response to positive interest rate shocks. Moreover, both responses are persistent. The response of the interest rate, however, becomes insignificant once I remove the restriction, suggesting that the monetary policy authority reverses course immediately after the shock. Furthermore, productivity and real GDP display an insignificant response over all horizons, which is consistent with monetary neutrality, both in the short and long-run. Overall, these findings are similar to those of Uhlig (2005). 'Contractionary' monetary shocks do not necessarily have to contract real GDP. In Sec-

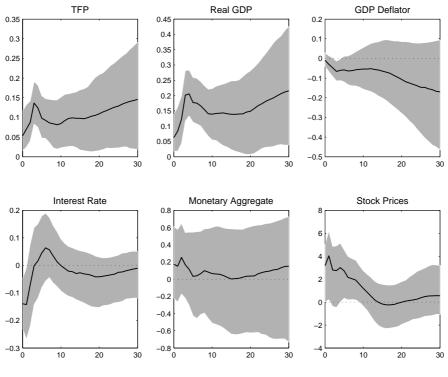


Figure 3.3: Technology shocks

Notes: See Figure 3.2

tion 3.3.6, I show that this conclusion is robust to tighter identifying restrictions, such as fixing the impact response of productivity and real GDP to zero. Most important, I draw the same conclusion for the impact of monetary shocks on real stock prices. There is no evidence of a contractionary effect of a monetary tightening on the real stock price index.

I identify technology shocks as having a positive impact on productivity for two years throughout, enough to induce a permanent upward shift in the level of productivity. Moreover, the response of real GDP is persistently positive as well, while interest rates and the GDP deflator tend to fall. In addition, there is no effect on the monetary aggregate. These findings are compatible with conventional wisdom and insensitive to an alternative productivity measure that adjusts for time-varying capacity utilization. I discuss this issue in Section 3.3.5. Finally, the response of real stock prices is positive and significant on impact and for most of the following ten quarters. This coincides with the idea that improvements in productivity are accompanied by stock market booms.

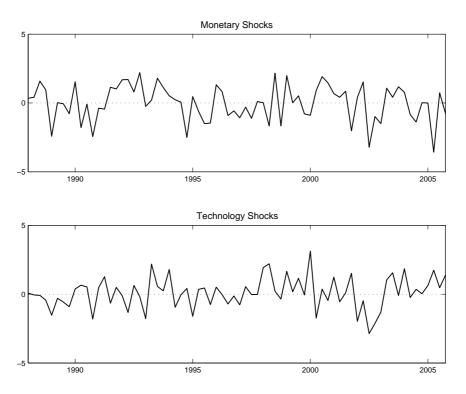


Figure 3.4: Estimated monetary and technology shocks

Notes: Entries are percent.

3.3.2 Explanatory power of the shocks

Before presenting the responses to the technology news shocks in Section 3.3.4, I investigate the explanatory power of monetary and technology shocks by means of a forecast error variance and a historical decomposition. Moreover, I assess their plausibility in Section 3.3.3.

I follow Fry and Pagan (2007) and perform the analysis on the basis of one particular draw from the posterior distribution. In particular, I choose that draw, which produces impulse responses that are as close as possible to the median responses. This procedure retains the orthogonality between the shocks, while it has the desirable property that variance shares sum exactly to one. Moreover, it preserves the consensus view that the median is a good summary statistic. I have checked that the selected draw indeed produces responses that are similar to those generated by the median of the posterior distribution so that the conclusions of the previous section are not altered (see Appendix C.3, Figures C.1 and C.2).

Figure 3.4 shows the estimated historical series for both the monetary (upper panel) and the technology shocks (lower panel). As we can see from the monetary series, the stance of

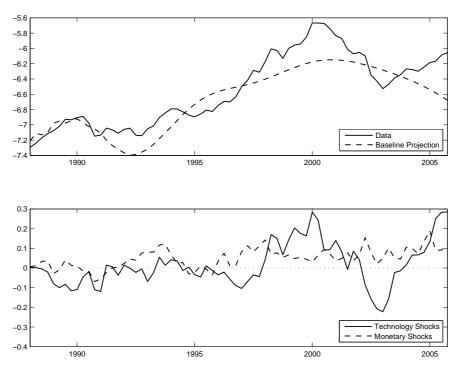


Figure 3.5: Historical decomposition of euro area stock prices

Notes: Entries are log levels.

monetary policy in the euro area is tight around 1992-93 and in the early 2000s. In addition, the series displays the responses to the terrorist attacks on 9/11 and financial market turmoils in 2002-03. Furthermore, I conclude from an investigation of the technology series that technology innovations behave similarly to real stock returns over the sample period (see also Figure 3.1, lower panel). There is a number of large positive shocks during the late 1990s as well as the early 2000s, while the years 2002-03 are associated with negative disturbances. Moreover, the correlation between the series is 0.48. These findings support my idea that stock prices are driven by technology innovations.

I report in Figure 3.5 how the estimated monetary and technology shocks contribute to historical movements in euro area stock prices. The upper panel plots the actual data, together with the estimated deterministic component or baseline projection. I obtain the baseline projection from a counterfactual simulation that no shocks occur during the sample period. Thus, the baseline projection mirrors the initial conditions, summarized in the first four data points. In the lower panel, I plot that part of the estimated stochastic component that I attribute to monetary and technology shocks, respectively.

