TECHNISCHE UNIVERSITÄT DRESDEN
Fakultät Wirtschaftswissenschaften

INFORMAL ECONOMIC ACTIVITIES

Dissertation zur Erlangung des akademischen Grades

Dr. rer. pol.

vorgelegt von

Andreas Bühn
Diplom-Volkswirt
geboren am 05. März 1978
in Bad Saarow-Pieskow

Dresden, 15. Juni 2010

ACKNOWLEDGEMENTS

This dissertation would not have been completed without the assistance and support of a number of people. I am indebted to Professor Alexander Karmann, providing me with the opportunity to work as a research assistant and to write my PhD thesis at his Chair of Monetary Economics at the Technische Universität Dresden. I’ve learned a lot from him and without his continuous support and guidance, active interest in my work, patience, motivation, and enthusiasm I would not have completed my dissertation successfully.

I also appreciate the advice of my second referee, Professor Marcel Thum, who presented me with helpful questions, gave me insightful comments and reviewed my work at very short notice. Besides my advisors, I would like to thank the rest of my thesis committee, Professor Alexander Kemnitz (who chaired the committee) and Professor Udo Buscher, for their willingness to become committee members and their critical comments. I am also greatly indebted to Professor Friedrich Schneider for getting me interested in informal economic activities and his tremendous support over the last 4 years. Thank you, Fritz!

I also would like to say ‘thank you’ to the following people: Professor Michael Berlemann, Professor Joseph P. Daniels, Gunnar Dittrich, Dr. Mohammad Reza Farzanegan, Professor Lars Feld, Stefan Freigang, Matthias Göthel, Professor Jac C. Heckelman, Christian Lessmann, Professor Dominik Maltritz, Dr. Gunther Markwardt, Stephan Rudolf, Karol Sobanski, and Dr. Andreas Werblow for productive discussions as well as their encouragement and hospitality.

Special thanks go to Stefan Eichler for reading and commenting on numerous, previous versions of this dissertation. He was always available to meet and talk about my ideas, to proofread and mark my papers and chapters, and to ask me thoughtful questions which helped me to think more about economics. Thank you, Stefan!

This whole thesis would not have looked like it does without the support of my English proof-readers Sunshine Moore and Ayla Rockliff. I more than appreciate their help.

There are many other people who directly and indirectly supported this work through discussions as well as through the exchange of knowledge and ideas at several conferences. To all of them I wish to express my gratitude and many thanks.

Most of all, I have to thank my parents and family. This dissertation would not have been achieved without their encouragement and understanding, as well as their patience as they listened to my complaints and frustrations. Through my childhood and studies, my parents always believed in me and encouraged me to follow my heart and mind in any direction this took me. They provided me with a loving home, educating me with aspects from both arts and sciences. Their unconditional support has made my study and dissertation possible.

Andreas Bühn

CONTENTS

Tables

FIGURES

Chapter One

Preface

"We're not children here. The law is – how should I put it? A convenience. Or a convenience for some people, and an inconvenience for other people. Like, take the law that says you can't go into someone else's house… I have a house, so, hey, I like that law. The guy without a house – what's he think of it? Stay out in the rain, schnook. That's what the law means to him…"

Paul Castellano (1915-1985)

1.1 Introduction

Why study the informal economy? Informal economic activities increasingly capture the interest of scholars, policymakers, journalists, and the public alike. In broad terms, the informal economy covers a wide range of economic activities that are not taxed, regulated, or reported to authorities, i.e., these activities take place outside a society's legal system and are thus not recorded in national (income) accounts. Although present in all types of economic systems in one way or another, it is generally agreed that the importance of the informal sector has varied in different periods and across different countries. For example, Schneider (2007a) estimates that the average size of the shadow economy – an important if not *the* most important part of the informal sector – amounted to 37% of the gross domestic product (GDP) of developing countries and 39% of the GDP of the transition countries of the former Soviet Union and Eastern Europe in 2005. While the shadow economies in developing and transition countries are relatively large, the shadow economies of developed countries are relatively small: on average, they amounted to "only" 15% of GDP in 2005 [Schneider (2007a)]. The informal economy has nevertheless reached a remarkable size in almost all countries around the world.

Three main aspects make the informal economy an interesting and relevant research topic for economists. First, according to the overwhelming majority of the empirical evidence available, the size of the informal economy has been growing in recent years [Gërxhani (2004); Schneider (2007a); Feige and Urban (2008)]. A second aspect is that effective policymaking requires accurate information about informal economic activities. Detailed information enables governments to effectively measure the extent of the informal economy, then to study its determinants, and finally to allocate resources to combat it. Third, tracking the development of informal economic activities over time also provides evidence as to how successful these efforts have been and may help governments to further improve their policies.

The character of the informal economic activities undertaken differs depending on the level of a country's development. In developed countries, informal economic activities often include tax evasion, the employment of undeclared labor such as illegal or undocumented immigrants, and the smuggling of illegal goods such as drugs and firearms. That is, the execution of these activities in the informal economy, which is in developed countries relatively small compared to the official economy, is primarily motivated by institutional restrictions or – in cases of neighborly help and do-it-yourself (DIY) activities – by individual market constraints. In developing countries, informal economic activities are often the source of employment for a significant portion of the labor force which is due to the weakness of the formal sector of the economy to create a sufficient number of (legal) jobs. That is, the informal economy, which is in developing countries relatively large compared to the official economy, often provides subsistence for families. Consequently, discussions about informal economic activities in developed countries focus on unemployment, problems of financing public expenditures, tax evasion, and antisocial behavior, while informal economic activities in developing countries are considered a central aspect of the economic as well as social life and strategies focus on policies needed to promote development and growth [Schneider and Enste (2002), pp. 30-32].

The concept of the informal sector originates from a study in a Third World context [Hart (1970)]. Hart uses the term to describe a part of the labor force outside the formal labor market made up of (small) self-employed individuals. In addition to Hart's influential work, the International Labour Organization's report on employment in Kenya is considered a pioneering study on the informal economy [ILO (1972)]. In it, the

ILO focuses on employment in unregistered enterprises and finds that providing subsistence to families is the main reason for the existence of the informal economy. The report concludes that growth of the informal economy in Kenya is mainly due to its positive effects on employment and income distribution. The informal sector, or the informal economy, thereafter typically referred to ways of making a living *outside* the formal economy – either as an alternative to or as a means of supplementing income earned in the formal economy [Bromley and Gerry (1979), pp. 4-6]. These studies make clear that the notion of the informal economy in the 1970s had been limited to self-employment and the provision of subsistence to families in developing countries.

In the 1980s and 1990s however, the literature established many other criteria to determine what constitutes informal economic activities. These criteria are rather heterogeneous across most authors: determinants, consequences, and the character of the activity. For example, Feige (1981; 1990) and Tanzi (1986) distinguish informal from formal economic activities by the incentive to evade taxes while Harding and Jenkins (1989) distinguish them by the consequences of these activities for employees such as whether employment is associated with fewer social benefits or lower than minimum-wages.[1] In his study of Peru, De Soto uses the legal status – unregistered/unlicensed versus registered/licensed enterprises – to distinguish informal from formal economic activities [De Soto (1989), pp. 151-172]. He relates the emergence of the informal economy to economic policy and to transaction costs and argues that deregulation of the market, greater private property rights, and a reduction of state intervention will reduce informal economic activities.

The terms these days found most often in the literature to classify *informal* economic activities include undeclared labor, tax evasion, unregulated or unlicensed enterprises, illegality, and criminality. Table 1.1 lists the most common characteristics used to define informal economic activities in alphabetical order together with a brief characterization and influential representatives who first used the respective criterion.[2]

---

[1] See Gërxhani (2004).

[2] Table 1.1 provides a brief overview of the literature's definitions of informal economic activities. For comprehensive reviews, see Thomas (1992), Schneider and Enste (2000), and Gërxhani (2004).

Table 1.1 Characteristics Typical for Informal Economic Activities

Category	Characteristics of informal economic activities	Author(s)
Government regulation	intension to avoid regulations	ILO (1972), Feige (1981; 1989), Harding and Jenkins (1989)
Illegality	generally illegal or unlawful	Feige (1981; 1989), Harding and Jenkins (1989), Renooy (1990)
Labor market	undeclared labor, lack of social benefits, lower than minimum-wages	ILO (1972), Harding and Jenkins (1989), Renooy (1990)
National accounts statistics	not included due to creative accounting or non- or under-reporting	Feige (1981), Tanzi (1982; 1986), Renooy (1990)
Professional status	self-employment, family workers, domestic servants	Hart (1970; 1973), ILO (1972), Swaminathan (1991)
Registration	unregistered or unlicensed enterprises	De Soto (1989), Swaminathan (1991)
Subsistence/survival	widespread in developing countries, less important for developed countries	Banerjee (1982), Swaminathan (1991)
Taxes/income	intension to evade/un- or underreported	Allingham and Sandmo (1972), Feige (1981; 1990), Tanzi (1982; 1986), Frey (1989), Alm (1991)

All of the activities that meet the criteria mentioned above have one thing in common: they all involve some kind of unlawfulness. For example, employing undeclared workers in order to save on labor costs and social security contributions is illegal. Tax evasion, non- or under-reporting of income, and the production, distribution, or consumption of illegal goods and services are also illegal. Another important characteristic of these activities is that they are not accounted in official national accounts statistics. For this reason, DIY activities – although perfectly legal – are also considered informal economic activities [Thomas (1992), p. 3].

Using a rigid list of criteria to distinguish between formal and informal economic activities has advantages and disadvantages. One advantage is that it enables researchers to distinguish between very different activities within the informal economy. For example, one can consider simultaneously goods and services produced within the household, forms of illegal employment, tax evasion and social security fraud, and even criminal economic activities like drug smuggling. The disadvantage is that it becomes difficult to develop a single, overarching definition for all informal economic activities. For this reason, many researchers tailor the definition of informal economic activities to the subject under consideration. The literature nevertheless agrees that, in general, the informal economy comprises all goods and services which normally should be included in the calculation of the GDP but which are not because of businesses not being legally registered as businesses, employing workers informally, failing to comply with laws and regulations, or failing to disclose transactions to authorities because the goods and/or services are illegal [Thomas (1992), pp. 1-9]. Examples of businesses operating in the informal economy range from family businesses and large companies that employ informal workers, avoid social security contributions, evade taxes, or avoid compliance with labor market regulations such as minimum wage and safety regulations, to criminal organizations.

One aspect of the informal economy on which much of the literature focuses is the shadow economy, i.e., the *unlawful (illegal)* production, sale, and/or consumption of otherwise *legal* goods and services.[3] These activities are typically referred to as the legal

[3] The following terms are used as mere synonyms in the literature: black, concealed, informal, non-observed, parallel, shadow, subterranean, underground, or unrecorded economy.

part of the shadow economy.[4] The DIY economy, i.e. the production and consumption of goods and services within the household sector, and the illegal part of the shadow economy, i.e., the (illegal) production, sale, and/or consumption of *illegal* goods and/or services such as drugs, are typically excluded from analyses of informal economic activities. Smuggling, for example, i.e., the illegal trade of legal and/or illegal goods, is usually studied in a completely separate branch of the literature. By definition, however, smuggling – as well as DIY activities – are informal economic activities and thus part of the informal economy.

For this reason, this dissertation takes a comprehensive approach to the study of the informal economy. It considers traditional shadow economic activities, household DIY activities, and the smuggling of illegal as well as legal goods as informal economic activities. The reason for this is because shadow economic activities, DIY activities, and smuggling, all meet one or another criterion presented in Table 1.1. DIY and shadow economic activities, for example, are part of the informal economy because they are not accounted for in official national accounts statistics, involve family or undocumented workers, or evade taxes. Legal goods smuggling is part of the informal economy because it is not accounted for in official international trade statistics and because it is motivated by tax and/or tariff evasion. Illegal goods smuggling is both an informal and illegal economic activity and is thus also part of the informal economy.

The empirical analyses in this dissertation are based on structural equation models (SEMs). These models are particularly appropriate for the analysis of informal economic activities for two reasons. First, SEMs are able to consider informal economic activities as unobservable, rather than observable variables. Second, SEMs divide observable variables into causes and indicators of the unobservable variable. This enables researchers to take into account the multiple determinants (causes) and the multiple effects (indicators) of informal economic activities. The SEM methodology is often applied to the shadow economy, but I use it for DIY activities and smuggling as well. This approach contributes to the literature by applying SEMs consistently to the empirical analysis of *all* informal economic activities studied in this dissertation.

---

[4] See, for example, Schneider and Enste (2002, pp. 10-13) for a detailed discussion on the classification of different types of shadow economic activities.

1.2 Outline and Main Findings

This dissertation is divided into ten chapters. Chapter 1 introduces the main topic, the outline, and presents the main findings. The bulk of the analysis is contained in Chapters 2, 3, and 4. Chapter 5 summarizes and concludes. Chapter 6 lists the references. Chapter 7 describes SEMs which have been used in the empirical analyses of Chapters 2, 3, and 4. Chapters 8, 9, and 10 contain the appendices of Chapters 2, 3, and 4, respectively.

Chapter 2 studies shadow economic and DIY activities and presents a dual estimation for the development of both types of informal economic activities in Germany from 1970 to 2005. DIY activities produce goods and services at home in one's spare-time, and are often associated with self-realization of the individual.[5] Shadow economic activities are carried out by small-scale producers who supply intermediate goods and services to other producers and by (large-scale) businesses which supply goods and services for final demand. While shadow economic goods and services are legal, the processes of production and distribution involve some kind of irregularity and unlawfulness such as tax evasion, social security fraud, or non-compliance with regulations such as minimum wages or safety standards. Although difficult to obtain (because individuals engaged in these activities wish not to disclose these activities), statistics on shadow economic activities are valuable for two reasons. First, without accurate statistics on the economy as a whole (whether formal and informal), such as unemployment, income, and consumption, the government's economic policies are likely to be inappropriate, ineffective, or both. Second, statistics on shadow economic activities can help policymakers to find and prosecute those who have evaded taxes and enforce labor and safety regulations. Failure to do so weakens not only the economy but society as well.

The calculations for Germany presented in Chapter 2 show that the informal economy, in particular shadow economic and DIY activities, in Germany accounted for a remarkable 22% of official GDP in 2005. German shadow economic activities are motivated primarily by institutional factors such as taxation and regulation while DIY

---

[5] While DIY activities in developed countries are often seen as something positive and creative, the nature of DIY activities in developing countries is different. In developing countries, household production and exchange of goods and services is often necessary for survival and motivated by self-sufficiency of households.

activities are driven by unemployment and individual constraints. Deregulation as well as lower tax and social security contribution burdens are two efficient means of shifting shadow economic activities into the formal economy.

Chapter 3 studies an informal economic activity that has attracted much attention recently: legal goods smuggling, or the illegal trade of otherwise legal goods. The main form of this informal economic activity is the falsification of trade documents. By reporting false amounts of exports and/or imports to authorities smugglers, or trade misinvoicers, seek to avoid paying taxes and/or tariffs. Both shadow economic activities and legal goods smuggling involve otherwise legal products and services. Unlike shadow economic activities, however, legal goods smuggling involves the distribution – rather than the production or consumption – of goods in order to evade taxes and tariffs. Smuggling also differs from shadow economic activities in that it is an international – rather than domestic – activity. It requires extra-legal resources, promotes corruption and bribery, puts a strain on international relations, and potentially diminishes the gains from international trade.

Due to the illegal nature of smuggling, data is difficult to obtain and little is known about the magnitude and extent of smuggling in different countries around the world. Chapter 3 contributes to the empirical literature on legal goods smuggling by applying an SEM to estimate an index of smuggling in 54 countries. The empirical analysis reveals that legal goods smuggling, or informal international trade, takes place when tariffs are high and/or when there are non-tariff barriers to trade. Thus, lowering tariffs and removing trade barriers may help shift the illegal smuggling of otherwise legal goods trade to the legal sector of international trade. Smuggling could also be reduced through more effective law enforcement because it would increase the expected cost of smuggling. Corruption, however, decreases the risk of illegal trade and makes it more profitable. The ranking of countries shows that illegal trade is less common in Western Europe – a region with relatively low corruption – and more common in Latin America, Asia, and Africa – regions with relatively high corruption.

Chapter 4 argues that the analysis of smuggling has been incomplete in the literature so far. To improve the understanding of illegal trade, I distinguish between the smuggling of *illegal* goods *and* the smuggling of *legal* goods. In particular, I study the smuggling of illegal and legal goods across the U.S.-Mexico border. Official estimates suggest that illegal cross-border transactions are on the rise in many parts of the world:

the trafficking of illegal immigrants into developed countries and the smuggling of illegal drugs have developed into multi-billion-dollar businesses [LeMay (2007), 33-35; United Nations (2009), pp. 9-19]. The U.S.-Mexican case is particularly interesting since most illegal drugs and immigrants in the United States arrive via the Mexican border. For example, 90 percent of the cocaine in the United States – between 300 and 460 metric tons – came from Mexico [Ford (2008), p. 25]. In addition, more than 400,000 Mexicans per year over the last decade entered the United States illegally via the southern border [Passel (2007)]. While Mexico's efforts focus mostly on the violent, well-armed and well-financed drug cartels, the focus in the United States is – according to the 2008 National Drug Threat Assessment Report – on enforcing the border and reducing the demand for illegal drugs [Department of Justice (2008), pp. 4-7].

The smuggling of legal goods differs from the smuggling of illegal goods. Legal goods smuggling is motivated by tariff and tax evasion and is commonly considered a *peccadillo* (petty offense). Illegal goods smuggling, on the other hand, often involves dangerous criminals committing serious offenses who, if caught, face severe punishment. The two types of smuggling are thus associated with different types of agents, incentives, and intensity of law enforcement.

Chapter 4 also provides the empirical analyses of illegal and legal goods smuggling. The first analysis shows that the smuggling of illegal goods from Mexico to the United States decreases when Mexican labor market conditions improve and U.S. border enforcement is intensified. Conversely, illegal goods smuggling increases when the Mexican economy suffers as during the Mexican recessions in 1982-83 and 1995 which led to large temporary increases in illegal goods smuggling. From 1984 to 2004, the smuggling of illegal goods decreased from $116 billion to $27 billion. This can be attributed to stricter border enforcement in the United States and better job prospects in Mexico. The second analysis shows that legal goods smuggling is motivated by tariff and tax evasion and decreases with tariff reductions. The General Agreement on Tariffs and Trade (GATT) in 1987 and the North American Free Trade Agreement (NAFTA) in 1994, for example, had a significant impact on the smuggling of legal goods across the U.S.-Mexico border.

Chapter 5 presents the most important findings of the dissertation and places them in the overall context of informal economic activities. It also explores avenues for future research.

CHAPTER TWO

SHADOW ECONOMIC AND DO-IT-YOURSELF ACTIVITIES: THE GERMAN CASE[*]

"Taxes grow without rain."
Jewish Proverb

This chapter presents a dual estimation of shadow economic and do-it-yourself (DIY) activities and tracks their development in Germany from 1970 to 2005. It shows that DIY activities in Germany are sizable and should be taken into account when formulating economic policy. It also considers the impact of German reunification on shadow economic and DIY activities and employs a proper estimate of domestic currency in circulation (M0) within Germany as an indicator variable for the shadow economy.

DIY activities – home repair, maintenance, and improvements – are, in developed country like Germany, often considered positive and creative spare time activities. Shadow economic activities, such as legal work for which income is not reported, on the other hand, are often considered negative and harmful. Most societies therefore attempt to control the shadow economy through punishment in order to spur growth in the official economy. While much is know about the size of the shadow economies in different parts of the world, its determinants, and impacts, the literature has paid less attention to DIY activities. One reason is that in developed countries DIY activities are less sizable and important compared to shadow economic activities.[6]

---

[*] This chapter follows Buehn et al. (2009). Copyright © 2009 Mohr Siebeck.

[6] In developing countries, however, DIY activities are an important part of life. As a way of making a living outside the formal economy, either as an alternative to it, or as means of supplementing the formally earned income, they often provide subsistence to families (see Chapter 1).

From a household perspective, shadow economic and DIY activities may be substitutes. If it is too risky to demand shadow economic activities – for fear of being caught and incurring fines and/or punishment – individuals may undertake DIY activities. The two could, however, be viewed as complements. Individuals may demand shadow economic activities, for example, to supplement the production of DIY goods and services for quality assurance and/or efficiency. For example, an individual may choose to renovate her home herself but may hire a handyman informally for tasks she does not know how to do or cannot do well. In this way, she is supplementing (or complementing) her own DIY activities with shadow economic ones.

Unfortunately, gathering accurate information on the shadow economy is difficult because individuals working in this sector do not readily volunteer details about their informal activities. Although literature on particular aspects of the shadow economy exists,[7] including one comprehensive survey on the shadow economy as a whole [Schneider and Enste (2000)], the subject still remains controversial. Measuring DIY activities, an even more neglected subject of the literature, is no less challenging. Previous investigations into the informal economy usually excluded DIY activities, claiming that they are less important and do not constitute a sizable portion of the economy. To the author's knowledge, only two early studies estimate both shadow economic and DIY activities [Karmann (1988; 1990a)]. My calculations show that German shadow economic activities increased from 1-2% of official GDP in 1970 to 17% of official GDP in 2005. Over the same period, DIY activities increased from 4% to around 5% of official GDP. Together, both types of activities accounted for approximately 22% of Germany's official GDP in 2005.

This chapter is organized as follows. Section 2.1 defines the shadow economy and DIY activities and provides a short review of existing estimates of the shadow economy in Germany. Section 2.2 describes the empirical methodology. Section 2.3 provides theoretical considerations as to why individuals turn to shadow economic and DIY activities. Section 2.4 presents the results of the estimations and calibrations of the size and development of shadow economic and DIY activities in Germany. Section 2.5

---

[7] See Frey and Pommerehne (1984), Schneider (1994; 1997; 2005), Loayza (1996), Lippert and Walker (1997), Johnson et al. (1997), Johnson et al. (1998), Pedersen (2003), and Gërxhani (2004).

concludes.

2.1 Definitions and Brief Literature Review

2.1.1 Shadow Economic and Do-it-Yourself Activities

Most authors attempting to measure the shadow economy face the difficulty to develop an appropriate working definition. One commonly used definition is all currently unregistered economic activities that would contribute to the officially calculated (observed) GDP. This definition is used, for example, by Frey and Pommerehne (1984) and Feige (1989, p.19; 1994). Smith (1994, p. 18) defines the shadow economy as “market-based production of goods and services, whether legal or illegal that escapes detection in the official estimates of GNP.” One of the broadest definitions interprets the shadow economy as those economic activities and the income derived from them that circumvent government regulation, taxation, or observation.[8] In this chapter, the following, more narrow definition of the shadow economy is used: The shadow economy includes all market-based, legal goods and services that are deliberately concealed from public authorities to avoid payment of income, value-added, or other taxes and social security contributions; to get around certain labor market standards, such as minimum wages, maximum working hours, and safety standards; or to avoid administrative procedures, such as filling in forms and statistical questionnaires.

DIY activities include all goods and services that are produced *by the household* in order to avoid gross wage payments, including taxes and social security contributions, in the official economy or to avoid any net wage payments in the shadow economy. That is, DIY activities are primarily undertaken to avoid labor costs either in the official or in the unofficial (shadow) economy. The treatment of the value added from these activities to GDP depends on whether the production is for capital formation or consumption. The broadest rule is that capital formation undertaken by family businesses should be included in GDP while production for consumption should not [Thomas (1992), pp. 16-

[8] Dell’Anno and Schneider (2003) use this definition. See also Thomas (1999) and Fleming et al. (2000). For an excellent discussion of the definition of the shadow economy, see Pedersen (2003).

17]. I follow this rule and focus on DIY activities for capital formation only and not on activities such as cleaning.[9]

It is important to note that the main difference between DIY and shadow economic activities is that the former are entirely lawful while the latter involve some kind of unlawfulness such as tax evasion or the violation of labor market regulations. This chapter does not deal with illegal/criminal (shadow economic) activities, such as burglary, robbery, and drug dealing. Rather, it considers the production of legal goods through shadow economic and DIY activities, which together form the hidden economy. Table 2.1 provides an overview of these different types of economic activities.

[9] This differentiation is due to the choice of the indicator variable for DIY activities in the empirical analysis, turnovers in DIY stores, which largely reflects the demand for inputs of DIY activities for capital formation.

Table 2.1 Types of Hidden Economic Activities

Type of activity	Monetary transactions		Non-monetary transactions	
Illegal activities	Trade in stolen goods, drug dealing and manufacturing, prostitution, gambling, smuggling, fraud, etc.		Barter of drugs, stolen goods, smuggling, etc., production or growing of drugs for own use, theft for own use	
	Tax evasion	Tax avoidance	Tax evasion	Tax avoidance
Legal activities	Unreported income from self-employment, wages, salaries and assets from unreported work related to official/lawful goods and services	Employee discounts, fringe benefits	Barter of official / lawful goods and services	All do-it-yourself work and neighborly help

Note: The structure of the table is taken from Lippert and Walker (1997, p. 5), with additional remarks.

2.1.2 Brief Literature Review

This section briefly reviews important studies that estimate the size and development of shadow economic and DIY activities in Germany. It discusses neither the various methodologies used in the literature nor the advantages or disadvantages of any one methodology. For such a discussion, see Karmann (1986) or Schneider and Enste (2000).

The oldest estimate of the German shadow economy uses the survey method of the Institute for Demoscopy (IfD) in Allensbach, Germany and determines that the shadow economy was 3.6% of official GDP in 1974 [IfD (1975)].[10] Pedersen (2003) and Feld and Larsen (2005) undertook extensive research projects using the survey method to estimate shadow economic activities in the years 2001 and 2004. Using the official wage rate, Feld and Larsen (2005, p. 22) conclude that these activities reached 4.1% and 3.1% of official GDP in 2001 and 2004. Using the (much lower) shadow economy wage rate, however, these estimates shrink to 1.3% and 1.0% of official GDP, respectively, confirming Pedersen's estimate of 1.3% of the official GDP [Pedersen (2003), p. 136]. Using the discrepancy method, the German shadow economy is much larger: using the discrepancy between expenditure and income, it amounts to approximately 11% of official GDP for the 1970s [Lippert and Walker (1997)] and using the discrepancy between official and actual employment, it amounts to roughly 30% of official GDP [Langfeldt (1983)].[11]

The physical input method produces values of around 15% of official GDP for the second half of the 1980s [Feld and Larsen (2005), p. 32]. The (monetary) transaction approach developed by Feige (1996) places the shadow economy at 30% of official GDP between 1980 and 1985. Yet another monetary approach – the currency demand approach, first used for Germany by Kirchgässner (1983) – yields values of 3.1% (1970) and 10.3% (1980) of official GDP. His estimates are quite similar to those obtained by Schneider and Enste (2000), who also use the currency demand approach and estimate the size of the shadow economy to be 4.5% and 14.7% of official GDP in 1970 and 2000. Karmann (1990a) however, using the same approach, estimates three alternative specifications and yields lower estimates. The specification that uses the marginal tax rate to measure the burden of taxation estimates that the shadow economy in Germany increased from 1.5% of official GDP in 1970 to 9.2% in 1987.[12]

Multiple Indicators Multiple Causes (MIMIC) model[13] and Dynamic Multiple

---

[10] See Schneider and Enste (2000).

[11] See Schneider and Enste (2000).

[12] The other two specifications – applying the gross hourly earnings of male workers in the small business sector and gross hourly earnings of male workers plus additional labor costs such as social security contributions – produce similar results.

[13] Weck-Hannemann (1983) and Frey and Weck-Hannemann (1984) pioneered this approach, applying it to cross-sectional data of 24 OECD countries for various years. Before turning to this

Indicator Multiple Causes (DYMIMIC) model estimations produce results similar to those of the currency demand approach. Karmann (1990a) – estimating two alternative model specifications – presents the smallest figures for the size of the shadow economy in Germany.[14] Schneider (2005) and others [e.g. Pickhardt and Sardà Pons (2006)] arrive at higher estimates.

In general, figures placing the size of the shadow economy at almost one-third of official GDP in the mid-1980s are most likely overestimates. The similarity of the much lower figures obtained using the currency demand and MIMIC approaches is not surprising given the fact that the MIMIC model determines only the development of the shadow economy *over time*. To calibrate "real world" estimates of the shadow economy, e.g. as a percentage of official GDP, point estimates from the currency demand approach are typically used. Table 2.2 presents an overview of estimates of the shadow economy for Germany.

---

approach, they developed the concept of "soft modeling" [see Frey et al. (1982); Frey and Weck (1983a; 1983b)], an approach which has been used to provide a ranking of the relative size of the shadow economy in different countries.

[14] The estimates of the two specifications are similar. I thus present the estimates of the "S-D-Model" only in Table 2.2.

Table 2.2 The Size of the Shadow Economy (% of Official GDP) in Germany According to Different Methods

Method	Shadow economy (% of official GDP) in:								Source
	1970	1975	1980	1985	1990	1995	2000	2005	
Survey	-	3.6[1]	-	-	-	-	-	-	IfD (1975)
	-	-	-	-	-	-	1.3[2]	-	Pedersen (2003)
	-	-	-	-	-	-	4.1[3]	3.1[3]	Feld and Larsen (2005)
	-	-	-	-	-	-	1.3[4]	1.0[4]	
Discrepancy between expenditure and income	11.0	10.2	13.4	-	-	-	-	-	Lippert and Walker (1997)
Discrepancy between official and actual employment	23.0	38.5	34.0	-	-	-	-	-	Langfeldt (1983)
Physical input method	-	-	-	14.5	14.6	-	-	-	Feld and Larsen (2005)
Transactions approach	17.2	22.3	29.3	31.4	-	-	-	-	Feld and Larsen (2005)
Currency demand approach	3.1	6.0	10.3	-	-	-	-	-	Kirchgässner (1983)
	12.1	11.8	12.6	-	-	-	-	-	Langfeldt (1983; 1984)
	1.5	4.9	7.5	8.5[5]	9.2[6]				Karmann (1990a)
	4.5	7.8	9.2	11.3	11.8	12.5	14.7	-	Schneider and Enste (2000)

(continued on next page)

Table 2.2 (cont.)

Latent ((DY)MIMIC) approach	5.8	6.1	8.2	-	-	-	-	-	Frey and Weck-Hannemann (1984)
	1.1	7.4	4.4	8.5 [6)]	7.0 [7)]				Karmann (1990a) [5)]
	-	-	9.4	10.1	11.4	15.1	16.3	-	Pickhardt and Sardà Pons (2006)
	4.2	5.8	10.8	11.2	12.2	13.9	16.0	15.4	Schneider (2005; 2007b)
Soft modeling	-	8.3 [8)]	-	-	-	-	-	-	Weck-Hannemann (1983)

1) 1974.

2) Estimate for 2001 calculated using actual "black" hourly wages.

3) Estimates for 2001 and 2004 calculated using wages in the official economy.

4) Estimates for 2001 and 2004 calculated using actual "black" hourly wages.

5) Size of the shadow economy according to the "S-D-Model" specification.

6) Estimate for 1983.

7) Estimate for 1987.

8) Average of 1974 and 1975.

Compared to the literature on shadow economic activities in Germany, the literature on DIY activities in Germany is rather limited. Brodersen (2003) provides a questionnaire-based survey of DIY activities in northwestern Europe.[15] For Germany, he finds that the likelihood of carrying out DIY activities depends positively on home ownership and negatively on age. Married or cohabitating respondents are also more likely to carry out DIY activities than unmarried or single respondents. Brodersen (2003, pp. 34-37) finds a negative significant correlation between income and DIY activities and strong regional influences – there is a greater likelihood to carry out DIY activities in the new federal states (Neue Bundesländer) of Germany than in the old federal states (Alte Bundesländer). Calculating the total value of DIY activities in the form of home repair, maintenance, and improvements, Brodersen (2003, p. 68) concludes that these activities correspond to approximately 1% of Germany’s GDP in 2001.

Karmann (1990a) pioneered joint macroeconomic measurements of shadow economic and DIY activities.[16] Using the MIMIC approach, he finds that financial constraints of households encourage DIY activities. Since 1970, the total value of these activities has increased steadily. In 1983, they accounted for 4.3% of official GDP. Between 1983 and 1987 however, DIY activities decreased by almost 1%, to 3.4% of official GDP. The analysis in this chapter expands on his work in two ways. First, it models the demand for *domestic* currency in circulation in Germany explicitly and takes into account the distortion in currency in circulation due to the introduction of the euro. Second, it accounts for different behavioral patterns in Eastern and Western Germany and structural changes to the German economy due to German reunification in 1990.

2.2 Empirical Methodology

To estimate the size and development of shadow economic and DIY activities in

[15] Merz and Wolff (1993) present a microeconomic analysis of the influence of regional long-term unemployment figures, social contacts, and family characteristics such as marital status, number of earners in the household, and occupational characteristics on household production. A recent contribution to the theoretical literature is Ngai and Pissarides (2008) who study the substitution between home and market production.

[16] See also Karmann (1988).

Germany, I employ two alternative structural equation model (SEM) specifications, one of them composed of two separate MIMIC models.[17] Formally, MIMIC models consist of two parts: the structural equation model and the measurement model. The structural equation model can be represented by:

$$\eta_t = \boldsymbol{\gamma}'\boldsymbol{x}_t + \varsigma_t , \tag{2.1}$$

where $\boldsymbol{x}_t' = \left(x_{1t}, x_{2t}, \ldots, x_{qt}\right)'$ is a q vector and each x_{it} , $i = 1, \ldots, q$ is a possible manifest cause of the latent variable η_t.[18] Here, $\boldsymbol{\gamma}' = \left(\gamma_1, \gamma_2, \ldots, \gamma_q\right)'$ is a q vector of coefficients describing the relationships between the latent variable and its causes. Thus, the latent variable η_t is determined by a set of exogenous causes. Since they only partially explain η_t, the error term ς_t represents the unexplained component. The variance of ς_t is denoted by ψ, and $\boldsymbol{\Phi} = \mathrm{E}\left(\boldsymbol{x_t x_t}'\right)$ is the $(q \times q)$ covariance matrix of the causes.

The measurement model represents the link between the latent variable and its indicators, i.e., the latent variable determines its indicators. The measurement model is specified by:

$$\boldsymbol{y}_t = \boldsymbol{\lambda}\eta_t + \boldsymbol{\varepsilon}_t , \tag{2.2}$$

where $\boldsymbol{y}_t' = \left(y_{1t}, y_{2t}, \ldots, y_p\right)'$ is a p vector of several indicator variables, $\boldsymbol{\lambda}$ is a p vector of regression coefficients, and $\boldsymbol{\varepsilon}_t$ is a p vector of white noise disturbances. Their $(p \times p)$ covariance matrix is denoted by $\boldsymbol{\Theta}_\varepsilon = \mathrm{E}\left(\boldsymbol{\varepsilon_t \varepsilon_t}'\right)$.

Substituting equation (2.1) into equation (2.2) yields a reduced form regression model where the indicators $\boldsymbol{y_t}$ of the latent variable η_t are the endogenous variables and the causes $\boldsymbol{x_t}$ the exogenous variables. This model can be written as:

$$\boldsymbol{y}_t = \boldsymbol{\Pi}\boldsymbol{x}_t + \boldsymbol{z}_t , \tag{2.3}$$

---

[17] Jöreskog (1970) and Goldberger (1972) first introduced SEMs into economics. Thereafter, very general SEMs were developed [see, for example, Keesling (1972); Jöreskog and Goldberger (1972); Jöreskog (1973)] and applied (see, for example, Jöreskog and Goldberger (1975)]. For a more comprehensive description of SEMs, see Appendix A or Bollen (1989).

[18] The subscript *t* indicates the time series dimension of the variables.

where $\boldsymbol{\Pi} = \boldsymbol{\lambda\gamma}'$ is a $(p \times q)$ matrix and $\boldsymbol{z}_t = \boldsymbol{\lambda}\varsigma_t + \boldsymbol{\varepsilon}_t$. The error term $\boldsymbol{z}_t$ in equation (2.3) is a p vector of a linear transformation of the white noise error terms ς_t and $\boldsymbol{\varepsilon}_t$ resulting from the structural equation and measurement models, i.e., $\boldsymbol{z}_t \sim (\boldsymbol{0}, \boldsymbol{\Omega})$. The covariance matrix $\boldsymbol{\Omega}$ is given as $\boldsymbol{\Omega} = \mathrm{Cov}(\boldsymbol{z_t}) = \mathrm{E}[(\boldsymbol{\lambda}\varsigma_t + \boldsymbol{\varepsilon}_t)(\boldsymbol{\lambda}\varsigma_t + \boldsymbol{\varepsilon}_t)'] = \boldsymbol{\lambda}\psi\boldsymbol{\lambda}' + \boldsymbol{\Theta}_\varepsilon$.

Since the latent variable is not observable, its size is unknown, and the parameters of the model must be estimated using the observed variables' variances and covariances. The goal of the estimation procedure is thus to estimate an SEM's covariance matrix $\boldsymbol{\Sigma}(\boldsymbol{\theta})$, $\hat{\boldsymbol{\Sigma}} = \boldsymbol{\Sigma}(\hat{\boldsymbol{\theta}})$, that is as close as possible to the sample covariance matrix of the observed causes and indicators.[19] Identification and estimation of the model is however not possible without placing restrictions on certain model parameters. Among others, a restriction often imposed on the model is that one element of the vector $\boldsymbol{\lambda}$, i.e., one indicator, is set to an *a priori* value (often 1 or -1). In this way the researcher also establishes an interpretable scale for the latent variable [Bollen (1989), pp. 91, 183].[20]

The first step in the estimation is to select those causes and indicators that are appropriate to define the latent variable and which address the hypothesized theoretical relationships. After model identification and determination of the latent variable's scale, the coefficients and model parameters are estimated and the hypothesized relationships between the latent variable and its causes and indicators tested. The second step is to use the estimated coefficients of the causes to calculate the latent variable score for each point in time. Finally, a benchmarking procedure is applied to estimate "real world" figures of the underlying latent variable. The next section presents the theoretical reasoning for the selection of causes and indicators.

---

[19] $\boldsymbol{\theta}$ is a vector that contains the parameters of the model and $\boldsymbol{\Sigma}(\boldsymbol{\theta})$ is the covariance matrix as a function of $\boldsymbol{\theta}$ implying that each element of the covariance matrix is a function of one or more model parameters.

[20] An alternative is to set the variance of the unobservable variable η_t to one. However, setting one element of $\boldsymbol{\lambda}$ to an a priori value is often more convenient for economic interpretation and thus typically done [Dell'Anno and Schneider (2009)].

2.3 Theoretical Considerations for the Choice of Variables

It is clear from the previous section that the meaning of the latent variable depends on the causes and indicators chosen to represent it. This makes the selection of appropriate causes and indicators the most demanding part of the SEM approach. The following explains the reasoning for the causes and indicators employed in this chapter of the dissertation based on theoretical and empirical evidence from the literature.

2.3.1 Causes of Shadow Economic and Do-it-Yourself Activities

2.3.1.1 Tax and Social Security Contribution Burdens

Studies point to tax and social security contribution burdens as one of the main reasons for the existence of the shadow economy because taxes affect labor-leisure choices and stimulate informal labor supply.[21] The greater the difference between the total cost of labor in the official economy and the after-tax earnings from work, the greater the incentive to reduce or avoid this difference by working in the shadow economy. Schneider (1986; 1994) demonstrates the strong influence of indirect and direct taxation on the shadow economies of Austria and the Scandinavian countries. Johnson et al. (1998) provide further empirical evidence to support this view. Higher taxes may also create an incentive to carry out DIY activities rather than buy the equivalent – but more expensive – products and services in the official economy. An alternative view is that higher taxation may drive up the prices of DIY goods, thereby making DIY activities more costly.

For the approximation of tax and social security contribution burdens, I use public revenues data (in % of GDP) provided by the Organization for Economic Cooperation and Development (OECD) which comprises total revenue of central and local

---

[21] See Schneider (1994; 1997), Lippert and Walker (1997), Johnson et al. (1998), Tanzi (1999), Mummert and Schneider (2002), and Giles et al. (2002). Loayza (1996) provides a theoretical macroeconomic analysis of the relationship between excessive taxation/regulation and the shadow economy. Neck et al. (1989) show that households' determinants to work in the shadow economy are similar to those of tax evasion.

governments. Its main components are income tax, value added and sales taxes, social security contributions as well as payroll taxes.

2.3.1.2 Intensity of Regulation

The intensity of regulation is another important reason for the existence of the shadow economy. Regulations not only increase labor costs in the official economy, but – since most of these costs can be shifted onto employees – also provide an incentive to work in the shadow economy – where these costs can be avoided. The intensity of regulation is often measured by the number of laws and regulations, such as license requirements, or the size of staff at regulatory agencies. Examples of labor market regulations include minimum wages, security standards, and restrictions on foreigners. Johnson et al. (1998) provide empirical evidence of the influence of (labor) market regulations on the shadow economy. The influence of labor market regulations on shadow economic activities is also clearly described and theoretically derived in other studies, for example in the findings of the German Deregulation Commission 1990/91 [Deregulation Commission (1991)] and in Pelzmann (2006, pp. 94-99) who applies the psychological foundations of the reactance theory to the shadow economy.

2.3.1.3 Other Influential Factors

Real disposable income is included as a control variable. Here, a positive relationship is assumed. Since real disposable income is positively correlated with the demand for goods and services in general, I hypothesize that the higher the real disposable income, the greater the demand not only in the official but also in the unofficial economy and, hence, the larger the shadow and DIY economies.

A zero one time dummy variable (Dummy) is included to control for structural changes of the German economy as a result of the reunification in 1990. Because German reunification offered remarkable opportunities not only in the formal but also in the informal economy, I expect a positive correlation between the dummy variable and shadow economic as well as DIY activities.

With respect to DIY activities, I focus on the labor market – which numerous studies identify as a driving force for informal economic activities.[22] It is generally agreed, for example, that high labor costs are the cause of unemployment in the OECD countries. The higher the unemployment is, the greater the incentive to engage in DIY activities because unemployed individuals have less money to purchase goods and services, either in the official or unofficial economy, and also more time to perform DIY activities. DIY activities may also boost individuals' self-esteem, thereby further stimulating DIY activities. It is also apparent that the higher the average gross hourly earnings in the official small business sector, the higher the costs for those individuals who demand such services. Given that they are able to do these activities themselves, they may replace demand both in the official small business sector and in the shadow economy – which runs the risk of punishment and fines – with DIY activities. I therefore postulate that higher average gross hourly earnings for craftsmen lead to an increase in the volume of DIY activities, *ceteris paribus*.

2.3.1.4 Summarizing the Hypotheses

Because it is not clear whether shadow economic and DIY activities can be treated as complements or substitutes, I do not formulate any hypotheses about the interaction between these activities. Instead, I undertake the attempt to estimate simultaneously the shadow economy and DIY activities according to the following hypotheses:

(1) An increase in tax and social security burdens increases shadow economic and DIY activities, *ceteris paribus*.

(2) The more the German economy is regulated, the greater the incentive to work in the shadow economy, *ceteris paribus*.

(3) The higher unemployment and wages in the official economy, the more individuals engage in DIY activities, *ceteris paribus*.