			Var	iable		
Shocks	tfp_t	y_t	p_t	i_t	m_t	s_t
Monetary	7.29	2.05	6.06	2.99	15.45	4.58
Technology	15.13	17.89	3.99	9.52	18.66	22.31
Other	77.58	80.06	89.95	87.49	65.89	73.11

Table 3.2: Historical business cycle variance decomposition

Notes: Entries are percent. Statistics are calculated on HP-filtered series. tfp = total factor productivity; y = real GDP; p = GDP deflator; i = interest rate; m = monetary aggregate; s = real stock prices.

As we can see from the lower panel, monetary policy mostly contributes positively to developments in euro area stock prices over the sample period. This finding is particularly evident after 1995 when the contribution of monetary shocks is always positive. However, their impact appears to be small when compared to technology shocks. While their effect on stock prices is moderate in the first part of the sample, technology disturbances are responsible for about half of the deviation from the baseline projection in 2000 and nearly all in 2002-03. These results suggest that the pronounced boom-bust cycle in euro area stock markets in 1995-2003 is to a large extent due to technology disturbances.

In order to quantify the importance of monetary and technology shocks for historical movements in stock prices and other variables, I conduct a historical business cycle variance decomposition and report the results in Table 3.2. The entries in the table refer to the fraction of the variance in variables that can be accounted for by the shocks, obtained from the counterfactual simulation that only a single shock occurs. Before constructing the variance shares, I apply the Hodrick-Prescott (HP) filter to the series resulting from the counterfactual simulation to emphasize fluctuations at business cycle frequencies.

I find an important role for technology shocks in explaining business cycle variations in stock prices. About 22% of the variation can be attributed to such shocks, hence they are more important than monetary shocks that explain less than 5%. Moreover, I identify technology shocks as an important driver of fluctuations in real GDP, explaining roughly 18% of the variation. In contrast, monetary shocks are responsible for a mere 2%. These findings are different from these of Galí (1999), who finds no role for technology in explaining aggregate fluctuations. However, they are consistent with Dedola and Neri (2007), Enders et al. (2008) or Peersman and

			Var	iable		
Shocks	$\overline{tfp_t}$	y_t	p_t	i_t	m_t	s_t
Monetary	10.69	10.31	21.35	1.98	7.47	6.25
Technology	18.15	20.82	2.15	8.17	7.87	11.91
Other	71.16	68.87	76.50	89.85	84.66	81.84

Table 3.3: Forecast error variance decomposition

Notes: Entries are percent. The horizon is 30 quarters. See notes to Table 3.2 for abbreviations.

Straub (2009), who all build their analysis on identifying sign restrictions. Of course, I cannot rule out that this difference is the result of other factors, like the choice of the sample period.

I end this part by presenting the forecast error variance decomposition in Table 3.3. The variance decomposition is based on the impulse responses of the previous section (i.e. on the chosen draw, not on the median). The entries in the table refer to the fraction of the variance in the forecast error that can be attributed to monetary, technology and other shocks, respectively. The forecast horizon is 30 quarters. I perform the exercise to provide insights about the predictive ability of the shocks over a long-term horizon rather than over the business cycle as in case of the business cycle variance decomposition.

Table 3.3 shows that more than 20% of the variability in real GDP can be accounted for by technology shocks, confirming such shocks as a main driver of aggregate fluctuations. Monetary shocks, however, explain only 10% of the variance in the forecast error of real GDP. Most important, technology shocks contribute around 12% to the variance in the forecast error of real stock prices. This number is smaller than the 22% coming from the business cycle decomposition but larger than the 6% that can be attributed to monetary shocks. Furthermore, across all variables between 68% and 89% of the variance in the forecast error is neither explained by monetary nor by technology shocks. These numbers are not unusual, given that shocks are identified on the basis of sign restrictions alone. In particular, technology shocks contribute not more than 18% to the variability in productivity even though I identify technology shocks as having a persistent effect on productivity. The same statistic obtained from the long-run restriction approach of Galí (1999) would be, nearly by construction, considerably larger. I return to this issue in Section 3.3.6.

Table 3.4: Granger causality tests

		Variable			
Shocks	Government expenditure	Hamilton oil shocks	Interest rate	R^2	\bar{R}^2
Monetary	0.9809	0.1234	0.6722	0.19	0.00
Technology	0.6888	0.1995	0.3055	0.16	0.00

Notes: Entries are probabilities from a F-test. The F-test is based on the regression of the estimated shocks on a constant and four lags of the variables. For the oil shocks, I also include the current value. The null hypothesis is that all of the coefficients on the variable in question are jointly equal to zero.

3.3.3 Are the estimated shocks plausible?

Before proceeding, I assess the plausibility of the approach by subjecting the estimated monetary and technology shocks to additional tests. If both shocks reflect exogenous innovations to monetary policy and productivity, they should be uncorrelated to other exogenous shocks or lagged endogenous variables. In detail, I investigate whether the government expenditure to GDP ratio, the Hamilton (1996) oil shock measure, and the nominal short-term interest rate Granger-cause the estimated shocks. Similar testing procedures are developed in Hall (1988) and Evans (1992) (so called 'Evans-Hall' tests) and frequently used in the literature (see, e.g., Francis and Ramey, 2005; Fisher, 2006, among others). The three variables are considered because they are associated with business cycle fluctuations, but not related to technology improvements. Moreover, Hoover and Perez (1994) and Bernanke et al. (1997) point out that peaks in oil prices and policy interest rates often coincide, making it difficult to distinguish between oil and monetary shocks.

The data on government expenditures and oil prices are from the AWM database. Furthermore, Hamilton calculates his oil shock measure by taking the difference between the quarterly oil price and the maximum oil price of the preceeding four quarters. He sets the value to zero in case the difference is negative. Though Hamilton (1996) convincingly argues in favor of such an asymmetric oil price measure, I consider the quarterly change in oil prices as an alternative. The Granger causality test is based on a regression of the estimated monetary and technology shocks on a constant and four lags of the government expenditure to GDP ratio, the oil shock measure and the interest rate. I also add the contemporaneous value for the oil shocks since I do not expect that they respond to technology improvements within the period. Moreover, interest rates enter the regression in first differences to ensure stationarity. I show the results in Table 3.4. For both shocks, the explanatory power of the set of variables is low. The R^2 is 0.19 for the regression involving the monetary shocks and 0.16 for the technology shocks while the adjusted \bar{R}^2 is zero in both cases. Furthermore, there is no evidence that any of the variables Granger-causes the two shock series. I cannot reject the null hypothesis that all of the coefficients on the variable in question are jointly equal to zero at conventional significance levels for any variable. I obtain the lowest probability values for the oil shocks (0.12 and 0.19 for the monetary and technology shocks, respectively). But even then the significance is above 10 percent. Moreover, these numbers do not significantly change when I replace the oil shock measure by the quarterly change in oil prices (see Appendix C.3, Table C.1). In this case I do not include the oil price contemporaneously to avoid endogeneity problems.

Hence, the Granger causality test supports my interpretation of the shocks as exogenous innovations to monetary policy and productivity. Given the fact that technology innovations coming from traditional long-run restriction methods or Solow residual regressions often fail 'Evans-Hall' type tests, this is encouraging.

3.3.4 Dynamic responses to technology news shocks

As an extension, I provide evidence on the effects of technology news shocks on stock prices. By construction, technology improvements no longer raise productivity immediately but with a delay of two quarters. Such a shock process is not easily supported by the data and I have to increase the number of candidate draws considerably. Less than 0.1% of the candidates are accepted. Figure 3.6 shows the results. As in Figure 3.2, I report the median of the posterior distribution, together with the area between the 16th and 84th percentiles, based on about 1,500 draws that fulfill the restrictions.

The exercise produces the following results. First, real GDP responds to the technology improvement only after productivity has increased, consistent with the notion that production capacities adjust slowly. Second, the GDP deflator as well as interest rates and monetary aggregates react immediately and display responses that are comparable to those in Figure 3.3. Moreover, stock prices show a large and positive response on impact, reflecting the anticipated increase in productivity. The response is significantly above zero for three years after the shock. Thus, stock prices (and all other variables, except productivity and real GDP) respond instantaneously to the news about the technology improvement with the actual increase in productivity having little or no effect. Third, the posterior distribution is less dispersed, probably due to the additional retrictions, leading to tighter confidence bands. Overall, the findings are consistent with the predictions of the class of diffusion models outlined in the introduction.

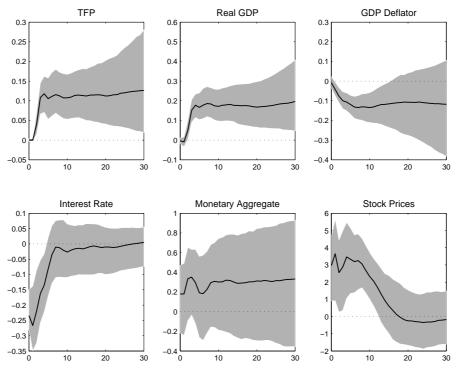


Figure 3.6: Technology news shocks

Notes: See Figure 3.2

3.3.5 Controlling for time-varying capacity utilization

As a first sensitivity check, I investigate whether the results depend on the specification of the productivity index. The literature does not provide a unique answer to the question how to best measure productivity. For example, O'Mahoney and Timmer (2009) control for changes in the composition of labor and capital. Moreover, Basu et al. (2006) construct a productivity series for the U.S. from disaggregated data while taking time variations in the utilization of labor and capital into account. Most of these adjustments, however, are either beyond the scope of this paper or not applicable because the relevant data are not available for the euro area. Here, I focus on the role of time-varying capacity utilization since it appears to be an important factor in Beaudry and Portier (2006) as well as Basu et al. (2006). Moreover, I have data on the usage of capital in the manufacturing sector and thus can proxy for variations in the utilization of the whole economy capital stock for which no data are available. I obtain the series from the OECD MEI database. I construct the adjusted (log) total factor productivity series as $tfp_t^A = log \left(GDP_t/H_t^{\bar{\alpha}} (CU_tK_t)^{1-\bar{\alpha}}\right)$, where CU_t is the rate of capacity utilization.

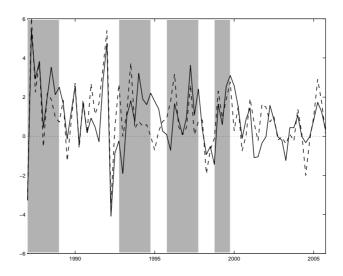


Figure 3.7: TFP measures

Notes: All entries are annualized quarterly growth rates. Solid line: unadjusted TFP; dashed line: TFP adjusted for time-varying capacity utilization. The shaded areas represent CEPR expansions.