---

[22] Schneider and Enste (2000) and Gërxhani (2004) provide comprehensive overviews of the literature.

2.3.2 Indicator Variables of Shadow Economic and Do-it-Yourself Activities

In addition to the causal variables described above, I use four indicator variables to estimate shadow economic and DIY activities in Germany. The first indicator variable is domestic M0, i.e., currency in circulation outside the banking system. Cash is the most common form of payment in the shadow economy because it protects both principal and agent by eliminating the "paper trail." I thus argue that cash holdings are a sign of shadow economic activities. I therefore expect a positive relationship between the shadow economy and domestic M0, i.e., the more currency in circulation, the larger the shadow economy, *ceteris paribus*.

An increase of the shadow economy can lead to reduced state revenues which in turn reduce the quality and quantity of publicly provided goods and services. Ultimately, this can lead to an increase in the tax rates for firms and individuals in the official sector, quite often combined with a deterioration in the quality of the public goods (such as the public infrastructure) and of the administration, with the consequence of even stronger incentives to participate in the shadow economy. Johnson et al. (1998) present a theoretical model of this relationship. Because the quantity and quality of the public infrastructure are key elements for economic growth, an increasing shadow economy – *ceteris paribus* – results in lower growth rates of the official economy. This negative view of the shadow economy is also held by e.g. Loayza (1996).

An alternative view – held by some authors [e.g. Asea (1996); Tanzi (1999)] – is that shadow economic activities are something positive and creative responding to the demand for services and small-scale manufacturing. Thus, the shadow economy adds a dynamic component to an economy promoting the creation of new markets and enhancing entrepreneurship. This, in turn, can spur competition and higher efficiency, which stimulates economic growth.

The average number of hours worked per week in the official economy can be another useful indicator of shadow economic activities. If individual increase labor supply in the shadow economy, the number of hours worked in the official economy will reduce, *ceteris paribus*. Recent empirical studies [e.g. Bosch and Lehndorf (1998); DIW (1998)] support this view identifying a negative relationship between shadow economic activities and working hours in the official economy.[23] Following these empirical findings, I expect a negative correlation between the shadow economy and the average number of hours worked per week in the official economy.

Inputs for DIY activities are typically bought in DIY stores. Hence, turnovers at DIY stores are an indication of DIY activity. Thus, I expect a positive correlation between DIY activity and turnovers in DIY stores, i.e., the more common DIY activities, the higher turnovers in DIY stores, *ceteris paribus*.

2.4 Empirical Analyses

2.4.1 Data

The data covers the period 1970 to 2005 on an annual basis. Data on turnovers in DIY stores is available from A.C. Nielsen Company GmbH starting in 1978, when they conducted the first annual survey on turnovers in DIY stores in Germany. To complete the time series for the entire period 1970-2005 I regress its annual growth rates on a constant term and on a linear time component and calculate estimates from 1970 to 1977. The estimation results are then used to predict the level of turnovers in DIY stores for the years 1971 to 1978. Table 2.3 presents the regression results.[24] Figure 2.1 provides a graphical representation of turnovers in DIY stores from 1970 to 2005. Turnovers in DIY stores increased until the mid 1990s followed by a short period of stagnation. Between 2002 and 2005 they decreased as a result of a recession in the Germany economy in 2002/2003, which followed the dot-com bubble crash in 2001.

---

[23] See Schneider and Enste (2000) for a detailed discussion.

[24] For a discussion on unit root tests, see Section 2.4.2.

Table 2.3 Regression of Turnovers on a Constant and Time

Variable	Growth rate of turnovers
Parameter estimates	
Constant	0.212***
	(12.548)
Time	-0.008***
	(7.946)
Test statistics	
Standard error of regression	0.039
Adjusted *R*-squared	0.713
DW-statistic	2.57
Unit root tests (growth rate of turnovers)	
ADF test	-6.391***
PP test	-6.367***
KPSS test	0.083

Note: *** Significance at the 1% level. ** Significance at the 5% level. * Significance at the 10% level. Absolute *t*-statistics in parentheses. The order of the autoregressive correction for the unit root tests was chosen using the Schwarz information criterion (ADF test) and the Bartlett kernel estimator and the Newey-West (1994) data-based automatic bandwidth parameter method (PP and KPSS test). The MacKinnon (1996) critical values for the ADF and PP tests are: -4.13, -3.49, and -3.17 for the 1%, 5%, and 10% significance levels, respectively. The LM statistics critical values of the KPSS test – taken from Kwiatkowski et al. (1992) – are: 0.216, 0.146, and 0.119 for the 1%, 5%, and 10% significance levels.

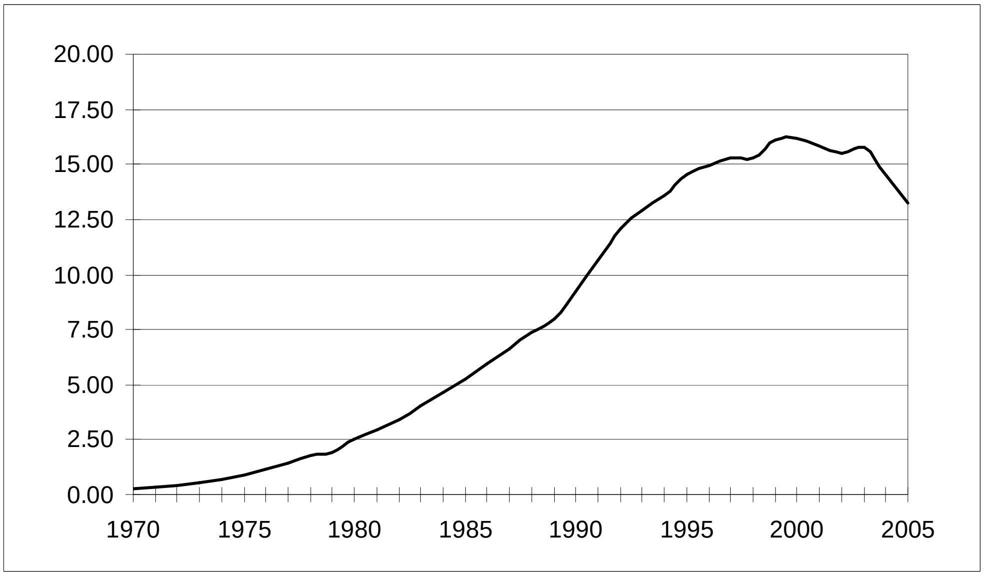

Figure 2.1 Turnovers in DIY Stores 1970-2005 (Billions of Euros)

M0 in Germany greatly increased until 2001. This cannot be explained on the basis of domestic transactions in the official and unofficial economies alone. One possible explanation is the rise in foreign – especially Eastern and Southeast European – demand for the deutsche mark after the breakdown of the Council for Mutual Economic Assistance (COMECON) in the 1990s [Seitz (1995)]. The unstable political situation in those countries in the early 1990s, the war in Kosovo, and the Bulgarian financial crisis of 1996-1997 increased foreign demand for the deutsche mark further.

Given that I am interested in shadow economic and DIY activities in Germany, it is essential to focus on domestic M0 as an indicator variable for the shadow economy. To estimate the level of domestic M0 in Germany from 1970 to 2005, I apply a vector error correction model using the methodology proposed by Seitz (1995). This enables me not only to adjust the total amount of M0 by foreign demand for the deutsche mark but also to take into account distortions caused by German reunification in 1990 and preparation for the 2002 introduction of the euro in the second half of 2001.[25]

---

[25] At that time, individuals substituted cash with demand deposits in order to avoid personally exchanging their deutsche mark for euros [Deutsche Bundesbank (2002)]. This triggered an enormous decrease in domestic M0, which cannot be attributed to changes in shadow economic

In equilibrium, real money demand is assumed to depend positively on real income and negatively on short-term interest rates (the Goldfeld equation). In countries with weak national currencies, however, often two or more sound currencies – typically the U.S. dollar and the euro/deutsche mark – are used as a means of payment and/or store of values. For example, during the war in Kosovo in the early 1990s the deutsche mark and the U.S. dollar were both used in the Balkan region but the actual amount of either currency individuals held depended on the USD/EUR exchange rate.[26] I take this fact into account and include the USD/EUR exchange rate to reflect both the strength of the euro relative to the U.S. dollar and the fact that the two currencies are close substitutes in such countries. The expected sign for the USD/EUR exchange rate is positive.[27] Dummy variables for the first and second quarters of 1991 are used to control for German reunification.

Data is on a quarterly basis from Q1 1970 to Q4 2005. Data for M0 – expressed in logs – and the short-term interest rate is taken from the Deutsche Bundesbank. Data for the German quarterly GDP (also expressed in logs) and the USD/EUR exchange rate is taken from the German Federal Statistical Office and Thomson Financial Datastream, respectively. All variables are found to be I(1). Using the Johansen methodology [Johansen (1991; 1995)], I find one cointegration equation at the 5% significance level. In order to achieve stationarity for the short-run estimation, I then difference all variables once. The results of the unit root and cointegration tests are shown in Table 2.4.[28] Table 2.5 presents the estimation results for domestic currency in circulation. The estimated coefficients for GDP, the short-term interest rate, and the USD/EUR exchange rate have the theoretically motivated signs and the model has a satisfactory fit.

Figure 2.2 displays the pattern of the predicted time series in comparison with the original one. It clearly shows the distortions in the original time series of currency in

---

activities.

[26] The USD/EUR exchange rate is defined as the amount of U.S. dollars one must pay for one euro.

[27] A stronger euro increases the USD/EUR exchange rate and should lead to more euro holdings compared to the U.S. dollar while a weaker euro should lead to less euro holdings. In portfolio theory, this effect is called return-chasing.

[28] For a discussion on unit root tests, see Section 2.4.2.

circulation which, on the one hand, are due to Eastern and Southeast European demand for the deutsche mark in the mid 1990s. The political situation in those countries, the war in Kosovo, and the Bulgarian financial crisis of 1996-1997 increased demand for deutsche mark above the level that can be explained by domestic transactions in the official and unofficial economies. On the other hand, the preparation for the introduction of the euro in 2002 – individuals substituted cash with demand deposits in order to avoid personally exchanging their deutsche mark for euros – triggered an enormous decrease in domestic M0 that cannot be attributed to changes in shadow economic activities. It is thus important to correct for these distortions and to use the estimated time series of *domestic* currency in circulation as indicator variable for shadow economic activities in Germany. Table B.1 in Appendix B presents a description of causes as well as indicators ultimately used in the SEM/MIMIC estimations and provides a complete list of sources.

Table 2.4 Unit Root and Cointegration Tests

Variable	ADF (PP) unit root test	
	Levels	First difference
M0	-2.233	-7.813***
	(-1.951)	(-11.850)***
GDP	-0.993	-11.794***
	(-1.422)	(-11.905)***
Short-term interest rate	-3.0510	-5.590***
	(-3.051)	(-9.291)***
USD/EUR exchange rate	-1.269	-9.649***
	(-1.389)	(-9.740)***
	Cointegration tests	
Trace test	54.361**	
	(0.011)	
Maximum eigenvalue test	30.097**	
	(0.023)	

Note: *** Significance at the 1% level. ** Significance at the 5% level. * Significance at the 10% level. Autoregressive correction is chosen using the Bartlett Kernel estimator and Newey and West's (1994) data-based automatic bandwidth parameter method (PP test). I use the Schwarz information criterion for the ADF test. All regressions in levels (first differences) include an intercept and a time trend (intercept). The ADF and PP test's MacKinnon (1996) critical values for a test equation with intercept and time trend (intercept) are: -4.13 (-3.55), -3.49 (-2.91), and -3.17 (-2.59) for the 1%, 5%, and 10% significance levels, respectively. The 5% critical value for the trace and maximum eigenvalue tests – taken from MacKinnon et al. (1999) – are 47.86 and 27.58, respectively. For these two tests *p*-values are reported in parentheses.

Table 2.5 Estimation of Domestic Currency in Circulation

Variable	Coefficient	Absolute *t*-statistic
Long-run equilibrium estimation		
M0 (dependent variable)		
Constant	-1.780***	7.150
GDP	1.337***	18.382
Short-term interest rate	-0.007*	1.945
USD/EUR exchange rate	1.049***	13.571
Dummy Q1 1991	-0.168	1.610
Dummy Q2 1991	-0.137	1.316
Adjusted *R*-squared	0.973	
Probability (*F*-statistic)	0.000	
Short-run dynamic estimation		
Δ M0 (dependent variable)		
Constant	0.013***	3.645
Δ GDP	0.461*	1.669
Δ short-term interest rate	0.003	0.666
Residuum(-1) long-run estimation	-0.108***	3.325
Dummy Q1 1991	-0.064	1.169
Dummy Q2 1991	-0.008	0.210
Adjusted *R*-squared	0.056	
Probability (*F*-statistic)	0.024	

Note: *** Significance at the 1% level. ** Significance at the 5% level. * Significance at the 10% level.

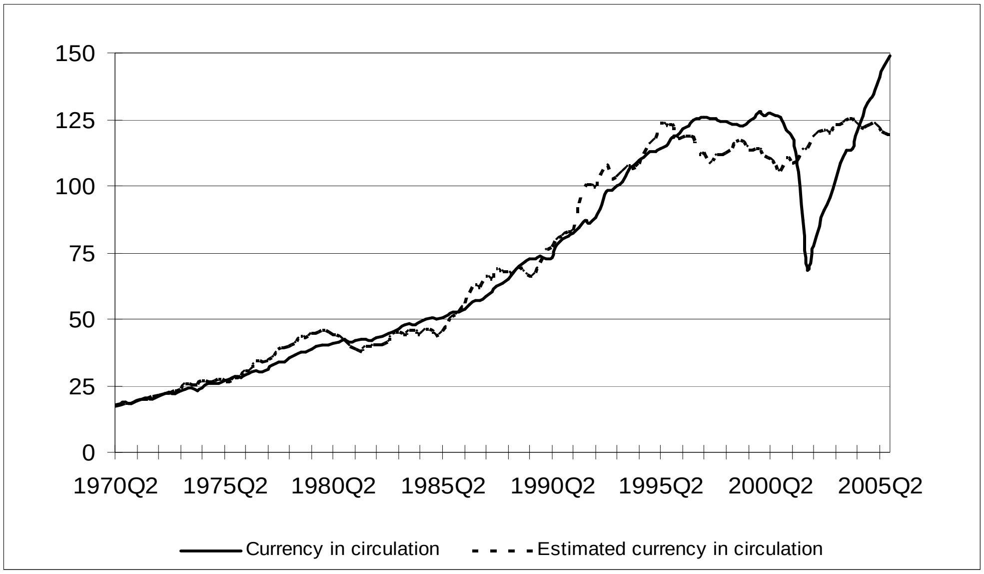

Figure 2.2 Currency in Circulation 1970-2005 (Billions of Euros)

2.4.2 Unit Root Tests

I begin the empirical analysis of shadow economic and DIY activities in Germany by pre-testing the data. Applying SEMs with nonstationary time series may result in misleading estimates – as is common in standard time series econometrics.[29] I therefore use three conventional unit root tests to figure out the time series' properties: the augmented Dickey-Fuller (ADF) test, the Phillips Peron (PP) test, and the Kwiatkowski et al. (1992) (KPSS) test. While the ADF and PP tests test the null hypothesis of a unit root against the alternative of stationarity, the KPSS test tests the null hypothesis of stationarity against the alternative of existence of a unit root. Because of the reversed null hypothesis, the KPSS test is often used as a confirmatory analysis to cross-check the ADF and PP tests' results.[30]

---

[29] In a seminal paper, Granger and Newbold (1974) conclude that in regressions using levels of integrated data, standard significance tests are usually misleading and suggest a significant relationship of one time series on another, even if the two are independent. This is the well-known phenomenon of spurious or nonsense regressions.

[30] This approach is taken by Choi (1994). For a discussion of unit root tests, their properties, and power, see, for example, Maddala and Kim (1998, pp. 47-97) or Greene (2008, pp.739-756).

In some cases, e.g. for the inflation rate (Inflation), unemployment (Unemployment), the average hours worked per week (Working hours), and domestic M0, the tests show ambiguous results. In general, however, I find that the variables are not stationary.[31] As a result – and to enable consistent estimation of the SEM/MIMIC models in first differences – I difference all time series, except for the indicator variable growth rate of real GDP (Growth rate GDP), once. Employing the same unit root tests, the first differences do not exhibit a unit root. The KPSS test largely confirms this result. As the time series for the turnovers in DIY stores (Turnovers) remains nonstationary – even after taking first differences – I employ the approach suggested by Schwert (1987) to detrend this series. Because of the limited sample size, the lag order used is set to 2. Table 2.6 summarizes the findings of the unit root tests.

[31] Conflicting results in unit root testing is a recognized problem in time series econometrics [see, for example, Maddala and Kim (1998), pp.126-128].

Table 2.6 Unit Root Tests

Variable	Levels			First differences		
	ADF test	PP test	KPSS test	ADF test	PP test	KPSS test
Causes						
Regulation	-0.930	-0.660	0.205	-4.775***	-4.775***	0.602
Income	-1.701	-1.701	0.186	-4.562***	-4.561***	0.515
Inflation	-3.365*	-2.878	0.058	-4.570***	-5.218***	0.056
Tax burden	-0.741	-1.023	0.143	-3.690***	-3.690***	0.446
Unemployment	-3.630***	-2.586	0.056	-3.334**	-3.550***	0.398
Wages	-4.988***	-4.852***	0.142	-4.064***	-4.101***	0.452
Indicators						
Growth rate GDP	-3.959***	-4.010***	0.187			
Working hours	-4.524***	-1.397	0.104	-3.044**	-3.073**	0.136
M0	-2.440	-1.661	0.093	-4.135***	-3.512**	0.384
Turnovers	-2.675	-1.055	0.111	0.020	-1.412	0.446
Turnovers (detrended)	-5.334***	-5.330***	0.069			

Note: *** Significance at the 1% level. ** Significance at the 5% level. * Significance at the 10% level. Autoregressive correction is chosen using the Bartlett Kernel estimator and Newey and West's (1994) data-based automatic bandwidth parameter method (PP and KPSS test). I use the Schwarz information criterion for the ADF test. All regressions in levels (first differences) include an intercept and a time trend (intercept). The ADF and PP test's MacKinnon (1996) critical values for a test equation with intercept and time trend (intercept) are -4.13 (-3.55), -3.49 (-2.91), and -3.17 (-2.59) for the 1%, 5%, and 10% significance levels, respectively. The LM statistics critical values of the KPSS test [Kwiatkowski et al. (1992)] are 0.216 (0.739), 0.146 (0.463), and 0.119 (0.347) for the 1%, 5%, and 10% significance levels, respectively.

2.4.3 Empirical Models

Following Karmann (1990a), the estimation of the shadow economy and of DIY activities is based on two alternative SEM specifications. The first model (S-DIY) considers shadow economic and DIY activities as two distinct latent variables estimated in a MIMIC approach. The second model (H-DIY) estimates the hidden economy (H) first as a whole. It then uses the estimate for the hidden economy to derive individual estimates of shadow economic and DIY activities. Following the earlier hypotheses, I use tax and social security contribution burdens as well as the intensity of regulation as the main causes of shadow economic activities. I use unemployment, tax and social security contribution burdens, and average gross hourly earnings as causes of DIY activities. Despite the ambiguous theoretical effect of inflation on the shadow economy and on DIY activities, I consider inflation as a causal variable in the models. Furthermore, I use a dummy variable (Dummy) to control for different behavioral patterns in Eastern and Western Germany and structural changes to the German economy as a result of German reunification in 1990. Figures 2.3 and 2.4 display the conceptual diagrams of the S-DIY and H-DIY models, respectively. Since the shadow economy (S) is a significant part of the hidden economy (H) in the H-DIY SEM, I consider all variables that cause S to cause H as well. Hence, the same set of indicator variables is used in both model specifications.[32]

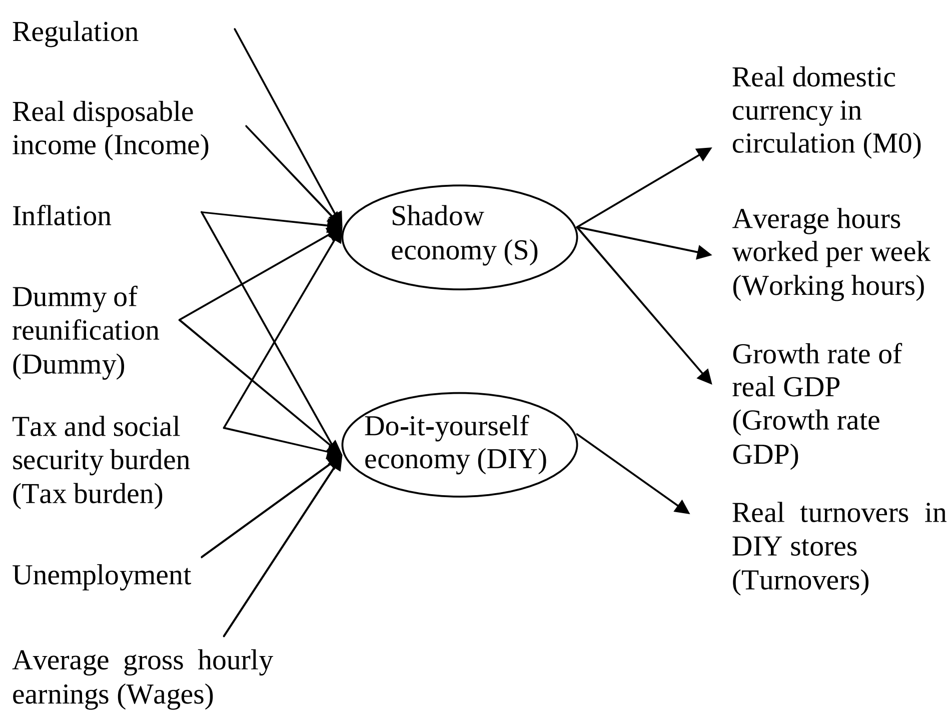

Figure 2.3 Conceptual Diagram of the S-DIY Model

[32] See Section 2.3.2 for the theoretical justification regarding the selection of indicators.