Figure 3.7 plots the adjusted productivity measure (dashed line), together with the unadjusted series (solid line). For comparability, I show annualized quarterly growth rates. To demonstrate the cyclical behavior of both series, Figure 3.7 displays the euro area expansions as dated by the Centre for Economic Policy Research (CEPR) (shaded area). The dates are available on the CEPR homepage and provided in Appendix C.1. The CEPR defines an expansion as a prolonged period of increasing growth of real GDP, where the starting (ending) point is the point of minimal (maximal) growth. As you can see, the unadjusted productivity measure is highly pro-cyclical. Troughs and peaks in the series often coincide with starting and ending points of expansions. Furthermore, the correlation of productivity with annualized quarterly real GDP growth (not shown here) is about 0.95. Correcting for time-varying capacity utilization, however, makes productivity less pro-cyclical. This results from the fact that capacity utilization itself is highly pro-cyclical. In this case, starting and ending points of expansions are often preceeded by troughs and peaks in productivity and the correlation with real GDP growth declines to 0.72. Of course, this correlation is still high and adjusted productivity is not counter-cyclical as in Basu et al. (2006). A possible explanation is that I do not (and simply cannot) control for unobserved labor effort as they do. Despite this drawback, the exercise is useful to examine the robustness of my previous results.

Do the responses to a technology improvement change when productivity is corrected for variations in the utilization of capital? Figure 3.8 provides an answer. Essentially, all of the

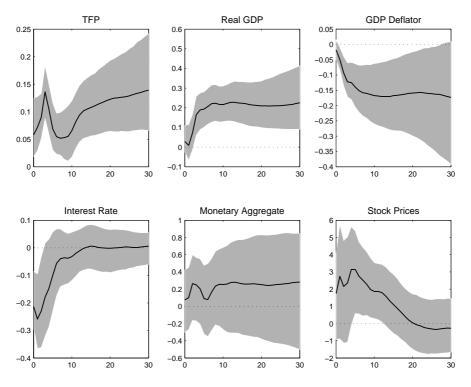


Figure 3.8: Technology shocks when controlling for time-varying capacity utilization

Notes: See Figure 3.2

variables show responses that are similar to those reported in Figure 3.3. However, the positive response of real GDP is delayed by about one year, and I cannot rule out a negative response on impact. This is consistent with the findings of Basu et al. (2006), who demonstrate that if capacity utilization is taken into account, technology improvements lead to a fall in hours worked and reduced utilization of capital in the short-run with real GDP being unchanged for some time. Moreover, this finding casts doubt on identification schemes which build on the assumption that real GDP immediately increases when technology improves (see, e.g., Dedola and Neri, 2007; Peersman and Straub, 2009, among others). Finally, the response for stock prices is not as sharp at the short end as before, but still significantly above its initial level over the medium-term.

3.3.6 Comparing the sign restrictions to short and long-run restrictions

As a second sensitivity check, I assess whether imposing additional short and long-run restrictions leads to qualitative changes in the impulse responses. In particular, I do not allow for a contemporaneous response of productivity and real GDP to monetary shocks and require that technology shocks account for at least half of the variation in productivity at a horizon of 30

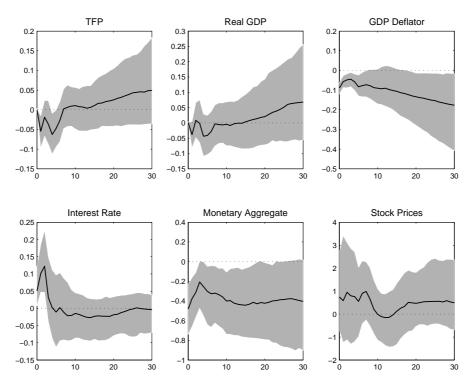


Figure 3.9: Monetary shocks when fixing the initial TFP and real GDP response to zero

Notes: See Figure 3.2

quarters. I impose the latter restriction on the forecast error variance share. Essentially, these additional restrictions move my identification scheme towards short and long-run restriction approaches.

My motivation for fixing the initial responses of productivity and real GDP to zero is the following. As you can see in Figure 3.2, both variables as well as real stock prices tend to increase after positive interest rate shocks (though not significantly), which is counterintuitive. Hence, I find it worth investigating if this finding is sensitive to the relatively weak identifying assumptions made. A delayed response of real GDP to monetary shocks is often assumed in the monetary VAR literature. Furthermore, I justify the restriction on the variance share as follows. It is difficult to find a decomposition of the covariance matrix that supports a large contribution of technology shocks to long-run movements in productivity when shocks are identified on the basis of sign restrictions alone. Therefore, among the draws that satisfy the set of restrictions, I extract those that are associated with exceptionally large and permanent effects on productivity. Of course, the horizon of 30 quarters (the 'long-run') as well as the 50 percent threshold ('large') are to some extent arbitrary, but the results of this exercise appear robust to variations in both.

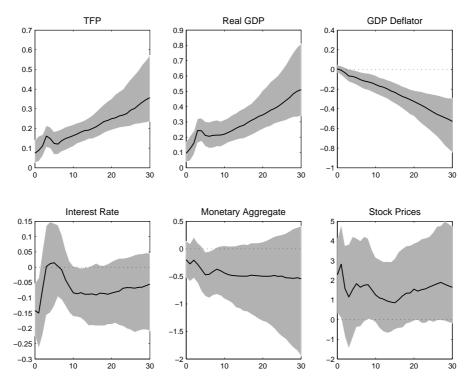


Figure 3.10: Technology shocks when requiring a large contribution to long-run TFP changes

Notes: See Figure 3.2

I show the responses to monetary and technology shocks under the extended set of restrictions in Figures 3.9 and 3.10, respectively. It seems that fixing the initial responses for productivity and real GDP to zero after a monetary shock hardly alters the findings of Section 3.3.1. Though both variables have now the tendency to fall in the short-run, they do so by little. Moreover, the response of the real stock price index is not affected. In contrast, restricting variance shares has consequences. The posterior distribution is less dispersed than those in Figure 3.3. Given that only 7% of the posterior draws satisfy the long-run restriction, this is not surprising. Specifically, the responses for productivity, real GDP and the GDP deflator display tight confidence bands. Moreover, the subset of technology shocks which is associated with exceptionally large and permanent effects on productivity increases productivity growth, not only the level of productivity. As a consequence, the median response for stock prices shifts upwards, suggesting a permanent impact of changes in productivity growth on the level of stock prices. This finding coincides with the result of the long-run restriction approach of Beaudry and Portier (2006).

3.4 Conclusion

In this chapter, I provide evidence on the impact of monetary and technology shocks on real stock prices using a Bayesian VAR model for the euro area. I achieve identification by imposing sign restrictions on impulse responses as in Canova and De Nicoló (2002) or Uhlig (2005). The results suggest an important role for technology shocks, but not monetary shocks, in explaining variations in stock prices. Over the sample period, technology shocks account for more than 22% of the movements in stock prices while monetary shocks contribute less than 5%. Specifically, the pronounced boom-bust cycle of 1995-2003 can almost completely be attributed to technology shocks. I also find a significant response of stock prices to technology news shocks.

Furthermore, I investigate the robustness of these findings with respect to (a) an alternative measure of productivity which adjusts for time-varying capacity utilization and (b) the inclusion of additional short and long-run restrictions. Moreover, I show that monetary and technology shocks are not correlated with omitted variables and shocks, such as government spending or oil prices.

This last result leads me to conclude that the estimated shocks are plausible, while the identification strategy is at the same time less dogmatic than those typically found in the literature. Moreover, I show how to combine short and long-run as well as sign restrictions in a convenient way. In particular, the use of zero restrictions, not only on impact but for an extended horizon, allows me to study the effects of anticipated shocks. An exercise which has been rarely undertaken yet. Needless to say, such a framework can be applied to anticipated shocks other than technology news shocks.

Finally, the analysis offers an explanation for the stylized fact that real stock returns and inflation are negatively correlated. Given the evidence of this paper that, first, real stock prices are to a large extent driven by technology shocks and, second, the conditional correlation of real stock returns and inflation is negative for technology shocks, I conclude that the correlation pattern in the data is to a certain degree the result of technology disturbances. This appears particularly relevant for the late 1990s when a series of positive technology shocks hit the euro area economy, leading to positive real stock returns and low inflation rates. Moreover, the analysis helps to understand why the stock market boom of 1995-2000 coincided with a period of falling interest rates. Rather than being the source of this boom, falling interest rates reflected an improved trade-off between output and inflation due to enhanced technology.

A Appendix to Chapter 1

A.1 The data

The data are from the OECD Main Economic Indicators data base and IMF's International Financial Statistics. The estimation period is 1980Q1-2007Q4. I obtain data on real GDP from the IMF with the exception of Canada and Italy where I use data from the OECD. For New Zealand, real GDP data for the early 1980s are not available on a quarterly basis. Therefore, I interpolate annual real GDP with the Chow and Lin (1971) procedure, using industrial production as an indicator series, and link this series to the quarterly OECD series starting in 1982Q2.

Data on consumer prices are from the OECD. If necessary, I deseasonalize consumer prices and real GDP using the X-11 filter. I take the U.S. dollar price of Brent crude oil from the OECD. Short-term interest rates are 3-month rates and, where available, I use Treasury bill rates from the IMF. For Australia, Austria, Germany, Japan, Korea, the Netherlands, Spain and Sweden, Treasury bill rates are not available and I use money market rates instead. Furthermore, in case of New Zealand and Norway I use interbank rates from the OECD. For the euro area economies, I replace domestic short-term interest rates by the 3-month EURIBOR rate after 1998. Data on long-term interest rates are from the IMF for Austria, Italy, Japan, Korea, Norway and Sweden; for all other countries from the OECD. In each case the long-term interest rate is the yield on a 10-year government bond. Stock prices are from the IMF, except for Switzerland and the United Kingdom where I use data from the OECD. For all countries, I use a broad stock price index. The real effective exchange rate is a trade weighted index, adjusted for relative consumer prices and comes from the IMF. In case of Korea the index is from the OECD.

In order to obtain current account to GDP ratios, I divide the nominal current account by nominal GDP of the same period. Current account data come from the IMF, except for Germany and Switzerland where the data are from the OECD. For Norway, I replace missing observations for 1992Q1-1993Q4 with data from Statistics Norway. Nominal GDP data are from the IMF and in case of New Zealand I again interpolate GDP from annual to quarterly frequency for the early 1980s. Since the current account is denominated in U.S. dollar, I convert it to domestic currency using bilateral U.S. dollar market exchange rates from the OECD, with the exception of Korea where I use data from the IMF. Finally, the bilateral trade flows that I use to construct trade weights are from the OECD. Unfortunately, there are missing values in trade flows between Belgium, Korea and New Zealand prior to 1988. I deal with this problem by setting trade flows between these countries equal to zero for all years up to 1988. Since trade between the three countries was limited until the late-1990s, it is unlikely that this contaminates the trade weights.