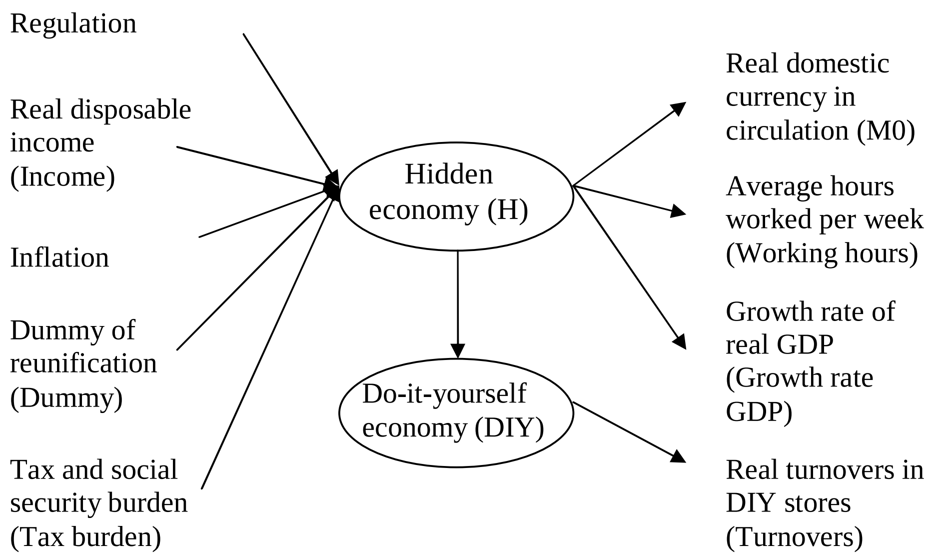

Figure 2.4 Conceptual Diagram of the H-DIY Model

Table 2.7 displays the results of both SEM estimations applying the maximum likelihood estimator for the S-DIY model as well as for the H-DIY model. For each model specification, the first column shows the parameter estimates for both causal and indicator variables for S and H. The parameter estimates relating to DIY activities are always displayed in the second column. The two rows above goodness-of-fit refer to the causal link between H and DIY in the H-DIY model.

Table 2.7 Estimation Results

	S-DIY model		H-DIY model	
	S	DIY	H	DIY
Causes				
Regulation	11.98***		11.24***	
	(2.54)		(2.51)	
Income	1.38***		1.43***	
	(3.34)		(3.54)	
Inflation	-0.32	-0.53***	-0.93	
	(0.50)	(2.44)	(1.44)	
Dummy	0.10***	0.05***	0.13***	
	(2.50)	(4.18)	(3.29)	
Tax burden	0.11**	-0.01	0.09**	
	(2.37)	(0.37)	(2.07)	
Unemployment		0.03**		
		(2.14)		
Wages		0.15		
		(0.85)		
Indicators				
M0 (fixed)	1.00		1.00	
Growth rate GDP	0.25***		0.22***	
	(3.32)		(3.22)	
Working hours	-0.02		-0.01	
	(1.32)		(1.10)	
Turnovers (fixed)		2.00		2.00

(continued on next page)

Table 2.7 (cont.)

Latent variables		
H → DIY		0.13**
		(2.05)
Goodness-of-fit statistics	S-DIY model	H-DIY model
Number of observations	36	36
Degrees of freedom	50	33
Chi-square	34.87	30.19
(*p*-value)	(0.95)	(0.61)
RMSEA	0.00	0.00

Note: *** Significance at the 1% level. ** Significance at the 5 % level. * Significance at the 10% level. Absolute *z*-statistics in parentheses. The degrees of freedom are determined by 0.5 (p + q) (p + q + 1) – t, where p = the number of indicators, q = the number of causes, and t = the number of free parameters. If the model fits the data perfectly and the parameter values are known, the sample covariance matrix equals the covariance matrix implied by the model. The null hypothesis of perfect fit corresponds to a *p*-value of 1. The root mean squared error of approximation (RMSEA) measures the model's fit based on the difference between the covariance estimated and the actual covariance matrix. RMSEA values smaller than 0.05 indicate a good fit [Browne and Cudeck (1993)].

All variables except Working hours and Tax burden are significant at the 5% level for both the shadow (S) and hidden (H) economy. For DIY activities (DIY) only the Tax burden variable is not statistically significant. The goodness-of-fit statistics of the two model specifications show satisfactory statistical properties.[33] I also estimate both model specifications excluding the insignificant variables (parsimonious models) and test for robustness by varying the observation period, for which the parameter estimates remain stable.[34] For the S-DIY model, the statistics of the full model indicate a slightly closer fit

[33] Further goodness-of-fit statistics are presented in Table B.2 in Appendix B. For a description of the goodness-of-fit statistics, see Section A.3 in Appendix A.

[34] In these estimations I consider the following time periods: 1970-2002, 1970-2003, 1970-

than those of the parsimonious model. For the H-DIY model, the reverse is true: the statistics of the parsimonious model indicate a slightly closer fit than those of the full model. To assure comparability between the estimates of both the S-DIY and the H-DIY models, I always use the full model to predict the size of shadow economic and DIY activities in Germany from 1970 to 2005.

Identification and estimation of SEMs requires the normalization of one indicator for each latent variable. A well-established way to normalize one of the indicators is to set its coefficient to a nonzero value.[35] For the shadow economy, I choose the variable M0 and set it to one. Because I am dealing with two latent variables simultaneously, it is also necessary to fix the scale for the other latent variable, DIY, as explained below.

According to the Federal Statistical Office of Germany, capital productivity in the construction business was 1.89 in 1991 (the approximate midpoint of the observation period).[36] The use of capital productivity as a scaling parameter is appropriate since capital productivity is the ratio of output to capital input and the measurement model for DIY activities employs a general input-output measure, i.e., the capital input of DIY activities (i.e., turnovers in DIY stores) is used as an indicator for the unobservable variable DIY (i.e., the output). Assuming that capital productivity in the construction business is nearly equal to that of DIY activities, I set the coefficient of the indicator variable turnovers in DIY stores (Turnovers) to this level, with the numerical value two. The following summarizes the findings from the estimations of the models presented and addresses the proposed hypotheses:

2004, 1971-2005, 1972-2005, and 1973-2005. The results of these estimations are presented in Tables B.3 and B.4 in Appendix B. Tables B.3 and B.4 present the main goodness-of-fit statistics only. The additional goodness-of-fit statistics, as shown in Table B.2, are not presented for the robustness estimations with variations in the observation period (Tables B.3 and B.4), because these statistics do not differ much from those of the full models. Further goodness-of-fit statistics for the parsimonious model specifications are presented in Table B.5.

[35] The choice of the indicator which establishes the scale of the latent variable does not affect the estimated coefficients because the maximum likelihood estimator is scale invariant [Swaminathan and Algina (1978)]. Typically, one selects the indicator that loads most on the unobservable variable, i.e., M0 in the S-DIY and H-DIY MIMIC models.

[36] For similar arguments, see also Karmann (1990a).

(1) The intensity of regulation (Regulation) and tax and social security contribution burdens (Tax burden) are always statistically significant and positively related to S and H, having the expected sign. I cannot confirm that the tax burden is a driving factor for individuals to engage in DIY activities.

(2) In both model specifications, the real disposable income (Income) – which measures per capita real disposable income – is highly statistically significant and positively related to S and H. One explanation for this is that the higher the disposable income of households, the higher the demand for goods and services. Demand rises not only in the official economy but also, in part, in the shadow economy, leading to a higher observed level of shadow economic activity.

(3) The inflation rate (Inflation) is significant for DIY activities only; that is, the higher the inflation rate – which increases the cost of materials for DIY activities – the fewer activities individuals perform, leading to a lower level of the latent variable DIY. The negative, though insignificant, influence of inflation on the shadow economy may be seen as a contribution to a reduction in real tax burdens, thereby reducing incentives to avoid taxation. Another important factor explaining DIY activities is unemployment (Unemployment): it is positively related to the latent variable DIY activities with the expected sign.

(4) The zero one dummy variable (Dummy) is, as expected, significantly positively related to all of the latent variables. This result reflects the catching up of East to West Germany after reunification in 1990 triggering a steep rise in the shadow economy due to the reconstruction period that followed.

(5) Average hourly earnings in the small business sector (Wages) do not influence DIY activities. Still, the parameter estimate – though not statistically significant – has the expected sign. This shows that higher wages lower the demand for small business services and hence raise the incentives for individuals to engage in DIY activities.

(6) The coefficient for the unemployment rate is statistically significant and has the expected positive sign. This confirms the hypothesis that unemployed individuals are more likely to perform DIY activities because they have, on the one hand, more time for these activities and, on the other hand, have less money to purchase goods and services in the official or unofficial economy.

(7) The estimated coefficient on the growth rate of real GDP (Growth rate GDP) is statistically different from zero and hence suggests a positive relationship between the shadow economy and the growth rate of real GDP. I cannot confirm that the size of the shadow economy affects the average hours worked per week (Working hours). This is in line with observations that unemployed individuals typically cannot compensate loss of income through work in the shadow economy unless they have already been engaged in the shadow economy.

2.4.4 Size of Shadow Economic and Do-it-Yourself Activities

As a result of data transformation, the model is estimated in first differences and thus provides estimates of the latent variables under the same transformation. I must therefore integrate the resulting time series to obtain index series for shadow economic and DIY activities as well as for the hidden economy. Another difficulty of SEM estimations is that one obtains an index describing the development of the latent variable only which needs to be converted into estimates of “real world” figures (% of official GDP). In the literature, this is usually done by calibration using a firm figure for the latent variable at some point in time within the observation period.

In this chapter, I refer to an assessment for the size of DIY activities using primary data by Niessen and Ollmann (1987, p. 151). According to them, households spent an average of 125 hours on DIY activities in 1983. Karmann (1990a) – using a currency demand approach – estimates that the value added (the size) of these activities corresponds to 4.4% of official GDP. For consistency, I also take Karmann’s (1990a) currency demand approach estimate for the size of the shadow economy. Thus, I use the estimates of 8.5% of official GDP for shadow economic activities and 4.4% for DIY activities and calibrate the estimated MIMIC/SEM indices into series measuring the size of these activities in % of official GDP.[37] In order to calibrate each estimated MIMIC/SEM index into an index in % of official GDP, I follow the benchmarking procedure proposed by Dell'Anno and Schneider (2003). According to this procedure, the time series $\Delta\hat{\eta}_t = \hat{\gamma}'\Delta x_t$, resulting from the estimated structural equation, are first integrated to an index $\tilde{\eta}_t$ – the base year of which is 1983 – indicating the development of the latent variables. The indices are then applied to the firm figure estimates, i.e., to 8.5% and 4.4% of official GDP for shadow economic and DIY activities, respectively, which finally yields the indices shown in Figures 2.5 and 2.6.

Figure 2.5 plots the size and development of shadow economic activities according to the S-DIY model. It shows a remarkable increase in these activities over the past 25 years, reaching 17.40% of official GDP in 2005. German reunification in 1990 triggered a steep rise in the shadow economy during the reconstruction period that followed. After East Germany caught up to West Germany's behavior patterns, growth in the shadow economy leveled out to the level of around 17% in 2005.

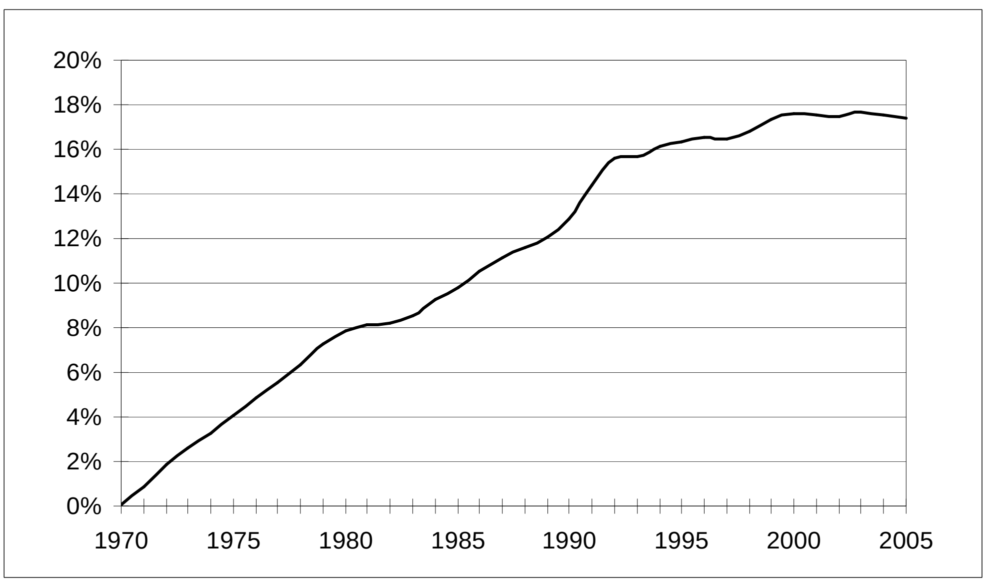

Figure 2.5 Shadow Economy in Germany 1970-2005 (% of Official GDP)

[37] Both firm figure (or benchmark point) estimates refer to 1983.

Figure 2.6 plots the size and development of DIY activities according to the S-DIY model. DIY activities increased from 4.05% of official GDP in 1970 to 4.94% in 1995 and remained more or less stable through 2005. Like shadow economic activities, DIY activities also experienced a big push following German reunification – though the dynamics were not as pronounced: between 1970 and 2005, DIY activities grew more slowly than did shadow economic activities. Altogether, the catch-up process in East Germany after reunification offered remarkable opportunities in the hidden economy.

When calculating the size and development of shadow economic and DIY activities in Germany according to the H-DIY model, I obtain similar results.[38] As illustrated in Figure 2.4, DIY activities are determined by the link between the latent variables and are measured as a portion of the hidden economy. Table 2.8 shows the estimates of all the different index series according to the S-DIY and H-DIY models.

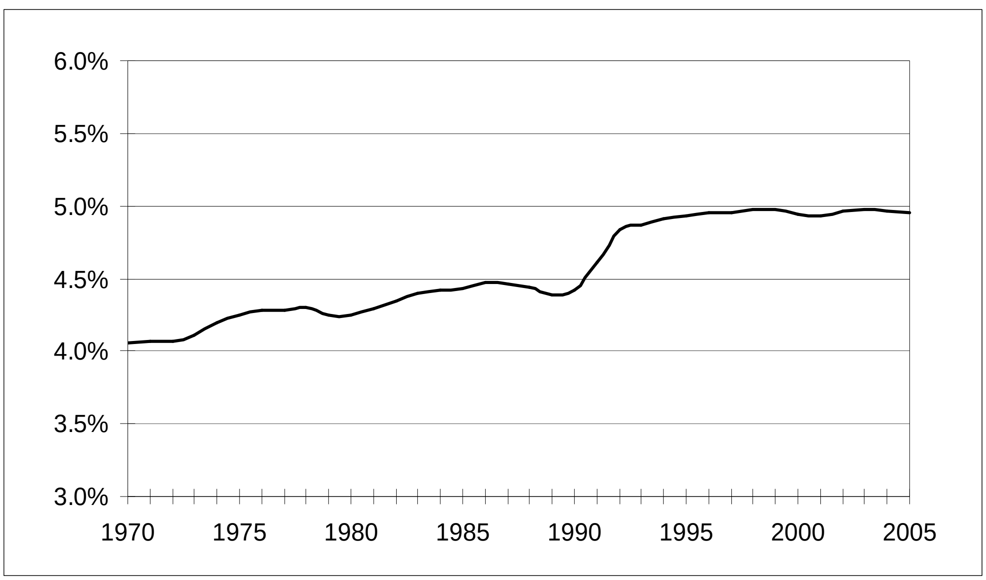

Figure 2.6 DIY Activities in Germany 1970-2005 (% of Official GDP)

[38] In this case, the benchmark value for the H-index is derived simply by summing up the firm figure values for shadow economic and DIY activities. As a result, the benchmark point estimate for the hidden economy in 1983 is 12.9% of official German GDP.

2.5 Summary and Conclusion

In this chapter, I have used SEM and MIMIC models to provide consistent estimates of the size and development of shadow economic and DIY activities in Germany. I found positive, highly statistically significant influences of regulation and tax and social security contribution burdens on the shadow economy. For DIY activities, I found a positive, highly statistically significant influence of unemployment. In general, the models show satisfactory statistical properties. According to my calculations, German shadow economic activities increased from 1-2% of official GDP in 1970 to around 17% in 2005. DIY activities amounted to 4% of official GDP in 1970, increased to 4.94% in 1995, and remained relatively constant through 2005. Taking both sectors together, the hidden economy in Germany reached a remarkable size of around 22% of official GDP in 2005. While shadow economic activities are driven by institutional factors such as taxation and regulation, DIY activities respond to unemployment.

The results suggest that shadow economic activities are contingent upon governmental policies while DIY activities are determined by individual constraints. It might also be that these constraints motivate individuals to engage into self-help and mutual aid. With respect to DIY activities, the results can also be interpreted by following the analysis of the household presented in Becker (1993). He shows that members of a household should allocate the various activities according to their comparative advantages, which implies not only the division of labor but also concerns investment in human capital. According to his theory, the household runs most efficiently when some members invest in human capital by working in paid employment while others work at home and maximize their individual utility through, for example, rearing children [Becker (1993), pp. 30-53].[39] The relatively stable index of DIY activities might be an indication of the relevance of this theory and the strong separation of responsibilities within a household. Because of their significant amount and specific dynamics, a comprehensive analysis of the hidden economy must take account of DIY activities.

---

[39] This argument is in line with Brodersen (2003, p. 34) who finds that married or cohabitating respondents are more likely to carry out DIY activities.

The analyses presented in this chapter imply the following policy conclusions. A reduction in regulations and/or taxes and social security contribution burdens seem to be efficient means of reducing the shadow economy by shifting shadow economic activities to the official economy. Either policy may also reduce labor costs in the official economy and thus decrease unemployment. Lower unemployment in turn reduces the incentive to engage in DIY activities. Though these results should be regarded as first steps in measuring the size of the hidden economy, I have demonstrated that – at least for Germany – both shadow economic and DIY activities are important and should be taken into account when seeking to stimulate the official economy through policy measures.

Table 2.8 The Hidden, Shadow, and DIY Economy in Germany (% of Official GDP)

Year	Hidden economy		Shadow economy		DIY activities	
	H-DIY model	S-DIY model	H-DIY model	S-DIY model	H-DIY model	S-DIY model
1970	5.50	4.02	1.63	0.04	3.87	4.05
1971	6.16	4.92	2.24	0.86	3.92	4.07
1972	7.08	5.95	3.10	1.88	3.98	4.07
1973	7.57	6.71	3.55	2.60	4.02	4.11
1974	8.17	7.48	4.11	3.28	4.06	4.20
1975	8.97	8.34	4.85	4.09	4.12	4.25
1976	9.76	9.16	5.59	4.88	4.17	4.28
1977	10.37	9.84	6.15	5.56	4.22	4.28
1978	11.17	10.65	6.90	6.35	4.28	4.30
1979	11.88	11.52	7.55	7.27	4.33	4.25
1980	12.28	12.11	7.93	7.85	4.36	4.25
1981	12.45	12.43	8.09	8.14	4.37	4.29
1982	12.54	12.58	8.17	8.23	4.37	4.35
1983	12.90	12.90	8.50	8.50	4.40	4.40
1984	13.60	13.66	9.15	9.24	4.45	4.42
1985	14.10	14.23	9.61	9.80	4.49	4.43
1986	14.92	15.01	10.38	10.54	4.55	4.47
1987	15.44	15.61	10.86	11.14	4.58	4.47
1988	15.77	16.03	11.16	11.59	4.61	4.44
1989	16.03	16.47	11.41	12.08	4.62	4.39
1990	16.78	17.31	12.10	12.90	4.68	4.42
1991	18.24	19.03	13.45	14.42	4.78	4.61
1992	19.50	20.44	14.63	15.60	4.87	4.84
1993	19.56	20.56	14.68	15.68	4.88	4.87
1994	20.05	21.05	15.13	16.15	4.91	4.91
1995	20.25	21.26	15.32	16.32	4.93	4.94
1996	20.40	21.46	15.46	16.51	4.94	4.96

(continued on next page)

Table 2.8 (cont.)

1997	20.33	21.44	15.40	16.48	4.93	4.96
1998	20.65	21.76	15.69	16.79	4.96	4.97
1999	21.12	22.29	16.13	17.31	4.99	4.97
2000	21.30	22.56	16.29	17.61	5.00	4.94
2001	21.23	22.48	16.23	17.54	5.00	4.94
2002	21.23	22.46	16.23	17.50	5.00	4.96
2003	21.39	22.63	16.38	17.66	5.01	4.97
2004	21.23	22.48	16.23	17.51	5.00	4.96
2005	21.10	22.35	16.11	17.40	4.99	4.96

CHAPTER THREE

SMUGGLING AROUND THE WORLD[*]

"Honesty is for the most part less profitable than dishonesty."
Plato (~428 BC~348 BC)

The preceding chapter has studied informal shadow economic and do-it-yourself activities in a national context. I now turn to the analysis of smuggling, an international informal economic activity. Smuggling is motivated by a desire to make or save money by avoiding taxes/tariffs and/or to make money by selling goods prohibited by the state. Smuggling often involves other crimes, such as fraud, fraudulent conversion, bribery, extortion, or violence. Although smuggling has attracted much attention in policy debates, the empirical literature is rather limited.[40] This chapter provides an empirical contribution to the literature by applying a structural equation model (SEM) to estimate an index of smuggling for 54 countries.