A.2 Error bands

To construct error bands for impulse responses, I use the continuous-path block-bootstrap of Politis (2003). The bootstrap takes the I(1) property of the series into account and is implemented as follows. Suppose a series z_t is non-stationary, t = 1, 2, ..., T, and an initial observation z_0 is available. First, I calculate the series of stationary first differences Δz_t , where $\Delta z_t = z_t - z_{t-1}$. Second, I perform a block-bootstrap of the first differences Δz_t by randomly drawing blocks of size four with replacement from $\Delta z_1, \Delta z_2, ..., \Delta z_T$, yielding $\Delta z_1^*, \Delta z_2^*, ..., \Delta z_T^*$. Letting the block size vary between 2 and 12 produces similar error bands. Third, I construct a bootstrap series for z_t by 'integrating' the Δz_t^* , i.e. $z_t^* = z_0 + \sum_{i=1}^t \Delta z_i^*$. Fourth, I use the bootstrap series z_t^* to re-estimate the coefficients of the panel VAR. Finally, I calculate the bootstrap impulse responses. I repeat the steps 1,000 times and hence obtain a distribution of impulse responses. I calculate 90 percent confidence intervals as follows

$$CI = \left[\hat{\phi} + 1.645 \times \left(var\left(\hat{\phi^*}\right)\right)^{\frac{1}{2}}, \quad \hat{\phi} - 1.645 \times \left(var\left(\hat{\phi^*}\right)\right)^{\frac{1}{2}}\right],$$

where $\hat{\phi}$ are the impulse responses based on the original data and $\hat{\phi}^*$ are the bootstrap counterparts.

B Appendix to Chapter 2

B.1 Transformation of the covariance matrix

Premultiply $Y_t = X_t \delta + u_t$ with

$$P = \begin{pmatrix} P_1^{-1} & 0 & \dots & 0 \\ 0 & I_G & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & I_G \end{pmatrix}_{NG \times NG}$$

which yields

$$PY_t = PX_t\delta + \epsilon_t,$$

where $\epsilon_t = (\epsilon'_{1t}, u'_{2t}, ..., u'_{Nt})$ and thus

$$\Sigma_{\epsilon} = E\left(\epsilon_{t}\epsilon_{t}'\right) = \begin{pmatrix} I_{G} & \Sigma_{\epsilon_{1},u_{2}} & \dots & \Sigma_{\epsilon_{1},u_{N}} \\ \Sigma_{u_{2},\epsilon_{1}} & \Sigma_{u_{2}} & \dots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ \Sigma_{u_{N},\epsilon_{1}} & \Sigma_{u_{N},u_{2}} & \dots & \Sigma_{u_{N}} \end{pmatrix}_{NG \times NG}$$

is the transformed covariance matrix with $\Sigma_{\epsilon} = P \Sigma_u P'$.

B.2 The data

Data on national accounts and government budget outcomes are from the OECD Economic Outlook database. I use the series CGV, IGV, GDPV, CPV, IPV, PGDP, and NLGXQ. Since the June 2006 volume is the most recent one that provides estimates of quarterly government budget outcomes for the G-7 countries (not for Italy though), I do not consider data later than 2005Q4. I obtain the series for Italy from the December 2004 vintage even though the last four observations are forecasts. Data on interest rates (3-month Treasury Bill or money market rates), monetary aggregates (M0 for the UK, M1 otherwise) and stock prices are from IMF's International Financial Statistics database. For Italy and France, M1 data are from Eurostat. In case of Germany, France and Italy, I use national figures on interest rates and monetary aggregates up to 1998Q4, but those for the euro area thereafter. Except for stock prices and interest rates, I deseasonalize all series.

C Appendix to Chapter 3

C.1 The data

I use data from five different sources which are all accessible through the web: the Area-wide Model database (http://www.eabcn.org/area-wide-model), the EU KLEMS Growth and Productivity Accounts (http://www.euklems.net/), the OECD Main Economic Indicators database (http://www.oecd.org), STOXX Limited (http://www.stoxx.com/index.html), and the CEPR (http://www.cepr.org/Data/euroCOIN/recession/). The estimation period is 1987Q1-2005Q4. To obtain quarterly data, I average daily figures and convert yearly series using interpolation methods.

Area-wide Model database (series are quarterly):

Real GDP in millions of euro with reference year 1995, seasonally adjusted, YER GDP deflator with reference year 1995, seasonally adjusted, YED Whole-economy capital stock in millions of euro with reference year 1995, KSR Nominal short-term interest rate in percent, STN Civilian labor force in thousands of persons, LFN Total employment in thousands of persons, LNN Government expenditure to GDP ratio, GEN_YEN Oil prices in U.S. dollars, POILU

EU KLEMS Growth and Productivity Accounts (series are yearly):

Total hours worked by employees in millions of hours, H_EMPE Labor compensation in millions of euro, LAB Capital compensation in millions of euro, CAP

OECD Main Economic Indicators database (series are quarterly):

Monetary Aggregate M1 in billions of euro, seasonally adjusted, EA6003DSA Rate of capacity utilization in percent, manufacturing, seasonally adjusted, EA2961DSA

STOXX Limited (series is daily):

Dow Jones EURO STOXX Net Return index (including dividends)

CEPR Expansion dates:

Jan 1988 - Feb 1989, Nov 1992 - Oct 1994, Nov 1995 - Nov 1997, Oct 1998 - Nov 1999

C.2 Rotation matrices

In the context of my six variable VAR a 6×6 Givens matrix $Q_{3,4}(\theta_{10})$ has the form

$$Q_{3,4}(\theta_{10}) = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & \cos(\theta_{10}) & -\sin(\theta_{10}) & 0 & 0 \\ 0 & 0 & \sin(\theta_{10}) & \cos(\theta_{10}) & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

i.e. the matrix is the identity matrix in which the (3,4) and (4,3) elements are replaced by the sine terms and θ_{10} lies within $[0, \pi]$. Accordingly, I replace the (3,3) and (4,4) elements by the cosine terms. To construct Q, I use the multiple of the basic set of Givens matrices: $Q = Q_{1,2}(\theta_1) \times Q_{1,3}(\theta_2) \times ... \times Q_{5,6}(\theta_{15})$.