The hidden and illegal nature of smuggling makes it difficult to analyze this economic activity. Often, estimates of the extent of smuggling rely on narrow proxies or anecdotal evidence. This chapter presents an alternative for the economic analysis of smuggling and contributes to the empirical literature on smuggling in the following two ways: firstly, using a specific form of an SEM with latent variables (that is, a Multiple Indicators Multiple Causes (MIMIC) model) it captures the unobservable nature of smuggling and accounts for the manifold potential causal and indicator variables of

---

[*] This chapter follows Buehn and Farzanegan (2008).

[40] The literature deals mostly with theoretical aspects of the effects of smuggling on social welfare and the economy [see, for example, Bhagwati and Hansen (1973); Pitt (1981); Martin and Panagariya (1984); Norton (1988); Thursby et al. (1991)].

smuggling.[41] Secondly, the MIMIC estimation results are used to rank the countries according to the extent of smuggling in the economy and to compute an index of smuggling for 54 countries over the period 1991-1999. This is, to my knowledge, the first comparable estimate of smuggling across countries.

In general, smuggling includes illegal trade of both illegal and legal goods.[42] This chapter follows Pitt's definition of smuggling: "Traded goods are misweighted, misgraded, misinvoiced or not invoiced at all with or without the cooperation of customs authorities" [Pitt (1981), p. 449]. Hence, it does not deal with the illegal trafficking of human beings, such as prostitutes or illegal immigrants, or with the illegal trade of generally forbidden goods such as drugs. Rather, chapter 3 considers the illegal trade of legal goods, often referred to as trade misinvoicing. Given this working definition, the main channel of smuggling is that traders report false amounts of their actual exports or imports to authorities circumventing high taxes and/or tariffs.[43]

The incentive to smuggle seems not to be exclusively linked to the level of taxes. For example, in countries with high taxes, such as in the Scandinavian countries in Europe, there is little evidence of smuggling. Contrary, in many Eastern European countries, where taxes are much lower, illegal trade is more common. This might be due to the fact that countries with a low level of taxes often have less effective systems of border control, tax collection, and less transparent administrative rules [Merriman et al. (2000)]. The MIMIC model enables me to analyze whether ineffective administrations and institutions or high tariffs and trade restrictions determine the level of smuggling.

The analysis reveals that tariffs and trade restrictions are important push factors of smuggling while a higher black market premium discourages smugglers. Better law enforcement reduces smuggling by increasing the expected costs of illegal trade. A more

---

[41] MIMIC approaches were previously applied to estimate the development of the shadow economy [see, for example, Dell'Anno and Schneider (2003); Schneider (2005); Buehn et al. (2009)] and to corruption [Dreher et al. (2007)]. Interesting, recent applications of this methodology to smuggling are presented in Farzanegan (2009) and Buehn and Eichler (2009).

[42] Chapter 4 distinguishes between the smuggling of illegal and legal goods in the context of the U.S.-Mexican border.

[43] Although this working definition of smuggling considers legal goods, it is an informal economic activity as trade documents are falsified in order to circumvent taxes and/or tariffs.

corrupt society makes it easier, however, for traders to increase profits by turning to illegal means of trade. The impact that smuggling has on the official economy is substantial: it reduces GDP per capita and tax revenues. The estimated smuggling index shows that smuggling is less common in Western European countries but seems to be widespread in Latin America, Asia, and Africa.

This chapter is organized as follows. Section 3.1 presents a short theoretical motivation, a literature review, and the main hypotheses for the empirical analysis. Section 3.2 briefly introduces the empirical methodology. Section 3.3 discusses the causes of smuggling and how this activity is reflected in observable indicator variables. Section 3.4 presents the estimation results and the smuggling index. Section 3.5 concludes.

3.1 Theoretical Motivation

In most countries, tariffs (taxes on imported goods) or quotas (restrictions on the quantity of goods that can be imported) limit the ability of consumers to choose between foreign or domestic goods. Although financial and capital markets are becoming more integrated, a lot of countries have had foreign exchange market restrictions until recently which limited the ability of traders to exchange domestic into foreign currency units. These two types of restrictions in international markets make smuggling more attractive. On the one hand, tariffs and trade restrictions create incentives for traders to resort to illegal means of trade such as the smuggling of products or the misinvoicing of exports and imports. The reason is obvious: evading tariffs or circumventing state controls increases their profits. On the other hand, capital controls and foreign exchange market restrictions create parallel or black foreign exchange markets and a premium of the parallel over the official exchange rate. This so called black market premium (BMP) is a very attractive incentive for traders: underinvoicing exports, they can realize additional profits by supplying the unrecorded revenues on the black foreign exchange market. However, the existence of a BMP might also cause a disincentive for illegal trade. Illegal importers, when underinvoicing imports, have to acquire foreign exchange in the black market for the amount of imports not reported to authorities. In this case, an increasing BMP means increasing costs for illegal importers and thus reduces the incentive to smuggle [see, for example, De Macedo (1987)]. The next section briefly reviews the literature presenting further theoretical and empirical evidence on the determinants of smuggling.

3.1.1 Literature Review

The existing literature on smuggling consists of two strands. One strand demonstrates that tariffs and trade restrictions lead to smuggling and misinvoicing in international transactions. The other strand analyzes the welfare effects of smuggling. In their seminal paper, Bhagwati and Hansen (1973) refute the common argument that smuggling, by evading taxes on trade which are always sub-optimal, improves social welfare. Instead, they find a welfare reducing effect of smuggling when it coexists with legal trade. Introducing a third non-traded good, Sheikh (1974) shows that this coexistence could, however, be welfare improving. Pitt (1981), in an alternative model of smuggling, demonstrates that the welfare consequences of smuggling are ambiguous. In his model legal and illegal trade do coexist, although, in addition, firms trading illegally use legal trade to camouflage the smuggling. This model explains the coexistence of legal trade, illegal trade, and a price disparity defined as the difference between the domestic market price and the tax-inclusive world price of a commodity.

The theoretical literature focusing on the determinants of smuggling confirms the obvious incentives for smuggling, i.e., the existence of trade taxes and restrictions. Several influential contributions prove [see, for example, Bhagwati (1964); Bhagwati and Hansen (1973); Sheik (1974)] that traders, facing high trade taxes or trade restrictions, resort to illegal means of trade such as smuggling and the misinvoicing of exports and imports, i.e., the false declaration of trade documents. Pitt (1981) shows that tariffs cause a price disparity which in turn provides an incentive for illegal imports. Pitt (1984) analyzes the BMP as a determinant for smuggling. He shows that the black market equilibrates the supply of foreign exchange from illegal exports and its demand for illegal imports. Biswas and Marjit (2007) find that import (export) underinvoicing is negatively (positively) correlated with the BMP, since the foreign exchange from unreported transactions is acquired (sold) on the black market.

Martin and Panagariya (1984) and Norton (1988) focus on the cost of smuggling and examine the effect of law enforcement. They show that increasing the probability or cost of confiscation by intensifying law enforcement is a deterrent to smuggling and enables authorities to reduce the extent of smuggling. The reason for this is that smugglers try to maximize their net gain from smuggling, i.e., the difference between expected revenues and expected costs. The expected costs of smuggling arise from the risk of being caught and punished by authorities. Better enforcement increases the costs of smuggling making it less attractive for illegal traders. Thursby et al. (1991) investigate the consequences of law enforcement on smuggling for welfare. Because the market price in the presence of smuggling is below the price when all sales are legal, smuggling can improve welfare if the price effect outweighs its cost. Hence, reducing smuggling by increasing law enforcement might come at the cost of lower welfare for consumers.

Most empirical studies use the trade discrepancy which is calculated using balance of payments data as a proxy for smuggling. For example, if import figures reported by the importing country (adjusted for shipping and insurance costs) significantly exceed (fall short of) export figures reported by the exporting country, these studies conclude that import overinvoicing (underinvoicing) will take place in the importing country. Bhagwati (1964) analyzes trade between Turkey and its major trading partners and observes import underinvoicing for machinery and transport equipment. McDonald (1985) analyzes trade in 10 developing countries and finds that export underinvoicing is positively correlated with export taxes and the BMP. Pohit and Taneja (2003) analyze informal trade between India and Bangladesh and find that the potential reduction of transaction costs is a strong motive for smuggling. Fisman and Wei (2004) present strong empirical evidence that higher tax rates cause tax evasion in the form of trade misinvoicing between China and Hong Kong. Fisman and Wei (2007) study illicit trade in cultural properties in the United States. They provide empirical evidence that misinvoicing is highly correlated with the extent of corruption in the exporting country. Berger and Nitsch (2008) confirm this finding in an extended analysis. Beja (2008) estimates that China’s unrecorded trade amounted to $1.4 trillion between 2000 and 2005. While Farzanegan (2009) uses the MIMIC approach to estimate the size of smuggling in Iran, Chapter 4 studies the illegal trade of illegal and legal goods across the U.S.-Mexico border. Table 3.1 summarizes the most important findings of the empirical smuggling literature.

Table 3.1 Review of the Empirical Literature on Trade Misinvoicing [1)]

Study	Subject of investigation	Approach	Main findings
Bhagwati (1964)	import underinvoicing in Turkey	descriptive analysis of trade from Turkey to its major trading partners France, Germany, Italy, Netherlands, and the United States	import underinvoicing of transport equipment and machinery
McDonald (1985)	incentives for export misinvoicing	OLS regressions for 10 developing countries; dependent variable: trade discrepancies; independent variables: BMP and export taxes	weak statistical evidence that the BMP and export taxes explain variations in trade discrepancies
Pohit and Taneja (2003)	informal trade between India and Bangladesh	direct survey approach encompassing 100 traders in each country	anonymous trading transactions characterize informal trade; motivations are the quick realization of payments as well as less paper work and procedural delay
Fisman and Wei (2004)	tax evasion in Chinese imports from Hong Kong	analysis of 2,043 product categories at the six-digit classification level; dependent variable: trade discrepancies (evasion gap); independent variables: tax rate (sum of tariffs and the VAT), tax on similar products, tariff exemptions, interaction terms	one percent increase in the tax rate increases evasion by three percent; evasion takes place in two ways: firstly, trough the reclassification of high-taxed product categories to lower-taxed categories and secondly, through the underinvoicing of imports

(continued on next page)

Table 3.1 (cont.)

Fisman and Wei (2007)[2)]	illegal trade in cultural properties in the United States	worldwide unbalanced panel for 1996-2005; dependent variable: trade discrepancies in cultural objects and antiques; independent variables: corruption, GDP per capita	highly positive correlation between trade discrepancies and corruption, i.e., more corrupt countries are more likely to misreport data
Beja (2008)	trade misinvoicing in China	descriptive analysis of trade discrepancies	trade misinvoicing occurs mainly between Hong Kong and the United States
Berger and Nitsch (2008)	bilateral trade discrepancies at the 4-digit product level	OLS regressions for misinvoicing in bilateral trade in the United States, Germany, China, the United Kingdom, and Japan; dependent variable: trade discrepancies; independent variables: corruption, GDP per capita, distance measure	trade discrepancies differ widely across importers; export underinvoicing is prevalent in antiques and bulky products; strong positive correlation to corruption in the source country
Farzanegan (2009)	illegal trade in Iran	MIMIC approach and trade misinvoicing; causes: penalties, BMP, tariffs, GDP per capita, unemployment rate, openness, education, institutional quality; indicators: government revenues, import price index, petroleum consumption	illegal trade is related positively to tariffs and negatively to fines and the unemployment rate; trade openness and a higher BMP encourage illegal trade while better institutional quality reduces it; adverse effects on government revenues and the import price index; smuggling is about 13% of total trade in Iran

(continued on next page)

Table 3.1 (cont.)

Chapter 4	determinants and long-term trends of smuggling across the U.S.-Mexico border [3)]	MIMIC approach for export and import misinvoicing; causes: BMP, real exchange rate, taxes on income/profits, taxes on international trade; indicators: errors and omissions, export misinvoicing, import misinvoicing	export misinvoicing is positively correlated to a real peso depreciation and to Mexican taxes on income/profits; import misinvoicing is negatively correlated to a real peso depreciation and Mexican taxes on income/profits, positively to Mexican import tariffs; Mexico's accession to GATT (1987) and NAFTA (1994) had a major impact on the smuggling of legal goods

1) The structure of Table 3.1 is taken from Buehn and Eichler (2009, p. 331) with additional remarks.

2) A shorter version of this working paper has also been published in the series *Applied Economics* of the *American Economic Journal* [Fisman and Wei (2009)].

3) Chapter 4 also deals with the case of illegal goods smuggling across the U.S.-Mexico border. However, Table 3.1 just presents the results for the case of legal goods smuggling, i.e., trade misinvoicing, because only these are relevant for the cross-sectional analysis of (legal goods) smuggling presented in this chapter.

3.1.2 Main Hypotheses

Following the theoretical motivation at the beginning of Section 3.1 as well as the theoretical and empirical literature on smuggling, Section 3.1.2 now summarizes and formulates the hypotheses on the determinants of smuggling. Section 3.3.2 will discuss the indicators and presents the hypotheses regarding the effects of smuggling on these variables.

Facing high tariff rates and trade restrictions, traders often resort to illegal methods of trade, such as the smuggling of products or the misinvoicing of exports and imports. Liberalizing foreign trade and eliminating non-tariff barriers and similar red tapes reduce traders' incentives to smuggle. Also, stronger law enforcement makes smuggling less profitable, and therefore, less attractive. Of course, if smugglers are apprehended and their operations exposed, they can facilitate their activities by bribing officials to turn a blind eye [Brodie et al. (2000), p. 16]. More corrupt bureaucrats, in exchange for a "small" fee, make it thus relatively easy for smugglers to get around certain export restrictions and to avoid punishment when caught. To summarize, my main hypotheses are as follows:

(1) The higher the number of trade restrictions, the higher the level of smuggling, *ceteris paribus.*

(2) The higher the tariffs, the higher the level of smuggling, *ceteris paribus*.

(3) The stronger the law enforcement is in a society, the lower the level of smuggling, *ceteris paribus.*

(4) The more corrupt a society is, the easier it is to smuggle, *ceteris paribus*.

Because of the two contrasting types of evidence in the literature regarding the effect of the BMP on smuggling, I do not formulate a specific hypothesis about the relationship between the BMP and smuggling. Depending on what kind of smuggling dominates in the countries included in the sample, i.e., import or export smuggling, I expect to observe a negative or positive effect of an increasing BMP on smuggling.

3.2 Empirical Methodology

I use a MIMIC model to analyze the relationships between the informal economic activity of smuggling and its determinants. Formally, the MIMIC model consists of two parts: the structural equation model and the measurement model.[44] The structural equation model is given by:

$$\eta = \boldsymbol{\gamma}'\boldsymbol{x} + \varsigma , \tag{3.1}$$

where η is a latent variable, i.e., smuggling in this case, $\boldsymbol{x}' = \left(x_1, x_2, \ldots, x_q\right)'$ is a q vector; each x_i , $i = 1, \ldots, q$ is a potential cause of η. The vector $\boldsymbol{\gamma}' = \left(\gamma_1, \gamma_2, \ldots, \gamma_q\right)'$ is a q vector of coefficients in the structural model describing the "causal" relationships between smuggling and its causes. Thus, η is linearly determined by a set of exogenous causes. Since they only partially explain η, the error term ς represents the unexplained component. The variance of ς is abbreviated by ψ and $\boldsymbol{\Phi} = \mathrm{E}\left(\boldsymbol{xx}'\right)$ is the $(q \times q)$ covariance matrix of the causes.

The measurement model links smuggling to its indicators, i.e., smuggling is expressed in terms of observable variables assuming that the indicators chosen are sound measures of the latent variables. Formally, the measurement model is specified as:

$$\boldsymbol{y} = \boldsymbol{\lambda}\eta + \boldsymbol{\varepsilon} , \tag{3.2}$$

where $\boldsymbol{y}' = \left(y_1, y_2, \ldots, y_p\right)'$ is a p vector of several indicator variables of smuggling and $\boldsymbol{\varepsilon}' = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_p)'$ is a p vector of disturbances. Every ε_j , $j = 1, \ldots, p$ is a white noise error term. The $(p \times p)$ covariance matrix of the error terms is given by $\boldsymbol{\Theta}_\varepsilon = \mathrm{E}\left(\boldsymbol{\varepsilon\varepsilon}'\right)$. The single λ_j , $j = 1, \ldots, p$ in the p vector of regression coefficients $\boldsymbol{\lambda}$ represents the magnitude of the expected change of the respective indicator for a unit change of smuggling.

Substituting equation (3.1) into (3.2) yields a reduced form regression model where the indicators of smuggling $\boldsymbol{y}$ are the endogenous variables and the causes $\boldsymbol{x}$ the exogenous variables. This model can be written as:

---

[44] Section 3.2 briefly explains the MIMIC model. See Appendix A for details.

$$\boldsymbol{y} = \boldsymbol{\Pi x} + \boldsymbol{z}\,, \tag{3.3}$$

where $\boldsymbol{\Pi} = \boldsymbol{\lambda\gamma}'$ is a $(p \times q)$ matrix and $\boldsymbol{z} = \boldsymbol{\lambda}\varsigma + \boldsymbol{\varepsilon}$. The error term $\boldsymbol{z}$ in equation (3.3) is a p vector of a linear transformation of the white noise error terms ς and $\boldsymbol{\varepsilon}$ resulting from the structural and the measurement model, i.e., $\boldsymbol{z} \sim (\boldsymbol{0}, \boldsymbol{\Omega})$. The $(p \times p)$ covariance matrix $\boldsymbol{\Omega}$ is given as $\boldsymbol{\Omega} = \mathrm{Cov}(\boldsymbol{z}) = \mathrm{E}[(\boldsymbol{\lambda}\varsigma + \boldsymbol{\varepsilon})(\boldsymbol{\lambda}\varsigma + \boldsymbol{\varepsilon})'] = \boldsymbol{\lambda}\psi\boldsymbol{\lambda}' + \boldsymbol{\Theta}_{\varepsilon}$.

The model is estimated using the observed variables' variances and covariances to produce an estimate of the SEM's covariance matrix $\boldsymbol{\Sigma}(\boldsymbol{\theta})$, $\hat{\boldsymbol{\Sigma}} = \boldsymbol{\Sigma}(\hat{\boldsymbol{\theta}})$, that is as close as possible to the sample covariance matrix of the observed causes and indicators.[45] Identification and estimation of the model is however not possible without placing restrictions on certain model parameters. Among others, a restriction often imposed on the model is that one element of the vector $\boldsymbol{\lambda}$, i.e., one indicator, is set to an *a priori* value (often 1 or -1). In this way the researcher also establishes an interpretable scale for the latent variable [Bollen (1989), pp. 91, 183].[46]

The coefficients are estimated under the assumption that smuggling generates the pattern of the variances and covariances among the causes and indicators of smuggling. The first step in the MIMIC model estimation is to confirm the hypothesized relationships between smuggling and its causes and indicators. Once these relationships are identified and the parameters estimated, the estimation results are used to calculate scores η_k for each country $k = 1, \ldots, \text{and } 54$ in the sample. These scores make up an index that finally provides the ranking of countries with respect to the level of smuggling.

---

[45] $\boldsymbol{\theta}$ is a vector that contains the parameters of the model and $\boldsymbol{\Sigma}(\boldsymbol{\theta})$ is the covariance matrix as a function of $\boldsymbol{\theta}$ implying that each element of the covariance matrix is a function of one or more model parameters.

[46] The alternative of setting the variance of the unobservable variable η to one is often less convenient for economic interpretation and thus typically not used [Dell'Anno and Schneider (2009)].

3.3 Causes and Indicators of Smuggling

3.3.1 Causes of Smuggling

3.3.1.1 Tariff Rates and Trade Restrictions

The theoretical and empirical literature (see Section 3.1.1) shows that tariffs and trade restrictions encourage traders to resort to illegal ways of trade, such as the smuggling of products or the misinvoicing of exports and imports. To test hypotheses (1) and (2), that more trade restrictions and higher tariffs encourage smuggling, I use a (trade) restriction index and the tariff rate provided by Waczirag and Welch (2003). For the tariff rate a positive correlation to smuggling is expected. The trade restriction index is part of the KOF Index of Globalization [Dreher (2006)] and comprises hidden barriers, mean tariff rates, taxes on international trade (% of current revenues), and capital account restrictions. The trade restriction index ranges from 0 to 100 with higher values of it indicating a better situation for free trade in a country. In the following, I thus refer to this index as a lack of trade restrictions index and expect a negative correlation to smuggling, i.e., by liberalizing foreign trade and eliminating non-tariff barriers and similar red tapes, the incentives to smuggle should decrease. Another alternative testing hypothesis (1) is to use the Openness Index of Penn World Table 6.1 [PWT (2002)] (Openness). Some estimated MIMIC model specifications employ this index, instead of the lack of trade restriction index, as a robustness check. The expected correlation between Openness and smuggling is negative.

3.3.1.2 Rule of Law

The literature also shows that law enforcement is a deterrent to smuggling because smugglers maximize their net gain of smuggling, i.e., the difference between their expected revenues and costs, including fines and punishment costs. The higher the expected costs and the lower the expected net gain, the less profitable smuggling is. The expected costs of smuggling depend on the probability of being caught and punished by law enforcing authorities, i.e., on the efficiency of the monitoring system and efforts of the police.