C.3 Additional tables and figures

	Vai	riable			
Shocks	Government expenditure	Oil price	Interest rate	R^2	\bar{R}^2
Monetary	0.8673	0.1354	0.6101	0.17	0.00
Technology	0.7741	0.1208	0.2449	0.16	0.00

Table C.1: Granger causality tests with oil price

Notes: Entries are probabilities from a F-test. The F-test is based on the regression of the estimated shocks on a constant and four lags of the variables. The null hypothesis is that all of the coefficients on the variable in question are jointly equal to zero.

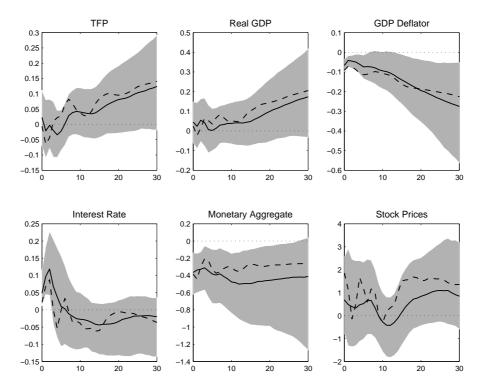


Figure C.1: Monetary shocks with responses under single draw restriction

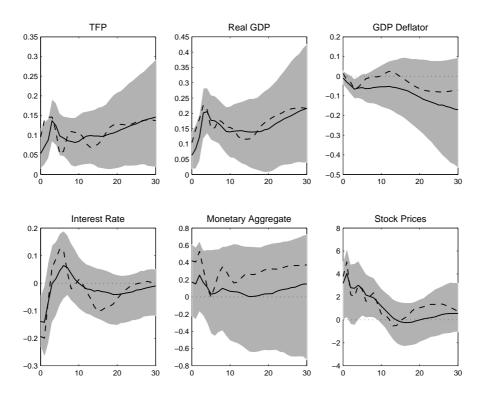


Figure C.2: Technology shocks with responses under single draw restriction

References

- Assenmacher-Wesche, K. and Gerlach, S. (2008). Financial structure and the impact of monetary policy on asset prices. Swiss National Bank and Goethe University Frankfurt, manuscript.
- Barnett, A. and Straub, R. (2008). What drives U.S. current account fluctuations? ECB Working Paper No. 959.
- Basu, S., Fernald, J. G., and Kimball, M. S. (2006). Are technology improvements contractionary? *The American Economic Review*, 96(5):1418–1448.
- Beaudry, P. and Portier, F. (2006). Stock prices, news, and economic fluctuations. *The American Economic Review*, 96(4):1293–1307.
- Bems, R., Dedola, L., and Smets, F. (2007). US imbalances: The role of technology and policy. *Journal of International Money and Finance*, 26:523–545.
- Bernanke, B. S. (2005). The global saving glut and the U.S. current account deficit. Speech, Sandridge Lecture, Virginia Association of Economics, Richmond, Virginia, March 10.
- Bernanke, B. S., Gertler, M., and Watson, M. (1997). Monetary policy and the effects of oil price shocks. *Brookings Papers on Economic Activity*, 1997(1):91–157.
- Blanchard, O., Giavazzi, F., and Sa, F. (2005). The U.S. current account and the dollar. NBER Working Paper No. 11137.
- Bussière, M., Fratzscher, M., and Müller, G. J. (2005). Productivity shocks, budget deficits and the current account. ECB Working Paper No. 509.
- Caivano, M. (2006). The transmission of monetary and technology shocks between the US and the euro area. manuscript, Bank of Italy.
- Canova, F. and Ciccarelli, M. (2009). Estimating multicountry VAR models. *International Economic Review*, 50(3):929–959.
- Canova, F., Ciccarelli, M., and Ortega, E. (2007). Similarities and convergence in G-7 cycles. *Journal of Monetary Economics*, 54:850–878.
- Canova, F. and De Nicoló, G. (2002). Monetary disturbances matter for business fluctuations in the G-7. *Journal of Monetary Economics*, 49:1131–1159.