The rule of law index from World Governance Indicators (WGI) [Kaufmann et al. (2007)] tests hypothesis (3), i.e., that stronger law enforcement reduces the level of smuggling. This index measures the quality of contract enforcement, the police, and the courts and is therefore an appropriate proxy for penalties and the perceived costs of smuggling. It ranges from -2.5 to 2.5 with higher values indicating a stronger police and judiciary system. I therefore expect a negative correlation between the rule of law index and smuggling.

3.3.1.3 Corruption

The previous empirical research shows (see Table 3.1) that smuggling is positively correlated to corruption: smuggling is easier in countries with corrupt bureaucrats who are more likely to abuse public power for private gains and allow smugglers, in exchange for a "small fee", an escape when caught.[47] The corruption index from the Index of Economic Freedom of the Heritage Foundation [Holmes et al. (2007)] tests hypothesis (4), i.e., that a more corrupt society has a higher level of smuggling. Alternatively, and as a robustness check, the measure of corruption from WGI [Kaufmann et al. (2007)] is used. Both corruption indices are defined in a way that higher values of the index indicate a lower level of corruption. Therefore I refer to each of them as a lack of corruption index and expect a negative correlation to smuggling.[48]

3.3.1.4 Black Market Premium

As explained above, a BMP can be an attractive incentive for smuggling. Smugglers can

---

[47] This is the most general definition of corruption commonly used in the literature. The World Bank provides a narrower one: "[corruption] distorts the rule of law, weakens a nation's institutional foundation, and severely affects the poor who are already the most disadvantaged members of the society." [Word Bank (2009a)].

[48] Corruption might also be an indicator of illegal trade in an economy. In fact, smuggling is in close connection with bribery and other forms of corruption. Increasing illegal trade may affect the perception of corruption in the society. To consider this issue, specification 10 uses the corruption index of the Economic Freedom Index of the Heritage Foundation [Holmes et al. (2007)] as an indicator.

underinvoice exports and supply the unrecorded revenues on the black foreign exchange market to realize additional profits. On the other hand, a high BMP means higher costs and thus reduces the incentive to smuggle. This is the case for illegal importers who have to acquire foreign exchange on the black market for the amount of imports not reported to authorities [De Macedo (1987)]. Because of the two contrasting types of evidence in the literature I do not formulate a specific hypothesis regarding the relationship between the BMP and smuggling. Depending on what kind of smuggling dominates in the sample, i.e., import/export smuggling, a negative/positive effect of an increasing BMP on smuggling may result.[49] The sources for the BMP are Easterly and Sewadeh (2002) and Reinhart and Rogoff (2004).

3.3.2 Indicators of Smuggling

3.3.2.1 Tax Revenues and GDP per capita

Smuggling involves both real and monetary costs. Real costs of smuggling arise from the transfer of production factors, such as capital and labor, to the informal part of the economy. Monetary costs arise from the evasion of taxes and tariffs. Tax revenues are the predominant source of government revenues in most countries. While developed countries rely more on direct taxes, such as taxes on income, profits, and capital gains, developing countries depend more on indirect taxes, including taxes on international trade [Askari (2006), p. 135]. This is due to the fact that administrative and implementation costs are lower for indirect taxes than for direct ones. It is thus easier for developing countries to levy taxes in an environment of lower institutional quality that often prevails in those countries.

Smugglers, by evading legal duties and taxes/tariffs, are an extra burden for a government's budget. Naturally, their activities reduce the government's ability

---

[49] The main analysis examines the effect of the BMP as a causal variable on smuggling. However, it can be argued that changes of the BMP are due to changes in smuggling transactions. Export smugglers supply unreported foreign exchange in the black market and import smugglers demand the foreign exchange in the black market for financing their operations. For this reason, specifications 8 and 9 use the BMP as an indicator of smuggling.

(especially in developing countries as they rely more on indirect taxes) to provide public goods. This may have harmful consequences because the provision of public goods increases productivity of firms in the official economy [see, for example, Loayza (1996); Johnson et al. (1997); Johnson et al. (1998)]. Thus, by wasting scarce resources, smuggling has a negative effect on tax revenues and thus on productivity, economic development, and growth.[50] My fifth hypothesis therefore is:

(5) The higher the level of smuggling, the lower the foreign trade tax revenues, economic development and growth, *ceteris paribus*.[51]

To test hypothesis (5) I use the GDP per capita and a measure of tax revenues as indicators.[52] The source of GDP per capita is PWT (2002) and the expected correlation between smuggling and the GDP per capita is negative. Unfortunately, international trade taxes data has lots of missing values, especially for developing countries. For this reason, I have decided, instead, to use a general measure of tax revenues, i.e., total tax revenues from the World Bank (2006). The expected correlation between smuggling and government's total tax revenues is negative.

3.3.2.2 Misinvoicing

Illegal foreign trade transactions are detectable using balance of payments data of partner country trade statistics. A reporting gap or trade data discrepancy occurs if the true value of exports or imports deviates from the amount of exports or imports reported to the authorities. Without smuggling (and measurement error) no systematic reporting gap

---

[50] See, for example, Norton (1988) and Deardorff and Stolper (1990).

[51] There is also another way to look at the relationship between smuggling and GDP per capita. If countries become richer, they can invest more in monitoring institutions and efficient and transparent trade procedures. Specification 10 tests this hypothesis using the GDP per capita as a cause. I expected a negative correlation between the GDP per capita and smuggling in specification 10.

[52] The indicator GDP per capita takes also into account a country's level of development and thus controls for the fact that smuggling in developing countries is often used to earn a sufficient income.

should exist. It is, therefore, common practice in the literature to use trade discrepancies in official trade data to uncover smuggling.[53] Following this approach and expecting a positive correlation between trade discrepancies and the level of smuggling the sixth and final hypothesis is:[54]

(6) The higher the level of smuggling, the higher the reporting gaps/trade discrepancies in the partner country trade statistics, *ceteris paribus*.

Hypothesis (6) is tested using official trade figures. The data is taken from the Directions of Trade Statistics (DOTS) database of the International Monetary Fund (IMF). In this database, the export figures are in FOB (Free on Board) and imports are in CIF (Cost, Insurance, and Freight) prices. The IMF (1993, p. 8) suggests multiplying the export figures by an adjustment factor of 1.1 in order to make them comparable to import figures that take into account transport and insurance costs. More precisely, the following two equations are used to calculate import and export misinvoicing:

$$\text{Export misinvoicing} = X_i - \left(X_c \cdot \text{CIF factor}\right), \tag{3.4}$$

$$\text{Import misinvoicing} = M_c - \left(M_i \cdot \text{CIF factor}\right). \tag{3.5}$$

The variables are defined as follows: X_i are imports from a specific country as recorded by industrial economies (or rest of the world), X_c are exports as reported by a specific country to industrial economies (or rest of the world), M_c are imports as reported by a specific country from industrial economies (or rest of the world), and M_i are exports of industrial economies (or rest of the world) to a specific country.

While positive values in equation (3.4) refer to underinvoicing of exports, negative ones refer to overinvoicing of exports. In equation (3.5), positive values refer to

[53] For recent empirical applications, see Fisman and Wei (2004; 2007), Berger and Nitsch (2008), Farzanegan (2009), and Buehn and Eichler (2009).

[54] I use two similar control groups, namely industrialized economies and the rest of the world, to calculate trade discrepancies. Under the assumption – as common in the smuggling literature – that trade data reported by industrialized countries are accurate, discrepancies in trade figures point to trade misinvoicing.

overinvoicing of imports and negative ones to import underinvoicing. The total misinvoicing is the sum of the absolute amount of import and export misinvoicing. The definitions and sources of all variables are summarized in Table C.1 in Appendix C.

3.3.3 The Multiple Indicators Multiple Causes Model of Smuggling

To summarize, the MIMIC model of smuggling estimated in this chapter uses the following causal variables: the lack of trade restrictions index, tariffs, the lack of corruption index, the BMP, and the rule of law. The precise specification of the structural equation (3.1) in the empirical model is:

$$\left[\text{Smuggling}\right] = \left[\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5\right] \begin{bmatrix} \text{Lack of trade restrictions} \\ \text{Tariffs} \\ \text{Lack of corruption} \\ \text{BMP} \\ \text{Rule of law} \end{bmatrix} + \varsigma \,. \tag{3.6}$$

The measurement model uses the GDP per capita, the trade discrepancy, and tax revenues as indicators. The measurement equation (3.2) of the MIMIC model is thus given by:

$$\begin{bmatrix} \text{GDP per capita} \\ \text{Trade discrepancy} \\ \text{Tax revenues} \end{bmatrix} = \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \end{bmatrix} \left[\text{Smuggling}\right] + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{bmatrix}. \tag{3.7}$$

Figure 3.1 shows the path diagram. The small squares attached to the arrows indicate the expected signs in the empirical analysis following hypotheses (1)-(6).

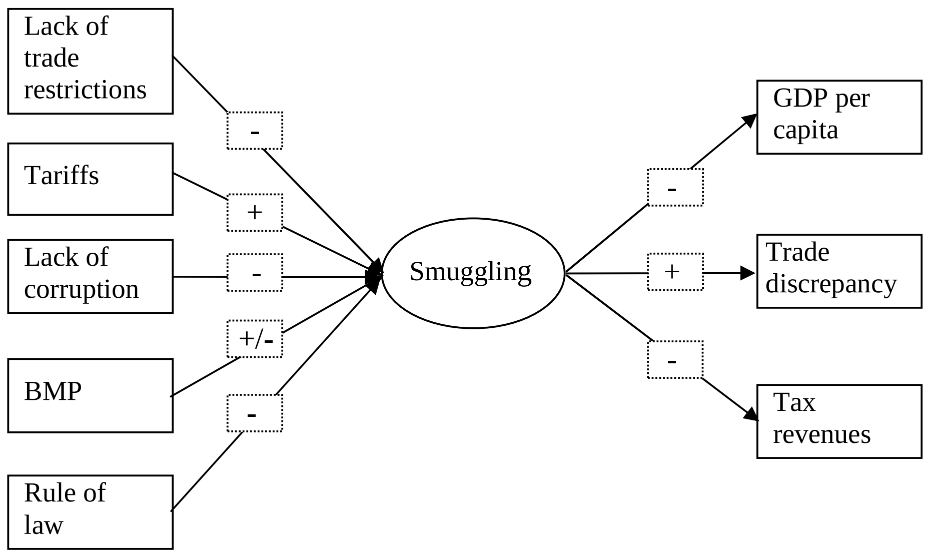

Figure 3.1 Path Diagram of the Smuggling MIMIC Model

3.4 Results

3.4.1 Estimation Results

Table 3.2 presents the estimation results of 10 different specifications of the MIMIC model for smuggling applying the maximum likelihood estimator.[55] Specification 1 serves as a baseline specification including the main causes of smuggling. The other nine specifications use different data sources and vary the set of causes and/or indicators in order to demonstrate the robustness of the results. The model is estimated over the period 1991-1999. I use the variables' average over the period for two reasons: data availability and to control for business cycle effects.[56] Table 3.2 reports standardized coefficients to

[55] All calculations have been carried out with LISREL® version 8.80. Applying the generalized least squares (GLS) estimator largely confirms the estimation results.

[56] The time period is limited to the cut-off of 1999 because of the unavailability of information on some key variables such as the BMP beyond this period. Moreover, some of the data – the tariff rate for example – is only available as averages over the estimation period.

highlight the relative effects of the causes on smuggling.[57] These coefficients indicate – *ceteris paribus* – the response in standard deviation units of smuggling for a one standard deviation change in an explanatory, causal variable [Bollen (1989), pp. 123-126]. The following explains the estimation results starting with the causes of smuggling.

[57] The standardized coefficients are calculated as $\hat{\gamma}_{ji}^{s} = \hat{\gamma}_{ji}\sqrt{\hat{\sigma}_{ii} / \hat{\sigma}_{jj}}$. Thereby the superscript s indicates the standardized coefficient; i denotes the causal and j the latent variable. $\hat{\sigma}_{ii}$ and $\hat{\sigma}_{jj}$ are the predicted variances of the ith and jth variable, respectively [Bollen (1989), p. 124].

Table 3.2 Estimations Results (Standardized Coefficients)

Specification	1	2	3	4	5	6	7	8	9	10
Causes										
Lack of trade restrictions index	-0.15*	-0.15*	-0.18*	-0.18*		-0.15*	-0.17*	-0.16*		
	(1.69)	(1.71)	(1.90)	(1.88)		(1.68)	(1.76)	(1.71)		
Tariffs	0.12**	0.12*	0.09	0.12*	0.18***	0.12*	0.11*	0.11*	0.18***	0.02
	(1.96)	(1.95)	(1.47)	(1.94)	(3.36)	(1.85)	(1.76)	(1.81)	(3.19)	(0.25)
Trade openness					0.04	0.03			0.04	-0.09
					(0.77)	(0.57)			(0.76)	(1.11)
Lack of corruption index	-0.21***	-0.21***	-0.26***	-0.30[3)]	-0.23**	-0.25***	-0.25**	-0.23***	-0.25***	
	(2.55)	(2.58)	(3.21)	(1.54)	(2.73)	(3.20)	(3.15)	(2.90)	(3.09)	
BMP	-0.10**	-0.10**	-0.05[2)]	-0.10**	-0.10**					-0.14*
	(2.00)	(1.98)	(1.08)	(1.96)	(2.06)					(1.68)
Rule of law	-0.54***	-0.54***	-0.56***	-0.51***	-0.74***	-0.56***	-0.56***	-0.59***	-0.69***	-0.36*
	(6.10)	(6.08)	(5.66)	(2.39)	(8.36)	(5.65)	(5.60)	(5.89)	(8.34)	(1.67)
GDP per capita										-0.66***
										(2.94)
Indicators										
GDP per capita (fixed)	-0.95	-0.95	-0.95	-0.95	-0.95	-0.95	-0.95	-0.95	-0.95	
Misinvoicing	0.50***	0.53[1)],***	0.52***	0.51***	0.49***	0.51***	0.51***	0.51***	0.50***	0.52***
	(4.17)	(4.45)	(4.28)	(3.97)	(4.03)	(4.27)	(4.27)	(4.25)	(4.11)	(4.13)
Tax revenues	-0.45***	-0.45***	-0.45***	-0.43***	-0.44***	-0.42***	-0.42***	-0.42***	-0.41***	-0.45***
	(3.64)	(3.64)	(3.39)	(3.48)	(3.55)	(3.35)	(3.37)	(3.35)	(3.25)	(3.50)

(continued on next page)

Table 3.2 (cont.)

BMP								0.33^{***}	0.34^{***}	
								(2.57)	(2.60)	
Lack of corruption index (fixed)										-0.86
Goodness-of-fit statistics										
Observations	54	54	54	54	54	54	54	54	54	54
Degrees of freedom	21	21	21	21	21	21	15	21	21	22
Chi-square	20.11	19.41	11.95	21.20	19.52	12.64	11.88	29.68	29.20	17.09
(*p*-value)	(0.51)	(0.56)	(0.94)	(0.45)	(0.55)	(0.92)	(0.69)	(0.09)	(0.11)	(0.76)
RMSEA	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.09	0.09	0.00

1) Misinvoicing with control group rest of the world.

2) BMP from Reinhart and Rogoff (2004).

3) Corruption index of WGI.

Note: *** Significance at the 1% level. ** Significance at the 5% level. * Significance at the 10% level. Absolute *z*-statistics in parentheses. The degrees of freedom are determined by 0.5 (p + q) (p + q + 1) – t; with p = number of indicators; q = number of causes; t = the number for free parameters. If the model fits the data perfectly and the parameter values are known, the sample covariance matrix equals the covariance matrix implied by the model. The null hypothesis of perfect fit corresponds to a *p*-value of 1. The root mean squared error of approximation (RMSEA) measures the model's fit based on the difference between the estimated and the actual covariance matrix. RMSEA values smaller than 0.05 indicate a good fit [Browne and Cudeck (1993)].

The lack of trade restrictions index has a negative effect on smuggling in all specifications. Higher values of this index indicate fewer trade restrictions. The observed negative relationship between the lack of trade restriction index and smuggling means that fewer trade restrictions will, as expected, lower the level of smuggling. With respect to the average tariffs on imports, the results show that tariffs are positively correlated to smuggling. This relationship is statistically significant in all estimated specifications, except for specification 3. That is, the higher tariffs the more smuggling takes place, *ceteris paribus*. For example, in specification 1, a one standard deviation increase in average tariffs increases smuggling by 0.12 standard deviations.

Trade openness enters in specifications 5, 6, 9, and 10. Its effect on smuggling is not conclusive. On the one hand, one can argue that more openness decreases the incentive for illegal trade, but on the other hand, as Pitt (1981) mentions, legal trade is used by illegal traders to camouflage their illegal activities.[58] However, neither the positive correlation of this variable to smuggling in specifications 5, 6, and 9 nor the negative correlation in specification 10 is statistically significant. In summary, the statistical evidence confirms hypotheses (1) and (2) that more trade restrictions and higher tariffs increase the level of smuggling. Openness does not seem to be an important determinant of smuggling.

All specifications demonstrate a negative and strongly significant impact of the rule of law index on smuggling. This index is used to proxy fine rates on smuggling and the quality of the police and the courts in a country as explained in Section 3.2. A one standard deviation increase in the rule of law index reduces smuggling by more than 0.50 standard deviations. The statistical evidence thus confirms hypothesis (3). Given the large standardized coefficient of the rule of law index it seems that it is the ability to circumvent administrative rules, rather than high tariffs and trade restrictions that determine the level of smuggling.

The lack of corruption index shows a consistent and negative effect on smuggling. This effect is statistically significant in all specifications, except for specification 4

[58] The causal variable Trade Openness also controls for the fact that small countries are relatively specialized in production, thus trade more, and have a higher degree of trade openness. Following Pitt (1981), this may also explain a positive correlation between Trade Openness and the level of smuggling.

which uses the corruption index from WGI [Kaufmann et al. (2007)].[59] A one standard deviation increase in the lack of corruption index decreases the smuggling by more than 0.20 standard deviations. The statistical evidence confirms hypothesis (4) that higher levels of corruption make smuggling easier, *ceteris paribus*.

Finally, the BMP shows a stable and significant negative effect on smuggling. This case is highly possible for import smuggling, in particular import underinvoicing, where smugglers must finance their illegal imports from the black market of exchange. An increasing premium functions like an extra burden for this group of illegal traders.[60]

Specification 10 uses the GDP per capita as a cause to test the hypothesis that richer countries have better monitoring institutions as well as efficient and transparent trade procedures, which then reduce smuggling. The empirical evidence supports this hypothesis. The observed correlation between GDP per capita and smuggling is significant negative. That is, the more developed a country the lower the level of smuggling, *ceteris paribus*.

The results for the indicators are fairly consistent across different specifications. As explained in Section 3.2, one of the coefficients of the indicators has to be normalized. I selected GDP per capita and set the coefficient of this variable to -1.[61] The reason is that smuggling canalizes resources of an economy from the productive, formal part to the grabby, informal part, hindering the entire use of the economy's potential capacity reducing economic growth and development.[62] The second indicator of smuggling is the trade discrepancy variable.[63] The standardized coefficients in the various specifications

---

[59] Recall from Section 3.2 that for both indices lower index values imply a higher level of corruption.

[60] Specification 3 making use of the BMP from Reinhart and Rogoff (2004) does however not confirm this effect at any convenient significance level.

[61] The coefficient of -1 corresponds to an estimated standardized coefficient of -0.95.

[62] The choice of the indicator which is chosen to establish the scale of the latent variable does not affect the estimated coefficients because the maximum likelihood estimator is scale invariant [Swaminathan and Algina (1978)]. Typically, one selects the indicator that loads most on the unobservable variable, i.e., GDP per capita in the MIMIC model of smuggling.

[63] Specification 2 demonstrates the robustness of the result using the rest of the world instead of the industrialized countries as control group for trade misinvoicing.

show that a one standard deviation increase in smuggling increases misinvoicing by approximately 0.50 standard deviations, *ceteris paribus*. The empirical results confirm hypothesis (6) that trade discrepancies, calculated as trade misinvoicing, are positively correlated to smuggling.

The last indicator is tax revenues. Smuggling is, because of the evasion of taxes and tariffs, an extra burden for government budgets. Increasing smuggling by one standard deviation reduces tax revenues by about 0.40 standard deviations. Again, this effect is stable and significant across different specifications and supports hypothesis (5).

While the main analysis examines the effect of the BMP as a causal variable on smuggling, specifications 8 and 9 use the BMP as an indicator in order to examine the argument that changes of the BMP can be due to changes in smuggling transactions.[64] Both specifications show a positive, statistically significant correlation between smuggling and the BMP. This positive correlation can occur in the case of import misinvoicing. The higher the level of smuggling the higher the BMP, *ceteris paribus*, because illegal importers have to acquire foreign exchange on the black market for imports not reported to authorities. A higher level of import smuggling increases the price for black foreign exchange.

All estimated specifications show satisfactory goodness-of-fit statistics. The main statistics such as the chi-square and the RMSEA are given in Table 3.2, while additional goodness-of-fit statistics are presented in Table C.2 in Appendix C.[65] The validity of the estimated MIMIC model is acceptable because the statistically significant determinants of smuggling have the theoretically expected signs and the goodness-of-fit statistics point to a good overall fit. The model is thus suitable to estimate an index of smuggling for the 54 countries in the sample. The next section presents this index.

3.4.2 The Smuggling Index

The smuggling index is calculated by applying the coefficients of the significant causal variables to the corresponding observed variables. For the numerical example of the baseline specification 1 the smuggling index is given as:

---

[64] See also footnote 48.