- Chow, G. C. and Lin, A.-L. (1971). Best linear unbiased interpolation, distribution, and extrapolation of time series by related series. *The Review of Economics and Statistics*, 53(4):372–375.
- Corsetti, G., Dedola, L., and Leduc, S. (2006). Productivity, external balance and exchange rates: Evidence on the transmission mechanism among G7 countries. NBER Working Paper, No. 12483.
- Corsetti, G. and Müller, G. J. (2006). Budget deficits and current accounts: Openness and fiscal persistence. *Economic Policy*, 48:598–638.
- Dedola, L. and Neri, S. (2007). What does a technology shock do? A VAR analysis with modelbased sign restrictions. *Journal of Monetary Economics*, 54:512–549.
- Dees, S., di Mauro, F., Pesaran, M. H., and Smith, L. V. (2007). Exploring the international linkages of the Euro area: A Global VAR analysis. *Journal of Applied Econometrics*, 22(1):1–38.
- Eichenbaum, M. and Evans, C. L. (1995). Some empirical evidence on the effects of shocks to monetary policy on exchange rates. *The Quarterly Journal of Economics*, 110(4):975–1009.
- Enders, Z., Müller, G., and Scholl, A. (2008). How do fiscal and technology shocks affect real exchange rates? New evidence for the United States. CFS Working Paper No. 2008/22.
- Engel, C. and Rogers, J. H. (2006). The U.S. current account deficit and the expected share of world output. *Journal of Monetary Economics*, 53:1063–1093.
- Erceg, C. J., Guerrieri, L., and Gust, C. (2005). Expansionary fiscal shocks and the US trade deficit. *International Finance*, 8(3):363–397.
- Evans, C. L. (1992). Productivity shocks and real business cycles. *Journal of Monetary Economics*, 29:191–208.
- Faust, J. (1998). The robustness of identified VAR conlusions about money. *Carnegie-Rochester Conference Series on Public Policy*, 49:207–244.
- Fernández, R. B. (1981). A methodological note on the estimation of time series. The Review of Economics and Statistics, 63(3):471–476.
- Fisher, J. D. M. (2006). The dynamic effects of neutral and investment-specific technology shocks. *Journal of Political Economy*, 114(3):413–451.
- Francis, N. and Ramey, V. A. (2005). Is the technology-driven real business cycle hypothesis

dead? Shocks and aggregate fluctuations revisited. *Journal of Monetary Economics*, 52:1379–1399.

- Fratzscher, M., Juvenal, L., and Sarno, L. (2007). Asset prices, exchange rates and the current account. ECB Working Paper No. 790.
- Fratzscher, M. and Straub, R. (2009). Asset prices and current account fluctuations in G7 economies. ECB Working Paper No. 1014.
- Fry, R. and Pagan, A. (2007). Some issues in using sign restrictions for identifying structural VARs. NCER Working Paper No. 14.
- Galí, J. (1999). Technology, employment, and the business cycle: Do technology shocks explain aggregate fluctuations? *The American Economic Review*, 89(1):249–271.
- Grilli, V. and Roubini, N. (1996). Liquidity models in open economies: Theory and empirical evidence. *European Economic Review*, 40:847–859.
- Hall, R. E. (1988). The relation between price and marginal cost in U.S. industry. *The Journal of Political Economy*, 96(5):921–947.
- Hamilton, J. D. (1996). This is what happened to the oil price-macroeconomy relationship. *Journal of Monetary Economics*, 38:215–220.
- Hoover, K. D. and Perez, S. J. (1994). Post hoc ergo propter once more: An evaluation of 'Does monetary policy matter?' in the spirit of James Tobin. *Journal of Monetary Economics*, 34:47–73.
- Kilian, L. and Murphy, D. (2009). Why agnostic sign restrictions are not enough: Understanding the dynamics of oil market VAR models. manuscript, University of Michigan.
- Kim, S. and Roubini, N. (2008). Twin deficit or twin divergence? Fiscal policy, current account, and real exchange rate in the U.S. *Journal of International Economics*, 74:362–383.
- Kraay, A. and Ventura, J. (2005). The dot-com bubble, the Bush deficits and the U.S. current account. NBER Working Paper No. 11543.
- Krugman, P. (2007). Will there be a dollar crisis? *Economic Policy*, 22(51):435–467.
- Mountford, A. and Uhlig, H. (2005). What are the effects of fiscal policy shocks? SFB 649 Discussion Paper 2005-039.

Nickell, S. (1981). Biases in dynamic models with fixed effects. Econometrica, 49(6):1417–1426.

- Obstfeld, M. and Rogoff, K. (1995). Exchange rate dynamics redux. *The Journal of Political Economy*, 103(3):624–660.
- O'Mahoney, M. and Timmer, M. P. (2009). Output, input and productivity measures at the industry level: The EU KLEMS Database. *The Economic Journal*, 119:374–403.
- Peersman, G. (2005). What caused the early millenium slowdown? Evidence based on vector autoregressions. *Journal of Applied Econometrics*, 20:185–207.
- Peersman, G. and Straub, R. (2009). Technology shocks and robust sign restrictions in a euro area SVAR. *International Economic Review*, 50(3):727–750.
- Pesaran, M. H., Schuermann, T., and Weiner, S. (2004). Modelling regional interdependencies using a global error-correcting macroeconometric model. *Journal of Business and Economics Statistics*, 22(2):129–162.
- Pesaran, M. H. and Smith, R. P. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, 68:79–113.
- Politis, D. N. (2003). The impact of bootstrap methods on time series analysis. *Statistical Science*, 18(2):219–230.
- Rubio-Ramírez, J. F., Waggoner, D., and Zha, T. (2005). Markow-switching structural vector autoregressions: Theory and application. Federal Reserve Bank of Atlanta Working Paper No. 2005-27.
- Scholl, A. and Uhlig, H. (2008). New evidence on the puzzles: Results from agnostic identification on monetary policy and exchange rates. *Journal of International Economics*, 76(1):1–13.
- Swamy, P. A. V. B. (1970). Efficient inference in a random coefficient regression model. *Econometrica*, 38(2):311–323.
- Uhlig, H. (2004). Do technology shocks lead to a fall in total hours worked? *Journal of the European Economic Association*, 2(2-3):361–371.
- Uhlig, H. (2005). What are the effects of monetary policy on output? Results from an agnostic identification procedure. *Journal of Monetary Economics*, 52:381–419.

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