[65] For a comprehensive discussion of these statistics, see Section A.3 in Appendix A.

$$\text{Smuggling} = 0.15 \cdot x_1 - 0.12 \cdot x_2 - 0.21 \cdot x_3 - 0.10 \cdot x_4 - 0.54 \cdot x_5 \text{ .}^{66} \quad (3.8)$$

The higher the amount of the smuggling index the higher is the level of smuggling over the period of 1991-1999 in a particular country. In addition to specification 1, the smuggling index is also calculated using specifications 5 and 10 to check for the robustness of the calculated index.[67] All three indices are presented in Table 3.3. The ranking of countries in the first column corresponds to specification 1 in column two, while the third and fourth columns give the countries' ranking according to specification 5 and 10.

Table 3.3 Ranking of Countries 1991-1999

Country	Specification 1	Specification 5	Specification 10
	Ranking (index value)	Ranking (index value)	Ranking (index value)
Switzerland	1 (-1.574)	1 (-1.709)	1 (-1.984)
Finland	2 (-1.453)	2 (-1.585)	12 (-1.242)
Sweden	3 (-1.429)	3 (-1.559)	7 (-1.452)
Singapore	4 (-1.413)	5 (-1.537)	3 (-1.609)
Austria	5 (-1.413)	4 (-1.544)	2 (-1.629)
Netherlands	6 (-1.404)	6 (-1.534)	4 (-1.520)
Iceland	7 (-1.324)	7 (-1.447)	8 (-1.437)
Canada	8 (-1.308)	8 (-1.437)	6 (-1.507)
Belgium	9 (-1.190)	9 (-1.312)	11 (-1.317)
Australia	10 (-1.175)	10 (-1.285)	5 (-1.508)
France	11 (-1.160)	11 (-1.282)	10 (-1.331)

(continued on next page)

[66] x_1, x_2, x_3, x_4, and x_5 represent the lack of trade restriction index, tariffs, the lack of corruption index, the BMP, and the rule of law, respectively.

[67] These two specifications are selected because specification 5 includes Trade Openness capturing the smuggling opportunities [Pitt (1981)] and specification 10 uses the lack of corruption index as an indicator of smuggling testing the relationship between illegal trade and the perception of corruption in a society.

Table 3.3 (cont.)

Japan	12 (-1.1)	12 (-1.225)	9 (-1.426)
Spain	13 (-0.875)	14 (-0.943)	14 (-0.828)
Portugal	14 (-0.874)	13 (-0.951)	16 (-0.641)
Italy	15 (-0.729)	15 (-0.815)	13 (-0.995)
Estonia	16 (-0.557)	16 (-0.507)	21 (-0.045)
Greece	17 (-0.436)	17 (-0.476)	18 (-0.285)
Republic of Korea	18 (-0.337)	18 (-0.412)	20 (-0.242)
Slovenia	19 (-0.304)	20 (-0.302)	17 (-0.582)
Malaysia	20 (-0.263)	19 (-0.330)	25 (0.086)
Uruguay	21 (-0.175)	21 (-0.214)	23 (0.042)
Cyprus	22 (-0.151)	22 (-0.187)	15 (-0.650)
Costa Rica	23 (-0.116)	24 (-0.135)	26 (0.210)
Mauritius	24 (-0.109)	23 (-0.164)	19 (-0.259)
Trinidad and Tobago	25 (0.028)	25 (-0.001)	22 (0.018)
Latvia	26 (0.097)	26 (0.118)	28 (0.334)
Croatia	27 (0.199)	27 (0.338)	27 (0.310)
Jordan	28 (0.331)	28 (0.339)	33 (0.581)
Jamaica	29 (0.388)	30 (0.429)	37 (0.712)
Panama	30 (0.389)	29 (0.364)	31 (0.541)
Tunisia	31 (0.423)	31 (0.450)	32 (0.542)
Mexico	32 (0.483)	32 (0.474)	35 (0.635)
Turkey	33 (0.499)	34 (0.512)	34 (0.621)
Algeria	34 (0.512)	52 (1.228)	24 (0.045)
Ghana	35 (0.539)	33 (0.499)	51 (1.104)
Brazil	36 (0.544)	36 (0.601)	30 (0.494)
Egypt, Arab Rep.	37 (0.559)	35 (0.587)	36 (0.672)
Bulgaria	38 (0.609)	37 (0.646)	29 (0.485)
Sri Lanka	39 (0.639)	38 (0.657)	41 (0.782)
Philippines	40 (0.678)	39 (0.706)	43 (0.795)

(continued on next page)

Table 3.3 (cont.)

Guatemala	41 (0.781)	40 (0.796)	49 (1.057)
China	42 (0.784)	44 (0.939)	39 (0.760)
Zambia	43 (0.797)	41 (0.821)	52 (1.163)
Ecuador	44 (0.837)	42 (0.896)	44 (0.841)
Peru	45 (0.850)	43 (0.908)	46 (0.928)
Ukraine	46 (0.855)	45 (0.958)	42 (0.787)
Nicaragua	47 (0.910)	46 (0.996)	47 (0.932)
Dominican Republic	48 (0.919)	47 (0.999)	38 (0.744)
Indonesia	49 (1.005)	48 (1.081)	48 (0.941)
Paraguay	50 (1.023)	50 (1.121)	45 (0.847)
India	51 (1.029)	49 (1.090)	40 (0.768)
Kenya	52 (1.125)	51 (1.183)	53 (1.273)
Pakistan	53 (1.407)	53 (1.457)	50 (1.072)
Cameroon	54 (1.627)	54 (1.698)	54 (1.360)

The ranking of the countries is not surprising; developing countries are typically reported as countries with higher levels of smuggling. According to specification 1, the country hit least by smuggling is Switzerland, followed by Finland, Sweden, Singapore, and Austria. With the exception of Singapore, Canada, Australia, and Japan, only Western European countries are among the top 15. At the bottom of the scale are Cameroon, Pakistan, Kenya, India, and Paraguay. Compared with the top, the bottom is more heterogeneous: among the 15 countries hit most by smuggling are 6 Latin American and Caribbean countries, 5 Asian countries, 3 African ones, and one country from Eastern Europe. A comparison of the three indices shows that the results are robust although some differences in the ranking exist. For example, Austria has the 5th lowest level of smuggling according to specification 1 but ranks 4th and 2nd according to specifications 5 and 10, respectively. It can also be seen that for some countries, for example Finland and Sweden, the ranking according to specification 10 is somewhat different compared to specifications 1 and 5. This might have to do with the different set of causes and indicators in specification 10. Specifications 1 and 5 use the GDP per capita as a causal variable and the corruption index of the Heritage Foundation as an indicator. Specification 10 however uses the GDP per capita as an indicator and the corruption index as a cause. Both variables, i.e., corruption and the GDP per capita are not perfectly interchangeable although almost all available evidence suggests that corruption varies strongly inverse with development [see, for example, Mauro (1995); Paldam (2003)]. Minor differences in the raking between specifications 1/5 and 10 are therefore not surprising. Moreover, the estimated standardized coefficients demonstrate that GDP per capita is the slightly better indicator. The selected three MIMIC model specifications yield nevertheless a similar outcome with respect to the ranking of countries. The correlation coefficients between the three indices are: 0.9948 (specification 1 and 5), 0.9575 (specification 5 and 10), and 0.9688 (specification 1 and 10). In order to test whether the correlation coefficients are significantly different from zero, I use Fisher's variance stabilizing transformation $Z = 0.5\ln\left[(1+r)/(1-r)\right]$, where r is the correlation coefficient. The Z-statistic is approximately normally distributed with a mean of $\mathrm{E}(Z) = 0.5\ln\left[(1+\rho)/1-\rho\right]$ and a variance of $\mathrm{V}(Z) = 1/(N-3)$, where ρ is the null, and N is the number of observations [see Kendall and Stuart (1973)]. Under $\rho = 0$ the test statistic is $\tilde{Z} = 0.5\ln\left[(1+r)/(1-r)\right]\sqrt{N-3}$. For the two-sided test, the rejection region is $\left|\tilde{Z}\right| > 2.5758,\ 1.9600,\ 1.6449$ at the 1%, 5%, and 10% level of significance, respectively. For the sample ($N = 54$) I can reject the null of a zero correlation coefficient at the 1%level of significance for each correlation pair.

Table 3.4 shows averages of the smuggling index for different regions/country groups in order to develop a better understanding of the regional differences in smuggling.[68] According to specification 1, smuggling is, by far lowest in the high-income countries of the OECD, with an average index value of -1.167. The ranking for the other regions is as follows: Eastern Europe (0.150), Asia (0.243), Middle East and North Africa (MENA) (0.362), Latin America and the Caribbean (0.528), and finally Africa (0.796). Within the high-income countries of the OECD smuggling is the biggest problem in Greece followed by Italy and Portugal. According to the smuggling index, the worst countries in

---

[68] The classification/grouping of countries is based on the World Bank's definition [World Bank (2009b)].

Eastern Europe are the Ukraine and Bulgaria. While Pakistan and India show the highest level of smuggling in Asia, Egypt and Algeria rank last in the MENA region. Uruguay, Costa Rica, and Trinidad and Tobago perform best, while Paraguay, the Dominican Republic, and Nicaragua perform worst in Latin America and the Caribbean. Although only a few African countries are in the sample, this region seems on average to be the most affected by smuggling. Within this region, smuggling is the biggest problem in Cameroon and Kenya.

Table 3.4 Ranking of Countries According to Geographical Regions

Country	Specification 1	Specification 5	Specification 10
	Ranking (index value)	Ranking (index value)	Ranking (index value)
High-income OECD countries			
Switzerland	1 (-1.574)	1 (-1.709)	1 (-1.984)
Finland	2 (-1.453)	2 (-1.585)	12 (-1.242)
Sweden	3 (-1.429)	3 (-1.559)	7 (-1.452)
Austria	5 (-1.413)	4 (-1.544)	2 (-1.629)
Netherlands	6 (-1.404)	6 (-1.534)	4 (-1.520)
Iceland	7 (-1.324)	7 (-1.447)	8 (-1.437)
Canada	8 (-1.308)	8 (-1.437)	6 (-1.507)
Belgium	9 (-1.190)	9 (-1.312)	11 (-1.317)
Australia	10 (-1.175)	10 (-1.285)	5 (-1.508)
France	11 (-1.160)	11 (-1.282)	10 (-1.331)
Spain	13 (-0.875)	14 (-0.943)	14 (-0.828)
Portugal	14 (-0.874)	13 (-0.951)	16 (-0.641)
Italy	15 (-0.729)	15 (-0.815)	13 (-0.995)
Greece	17 (-0.436)	17 (-0.476)	18 (-0.285)
Average	*-1.167*	*-1.227*	*-1.263*

(continued on next page)

Table 3.4 (cont.)

Eastern Europe			
Estonia	16 (-0.557)	16 (-0.507)	21 (-0.045)
Slovenia	19 (-0.304)	20 (-0.302)	17 (-0.582)
Latvia	26 (0.097)	26 (0.118)	28 (0.334)
Croatia	27 (0.199)	27 (0.338)	27 (0.310)
Bulgaria	38 (0.609)	37 (0.646)	29 (0.485)
Ukraine	46 (0.855)	45 (0.958)	42 (0.787)
Average	*0.150*	*0.209*	*0.215*
Asia			
Singapore	4 (-1.413)	5 (-1.537)	3 (-1.609)
Japan	12 (-1.1)	12 (-1.225)	9 (-1.426)
Republic of Korea	18 (-0.337)	18 (-0.412)	20 (-0.242)
Malaysia	20 (-0.263)	19 (-0.330)	25 (0.086)
Sri Lanka	39 (0.639)	38 (0.657)	41 (0.782)
Philippines	40 (0.678)	39 (0.706)	43 (0.795)
China	42 (0.784)	44 (0.939)	39 (0.760)
Indonesia	49 (1.005)	48 (1.081)	48 (0.941)
India	51 (1.029)	49 (1.090)	40 (0.768)
Pakistan	53 (1.407)	53 (1.457)	50 (1.072)
Average	*0.243*	*0.243*	*0.193*
MENA			
Cyprus	22 (-0.151)	22 (-0.187)	15 (-0.650)
Jordan	28 (0.331)	28 (0.339)	33 (0.581)
Tunisia	31 (0.423)	31 (0.450)	32 (0.542)
Turkey	33 (0.499)	34 (0.512)	34 (0.621)
Algeria	34 (0.512)	52 (1.228)	24 (0.045)
Egypt, Arab Republic	37 (0.559)	35 (0.587)	36 (0.672)
Average	*0.362*	*0.488*	*0.301*

(continued on next page)

Table 3.4 (cont.)

Latin America and the Caribbean			
Uruguay	21 (-0.175)	21 (-0.214)	23 (0.042)
Costa Rica	23 (-0.116)	24 (-0.135)	26 (0.210)
Trinidad and Tobago	25 (0.028)	25 (-0.001)	22 (0.018)
Jamaica	29 (0.388)	30 (0.429)	37 (0.712)
Panama	30 (0.389)	29 (0.364)	31 (0.541)
Mexico	32 (0.483)	32 (0.474)	35 (0.635)
Brazil	36 (0.544)	36 (0.601)	30 (0.494)
Guatemala	41 (0.781)	40 (0.796)	49 (1.057)
Ecuador	44 (0.837)	42 (0.896)	44 (0.841)
Peru	45 (0.850)	43 (0.908)	46 (0.928)
Nicaragua	47 (0.910)	46 (0.996)	47 (0.932)
Dominican Republic	48 (0.919)	47 (0.999)	38 (0.744)
Paraguay	50 (1.023)	50 (1.121)	45 (0.847)
Average	*0.528*	*0.556*	*0.615*
Africa			
Mauritius	24 (-0.109)	23 (-0.164)	19 (-0.259)
Ghana	35 (0.539)	33 (0.499)	51 (1.104)
Zambia	43 (0.797)	41 (0.821)	52 (1.163)
Kenya	52 (1.125)	51 (1.183)	53 (1.273)
Cameroon	54 (1.627)	54 (1.698)	54 (1.360)
Average	*0.796*	*0.807*	*0.928*

As argued above and also demonstrated by others [see, for example, Fisman and Wei (2007); Berger and Nitsch (2008)], smuggling often involves other types of criminal and corrupt activities. Figure 3.2 also illustrates the strong positive correlation between smuggling and corruption using specification 1 of the smuggling index calculated in this chapter and the 1999 corruption perception index of Transparency International (1999) (henceforth, CPI99). Because higher levels of the CPI99 represent a lower level of corruption in a particular country, its reverse is used. The reverse of the CPI99, displayed on the horizontal axis, ranges from 0 to 9 while the estimated index of smuggling is displayed on the vertical axis. Figure 3.2 shows that countries such as Switzerland or Australia have low levels of corruption and smuggling. They are among the best performing countries according to the smuggling index. On the contrary, countries with very high levels of corruption such as Cameroon, Kenya, and Pakistan also show very high levels of smuggling. Some exceptions should be noted. Belgium, for example, has a much lower level of smuggling compared to Slovenia or Estonia but performs worse with respect to corruption. The same holds true, for example in the case of Croatia, where corruption is as prolific as it is in the most corrupt countries but smuggling is a smaller problem. Nevertheless, despite few exceptions, Figure 3.2 clearly demonstrates the positive relationship between smuggling and corruption.

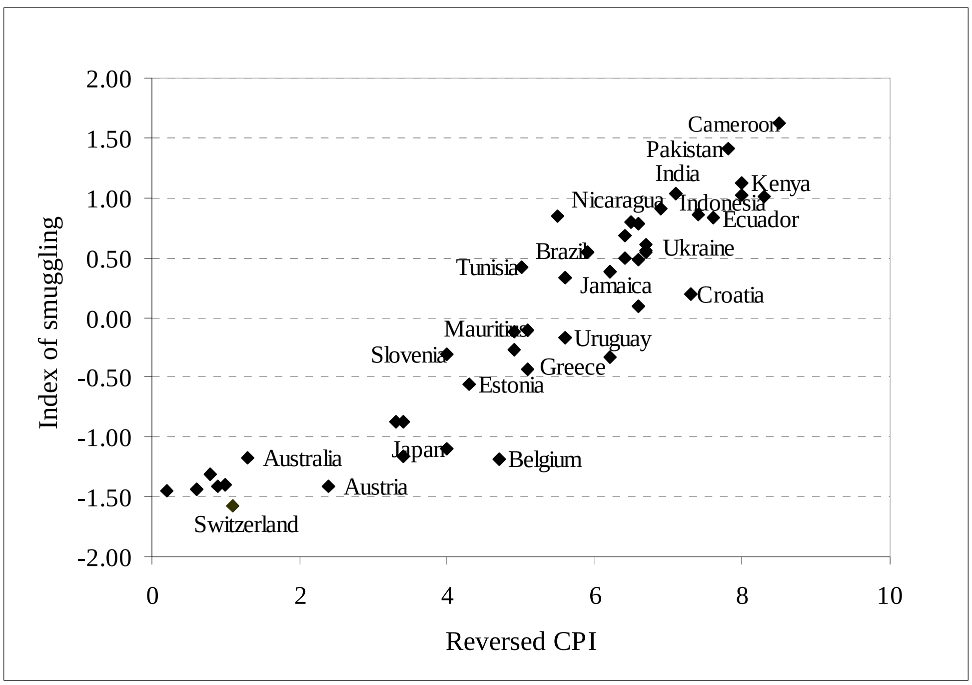

Figure 3.2 Relationship Between Smuggling and Corruption

3.5 Summary and Conclusion

The smuggling index presented in this chapter provides the first ranking of smuggling around the world during the 1990s. While previous research mostly employs trade discrepancies to uncover smuggling, this chapter uses a structural model that simultaneously deals with the causes and indicators of smuggling within a unified framework for 54 countries. This approach has two important advantages. Firstly, in contrast to existing empirical studies, which use narrow concepts as a proxy of smuggling, the MIMIC approach uses its most important determinants simultaneously. The empirical analysis shows a highly statistically significant influence of the rule of law and of the level of corruption on smuggling. Trade restrictions and tariffs provide incentives for traders to engage in smuggling. The magnitude of the standardized coefficients indicates that it is the inferiority of institutions, rather than high tariffs and trade restrictions, which drive smuggling, although the latter are also important determinants. The second advantage of the MIMIC approach is that the ranking one retrieves across countries is tied to the causal variables that were used to estimate the model. As such, the model produces a cardinal index of smuggling and considers the common criticisms aimed at perception based indices. According to the index of smuggling presented in this chapter, Switzerland, the Scandinavian countries Sweden and Finland, the Netherlands, Singapore, and Austria are among the countries with the lowest level of smuggling. Paraguay, India, Kenya, Pakistan, and Cameroon have the highest level.

Of course, one may argue that the estimated model does not capture the extent of smuggling. There are two ways to test for the validity of a structural model. Firstly, it is necessary to examine the fit of the model. Secondly, variables that determine smuggling from a theoretical point of view should have the expected impact [Dell'Anno (2007)].[69] I have dealt with these two validity tests above: all variables show the theoretically expected correlation to smuggling and the various estimated specifications show satisfactory goodness-of-fit statistics.

Some policy conclusions may be drawn. Countries that endeavor to reduce the size of smuggling can strengthen their institutions. Increasing the rule of law and reducing corruption are suitable policies to get control of smuggling. Reducing trade barriers such as tariffs and quotas is another possibility. Although even the countries most committed to free trade still have restrictions, the situation has changed for the better since the mid 1990s: average tariffs have become lower and are continuing to decrease.

---

[69] For a detailed discussion on validity and reliability with respect to structural equations models see, for example, Bollen (1989, pp. 184-223).

The smuggling index based on the MIMIC approach is likely to be of interest for different user groups. One such group is the policy-based academic community which evaluates the consequences of smuggling. For various non-governmental organizations such as the Institute for New Democracies that base their decisions on the institutional environment of a particular country, the MIMIC approach would also be useful. Calculating an index of smuggling, as outlined here for different time periods, may help non-governmental organizations to monitor how smuggling (being a potential indicator of the general institutional quality in a country) varies over time. Since the MIMIC approach is based on measurable time variant causes and indicators, the performance of a country in controlling smuggling can be measured.

Clearly, the MIMIC approach to smuggling presented in this chapter is only an additional step in furthering the understanding of smuggling. Depending on data availability, the model can be estimated over different sub-periods to assess how smuggling has changed over time for each country. Another promising avenue for future empirical research on smuggling is the analysis of the impact of economic, political, and institutional reforms, such as the implementation of free trade zones or the improvement of institutional quality, on smuggling.

CHAPTER FOUR

SMUGGLING ILLEGAL AND LEGAL GOODS ACROSS THE U.S.-MEXICO BORDER*

"If you have a lot of what people want and can't get, then you can supply the demand and shovel in the dough."

Charles "Lucky" Luciano (1896-1962)

While the preceding chapter has estimated an index of smuggling for 54 countries, this chapter studies smuggling across the U.S.-Mexico border from 1975 to 2004. Using Multiple Indicators Multiple Causes (MIMIC) models I capture the latent nature of smuggling and identify its determinants and long-run trends.[70] I also argue that the analysis of smuggling has been incomplete so far: existing studies merely analyze the causes of trade misinvoicing (see Table 3.1), i.e., illegal trade or smuggling of legal goods, which represents only a fraction of total illegal trade. To improve the understanding of illegal trade further, I now distinguish between smuggling *illegal* goods and smuggling *legal* goods in the U.S.-Mexican context.

The types of smuggling differ with respect to the goods being smuggled, the agents involved in smuggling, the smuggling incentive, and the intensity of law enforcement. Trade misinvoicing occurs when entrepreneurs misreport the value of legal exports or imports to evade tariffs and taxes and is commonly considered a *peccadillo* (petty

---

* This chapter follows Buehn and Eichler (2009).

[70] MIMIC approaches were previously applied to estimate the development of the shadow economy [see, for example, Dell'Anno and Schneider (2003); Schneider (2005); and Dell'Anno (2007)]. A comprehensive overview of such studies is provided in Schneider and Enste (2000; 2002).

offense): smugglers usually bribe officials or are fined a fee. Smuggling illegal goods such as illegal drugs and illegal immigrants, however, often involves dangerous criminals who commit serious offenses and, if caught, face severe punishment. As a result, their incentive to smuggle is related to the intensity of law enforcement rather than tax or tariff evasion.

Studying the U.S.-Mexican case is particularly interesting as most illegal drugs and immigrants enter the United States via the Mexican border. The large income disparity between the two nations may explain the high U.S. demand for illegal goods, which relatively poor Mexicans are willing to meet despite the risks involved. I also examine whether the Clinton and Bush Administrations succeeded in reducing smuggling across the border through intensified border enforcement.

Using a (simple) microeconomic framework, I determine which microeconomic incentives affect the two types of smuggling. The hypotheses are then tested in a MIMIC model which studies the impact of observable causes (the microeconomic incentives to smuggle) on the unobservable phenomenon, smuggling, as indicated by observable macroeconomic variables. Applying the benchmarking procedure promoted by Dell'Anno and Schneider (2006) and Dell'Anno (2007), I calculate a time series for each type of smuggling.

I find that smuggling in illegal goods from Mexico to the United States decreases when Mexican labor market conditions improve and U.S. border enforcement is intensified. The Mexican recessions in 1982/83 and 1995 led to large temporary increases in smuggling to \$113 billion and \$87 billion, respectively. Smuggling in illegal goods decreased overall, however, from \$116 billion in 1984 to \$27 billion in 2004, which can be attributed to stricter U.S. border enforcement and better Mexican job prospects.

Smuggling legal goods is driven by the real exchange rate and tariff and tax evasion. Export misinvoicing fluctuated between underinvoicing values of \$0.2 billion and overinvoicing values of \$0.7 billion while import misinvoicing switched from underinvoicing – peaking at \$1.6 billion in 1983 – to recent overinvoicing – up to \$3.8 billion in 2002. This pattern can be attributed to substantial tariff reductions in accordance with the General Agreement on Tariffs and Trade (GATT) in 1987 and the North American Free Trade Agreement (NAFTA) in 1994.

The chapter is organized as follows. Section 4.1 briefly addresses the theoretical smuggling literature. Section 4.2 considers the incentives driving the two types of smuggling in a microeconomic framework. Section 4.3 explains the empirical methodology. Section 4.4 describes the indicators of smuggling. Section 4.5 presents the estimation results and long-term trends for the smuggling of illegal and legal goods. Section 4.6 concludes.

4.1 Literature

The literature on smuggling has already been reviewed in Section 3.1.1. For this reason, I only summarize the main findings of the theoretical literature – which motivate the theoretical analysis of illegal and legal goods smuggling in Section 4.2 – in Section 4.1. For the empirical literature on smuggling I refer to Section 3.1.1 and Table 3.1.

The theoretical literature on smuggling focuses on trade misinvoicing, i.e., the false declaration of legal imports and exports. One strand of the theoretical literature analyzes the welfare effects of trade misinvoicing. Bhagwati and Hansen (1973) show that smuggling – despite the classic view – can distort welfare as legal traders are squeezed out by smugglers who operate at inferior terms of trade but profit by circumventing tariffs. Pitt (1981) shows that the welfare consequences of smuggling are ambiguous. He argues that legal trade and smuggling coexist as firms camouflage their smuggling activities by also conducting legal trade.

Another strand of the theoretical literature, initiated by Pitt (1981), analyzes the determinants of trade misinvoicing. He argues that smuggling is positively correlated with a price disparity, defined as the difference between the actual domestic and the tariff-inclusive world market price. If, for example, the domestic price of an exportable good exceeds its world market price, it can only be exported legally at a loss, suggesting that most of the actual exports are traded illegally. Martin and Panagariya (1984) and Norton (1988) consider the costs of smuggling. They find that stricter law enforcement serves as a deterrent to smuggle. Pitt (1984) analyzes the black market premium (BMP) for foreign exchange as a determinant of smuggling. He finds that the black market equilibrates the supply of foreign exchange from illegal exports and its demand to purchase illegal imports. Biswas and Marjit (2007) find that export (import) underinvoicing is positively (negatively) correlated with the BMP since the foreign exchange from the unreported transaction is sold (acquired) on the black market.

4.2 Micro-Foundations of Smuggling Incentives

I argue that smugglers of illegal goods respond to different incentives than smugglers of legal goods. The following uses a (simple) microeconomic approach to determine the expected impact of different determinants on both types of smuggling.[71]

4.2.1 Determinants of Illegal Goods Smuggling

The representative risk-neutral Mexican smuggler maximizes her expected profit with respect to the amount of illegal goods or persons to be smuggled into the United States, S^{ill}. Equation (4.1) outlines the revenue from smuggling illegal goods, $R\left(S^{ill}\right)$:

$$R\left(S^{ill}\right)=\left(1+v\right)ep^{US}S^{ill}. \tag{4.1}$$

The smuggler sells S^{ill} illegal Mexican goods at price p^{US} in the United States and converts the dollar-denominated proceeds on the black market into Mexican pesos, earning the BMP v over the official exchange rate e.[72] The expected costs of smuggling, $E\left[C\left(S^{ill}\right)\right]$, arise from the risk of being caught by U.S. Border and Customs Protection[73] as outlined in equation (4.2):

$$E\left[C\left(S^{ill}\right)\right]=prob\left(S^{ill},H\right)F, \tag{4.2}$$

with $\partial prob\left(S^{ill},H\right)\big/\partial S^{ill}>0$, $\partial^2 prob\left(S^{ill},H\right)\big/\left(\partial S^{ill}\right)^2>0$, and $\partial prob\left(S^{ill},H\right)\big/\partial H>0$. The smuggler is apprehended with probability $prob\left(S^{ill},H\right)$ and faces the punishment cost F. I assume that the probability of apprehension is a convex function of the amount of illegal goods being smuggled and depends positively on the exogenous border

---

[71] Biswas and Marjit (2007) use a similar approach to study the rationale for trade mis-invoicing.

[72] The exchange rate e is defined as the price of one U.S. dollar in terms of Mexican pesos. Thus, a rise in the exchange rate corresponds to a depreciation of the peso against the U.S. dollar.

[73] Until 2003, the U.S. Customs Service.

enforcement, H, i.e., the more officers patrolling the U.S.-Mexico border, the more likely smugglers are to be caught.

If the smuggler is apprehended, she will be sentenced to prison. The cost of punishment F therefore represents the opportunity cost of lost labor income, $(1-u)w$, during imprisonment. The higher Mexican wages, w, are, and the lower the Mexican unemployment rate, u, is, the higher the cost of punishment, F:

$$F = f\left\{(1-u)w\right\}, \tag{4.3}$$

with $\partial f\left\{(1-u)w\right\}/\partial u < 0$ and $\partial f\left\{(1-u)w\right\}/\partial w > 0$. Using equations (4.1)-(4.3), the expected nominal profit from smuggling illegal goods is:

$$E\left(\pi^{ill}\right) = (1+v)\,ep^{US}S^{ill} - prob\left(S^{ill}, H\right) f\left\{(1-u)w\right\}. \tag{4.4}$$

To study the determinants of smuggling illegal goods in real terms, I denominate the expected profit in Mexican goods by dividing equation (4.4) by the Mexican price index, p^{MEX}. Equation (4.5) shows the expected real profit from smuggling, whereby the real exchange rate is defined as $\varepsilon = ep^{US}/p^{MEX}$:

$$\frac{E\left(\pi^{ill}\right)}{p^{MEX}} = (1+v)\,\varepsilon S^{ill} - prob\left(S^{ill}, H\right)\frac{f\left\{(1-u)w\right\}}{p^{MEX}}. \tag{4.5}$$

Real profit optimization with respect to the amount of smuggling, S^{ill}, yields the result that the marginal revenue from smuggling equals the marginal cost of smuggling:

$$(1+v)\,\varepsilon = \frac{\partial prob\left(S^{ill}, H\right)}{\partial S^{ill}}\frac{f\left\{(1-u)w\right\}}{p^{MEX}}, \tag{4.6}$$

with $\partial^2 prob\left(S^{ill}, H\right)/\left(\partial S^{ill}\right)^2 > 0$. Equation (4.6) determines how the optimal amount of illegal goods to smuggle, S^{ill}, reacts to changes in the incentive variables. I derive the following hypotheses:

(1) A higher ***BMP***, v, increases the incentive to smuggle, $dS^{ill}/dv > 0$, *ceteris paribus*, as converting U.S. dollars into pesos on the black market is more profitable.

(2) A higher real exchange rate, i.e., ***a real depreciation of the peso*** against the U.S. dollar, increases smuggling, $dS^{ill}/d\varepsilon > 0$, *ceteris paribus*, as revenues rise in terms of Mexican goods.[74]

(3) Higher ***Mexican wages*** and lower ***Mexican unemployment*** reduce the incentive to smuggle, i.e., both $dS^{ill}/dw < 0$ and $dS^{ill}/du > 0$ hold. Hence, better Mexican job prospects decrease smuggling by raising the opportunity costs $(1-u)w$ of imprisonment if apprehended. Thus, I expect smuggling activities to rise during Mexican recessions when Mexican labor market conditions worsen.

(4) More intense ***border enforcement*** should lead to a decrease in the smuggling of illegal goods, $dS^{ill}/dH < 0$, *ceteris paribus*, as this increases the probability of apprehension and, thus, the expected cost of smuggling.

4.2.2 Determinants of Legal Goods Smuggling/Trade Misinvoicing

4.2.2.1 Export Misinvoicing

A Mexican entrepreneur exports a given amount of legal goods X to the United States. In order to save on Mexican income taxes and to benefit from the BMP, she has an incentive not to report the total amount of exports. Export underinvoicing, $S^x > 0$, thus means that the reported amount of exports, $X - S^x$, is lower than the actual amount of exports, X.[75] Equation (4.7) describes the Mexican exporter's expected profit, $E(\pi^x)$:

$$E(\pi^x) = (1-t)ep^{US}(X - S^x) + (1+v)ep^{US}S^x - prob(S^x)F, \tag{4.7}$$

where $\partial prob(S^x)/\partial S^x > 0$ and $\partial^2 prob(S^x)/(\partial S^x)^2 > 0$. Given the total amount of

---

[74] Per definition, $v > -1$ holds and, thus, $dS^{ill}/d\varepsilon > 0$ generally applies.

[75] I define misinvoicing as underinvoicing, i.e., as the difference between the actual and the reported export/import figures. Defining misinvoicing as overinvoicing would just reverse the theoretical hypotheses.

exports, X, the Mexican exporter decides how many exports to report and how many to underinvoice. She sells the reported (legal) exports $X - S^x$ at p^{US} in the United States and converts the dollar-denominated proceeds at the official exchange rate e into pesos, generating a legal after-tax export revenue of $(1-t)ep^{US}\left(X - S^x\right)$.[76] The unreported (misinvoiced) exports, S^x, are sold at p^{US} in the United States. The dollar-denominated smuggling revenue is then converted into pesos on the black market where the misinvoicer profits from the BMP, v, over the official exchange rate, e.

The expected cost of export underinvoicing arises from the risk that the misinvoicing will be detected by the authorities with probability $prob(S^x)$ and that the exporter will subsequently face the punishment cost F – which represents exogenous expenses for bribes or fines. The detection probability is assumed to be convex in the amount of export underinvoicing. Dividing equation (4.7) by the Mexican price index, p^{MEX}, and using the definition of the real exchange rate, $\varepsilon = ep^{US} / p^{MEX}$, yields the Mexican export underinvoicer's real expected profit:

$$\frac{E\left(\pi^x\right)}{p^{MEX}} = (1-t)\varepsilon X + (v+t)\varepsilon S^x - prob\left(S^x\right)\frac{F}{p^{MEX}}. \tag{4.8}$$

Real profit optimization with respect to the amount of export underinvoicing, S^x, again yields the result that the marginal revenue equals the marginal cost of smuggling:

$$(v+t)\varepsilon = \frac{\partial prob\left(S^x\right)}{\partial S^x}\frac{F}{p^{MEX}}, \tag{4.9}$$

with $\partial^2 prob\left(S^x\right) \Big/ \left(\partial S^x\right)^2 > 0$. I hypothesize the following effects of smuggling incentives on export underinvoicing:

(1) A higher ***BMP***, v, should cause export underinvoicing to rise *ceteris paribus*, $dS^x / dv > 0$, as the exchange rate-adjusted price spread between unreported and reported exports increases.

---

[76] The variable t denotes the Mexican profit/income tax. Obviously, only legal transactions are subject to taxation. For simplicity, I do not consider any production or procurement costs.

(2) A ***real depreciation of the peso*** against the U.S. dollar should lead to higher export underinvoicing *ceteris paribus*, $dS^x/d\varepsilon > 0$, as Mexican goods become more competitive.[77]

(3) Higher ***Mexican income/profit taxes***, t, should lead to more export underinvoicing *ceteris paribus*, $dS^x/dt > 0$, as illegal/unreported Mexican exports are not subject to taxation and thus become more competitive over legal/reported Mexican exports. Tax evasion therefore appears to be an important motive for export misinvoicing.

4.2.2.2 Import Misinvoicing

The Mexican entrepreneur imports a fixed amount of legal goods M from the United States and decides how many imports to report, $M - S^M$, and how many to underinvoice, $S^M > 0$. Equation (4.10) describes the Mexican importer's expected profit, $E\left(\pi^M\right)$:

$$E\left(\pi^M\right) = (1-t)\left[R(M) - ep^{US}(1+q)\left(M - S^M\right)\right] - (1+v)\,ep^{US}S^M - prob\left(S^M\right)F\,, \tag{4.10}$$

where $\partial prob\left(S^M\right)/\partial S^M > 0$ and $\partial^2 prob\left(S^M\right)/\left(\partial S^M\right)^2 > 0$. The Mexican entrepreneur imports M goods – some reported, some unreported – from the United States and sells them in Mexico, earning $R(M)$ pesos. She spends $ep^{US}(1+q)\left(M - S^M\right)$ pesos to import the reported (legal) American goods, where q denotes the Mexican import tariff levied on reported American goods. After paying the Mexican income/profit tax, t, the Mexican importer makes an after-tax profit of $(1-t)\left[R(M) - ep^{US}(1+q)\left(M - S^M\right)\right]$ pesos on her reported transactions. For the unreported (misinvoiced) U.S. imports, S^M, she spends $(1+v)\,ep^{US}S^M$ pesos paying the BMP, v, to buy the required U.S. dollars on

---

[77] $dS^x/dv > 0$ is true as $v + t > 0$ holds in the sample.

the black market. The import misinvoicer faces the expected cost of punishment $prob\left(S^M\right)F$, where $prob\left(S^M\right)$ denotes the probability of being caught and F the subsequent bribes or fines. Equation (4.11) describes the Mexican importer's real expected profit:

$$\frac{E\left(\pi^M\right)}{p^{MEX}} = (1-t)\left[\frac{R(M)}{p^{MEX}} - \varepsilon(1+q)M\right] + \left[(1-t)(1+q)-(1+v)\right]\varepsilon S^M - prob\left(S^M\right)\frac{F}{p^{MEX}}. \tag{4.11}$$

Real profit optimization with respect to the amount of import underinvoicing, S^M, yields the result that the marginal benefit equals the marginal cost of smuggling:[78]

$$\left[(1-t)(1+q)-(1+v)\right]\varepsilon = \frac{\partial prob\left(S^M\right)}{\partial S^M}\frac{F}{p^{MEX}}, \tag{4.12}$$

with $\partial^2 prob\left(S^M\right) \big/ \left(\partial S^M\right)^2 > 0$. Intuitionally, the optimal amount of import underinvoicing S^M reacts to changes in incentives in the opposite direction of the optimal amount of export underinvoicing:

(1) A higher ***BMP***, v, decreases the incentive to underinvoice imports *ceteris paribus*, $dS^M \big/ dv < 0$, as it becomes more expensive to buy U.S. dollars for unreported imports on the black market.

(2) A ***real depreciation of the peso*** against the dollar should decrease the amount of import underinvoicing *ceteris paribus*, $dS^M \big/ d\varepsilon < 0$, as Mexican products gain competitiveness over misinvoiced American products.

(3) A rise in ***Mexican income/profit taxes*** should reduce import underinvoicing *ceteris paribus*, $dS^M \big/ dt < 0$, as illegal/unreported Mexican imports cannot be

[78] The profit maximizing Mexican importer focuses on minimizing costs. Underinvoicing imports, $S^M > 0$, therefore means cutting back on legal expenditures $(1-t)(1+q)\varepsilon S^M$ but increasing illegal expenditures $(1+v)\varepsilon S^M$. Thus, the importer underinvoices if avoided legal costs exceed additional illegal costs, $(1-t)(1+q)-(1+v) > 0$.

claimed as tax exempt and, thus, lose profitability compared to legal/reported Mexican imports.

(4) Finally, I expect higher ***tariff rates*** to increase import underinvoicing, *ceteris paribus*, $dS^M/dq > 0$, as tariff evasion increases the profitability of unreported imports.

4.3 Empirical Methodology

The MIMIC model relates observable causal and indicator variables to a per se unobservable phenomenon.[79] Thus, it allows me to deal with the multiple causes and the multiple effects of illegal and legal goods smuggling across the U.S.-Mexico border. The MIMIC model has two parts: the structural equation model and the measurement model.[80] In the structural equation model, smuggling is determined by a set of exogenous causes, here the microeconomic smuggling incentives described above. The structural equation model is given by:

$$\eta_t = \boldsymbol{\gamma}'\mathbf{x}_t + \varsigma_t , \tag{4.13}$$

where each x_{it} , $i = 1,\dots,q$ in the q vector $\mathbf{x}_t$ is a potential cause of the latent variable η_t and $\boldsymbol{\gamma}' = \left(\gamma_1, \gamma_2, \dots, \gamma_q\right)'$ is a q vector of coefficients describing the relationships between the latent variable and its causes.[81] The error term ς_t represents the component of the latent variable η_t not explained by the causes. The variance of ς_t is denoted by ψ .

The measurement model links the latent variable to its indicators:

$$\mathbf{y}_t = \boldsymbol{\lambda}\eta_t + \boldsymbol{\varepsilon}_t . \tag{4.14}$$

---

[79] While Section 4.3 describes the MIMIC model in brief, Appendix A provides a detailed description.

[80] A similar presentation of the MIMIC methodology is presented in Chapter 2 and can be found in Buehn and Schneider (2008) and Buehn et al. (2009).

[81] As denoted in Chapter 2, the subscript *t* indicates the time series dimension of the variables.

In the measurement model, $\boldsymbol{y}_t' = \left(y_{1t}, y_{2t}, \ldots, y_{pt}\right)'$ is a p vector of indicator variables that measure the latent variable smuggling (see Section 4.4), $\boldsymbol{\lambda}$ is a p vector of regression coefficients, and $\boldsymbol{\varepsilon}_t$ is a p vector of white noise disturbances, i.e., $\boldsymbol{\varepsilon}_t \sim \left(\boldsymbol{0}, \boldsymbol{\Theta}_\varepsilon\right)$.

The structural and the measurement model equations can be used to derive a reduced-form regression model:

$$\boldsymbol{y}_t = \boldsymbol{\Pi x}_t + \boldsymbol{z}_t\,, \tag{4.15}$$

where $\boldsymbol{\Pi} = \boldsymbol{\lambda\gamma}'$ is a $\left(p \times q\right)$ matrix. The endogenous variables y_{jt}, $j = 1, \ldots, p$ in equation (4.15) are the indicators for smuggling, and the exogenous variables x_{it}, $i = 1, \ldots, q$ are its causes. The error term $\boldsymbol{z}_t = \boldsymbol{\lambda}\varsigma_t + \boldsymbol{\varepsilon}_t$ is a p vector of a linear transformation of the white noise error terms ς_t and $\boldsymbol{\varepsilon}_t$ resulting from the structural equation and the measurement model, i.e., $\boldsymbol{z}_t \sim \left(\boldsymbol{0}, \boldsymbol{\Omega}\right)$. The $\left(p \times p\right)$ covariance matrix $\boldsymbol{\Omega}$ is given by $\boldsymbol{\Omega} = \mathrm{Cov}\left(\boldsymbol{z_t}\right) = \mathrm{E}\left[\left(\boldsymbol{\lambda}\varsigma_t + \boldsymbol{\varepsilon}_t\right)\left(\boldsymbol{\lambda}\varsigma_t + \boldsymbol{\varepsilon}_t\right)'\right] = \boldsymbol{\lambda}\psi\boldsymbol{\lambda}' + \boldsymbol{\Theta}_\varepsilon$ and $\boldsymbol{\Theta}_\varepsilon = \mathrm{E}\left(\boldsymbol{\varepsilon_t \varepsilon_t}'\right)$.

The goal of the SEM estimation procedure is to estimate a model covariance matrix $\boldsymbol{\Sigma}(\boldsymbol{\theta})$, $\hat{\boldsymbol{\Sigma}} = \boldsymbol{\Sigma}(\hat{\boldsymbol{\theta}})$, that is as close as possible to the sample covariance matrix of the observed causes and indicators.[82] Identification and estimation of the model is however not possible without placing restrictions on certain model parameters. Among others, a restriction often imposed on the model is that one element of the vector $\boldsymbol{\lambda}$, i.e., one indicator, is set to an *a priori* value (often 1 or -1). In this way the researcher also establishes an interpretable scale for the latent variable [Bollen (1989), pp. 91, 183].[83]

The first step in the estimation is selecting appropriate causes and indicators of illegal and legal goods smuggling that address the hypothesized theoretical relationships as

---

[82] $\boldsymbol{\theta}$ is a vector that contains the parameters of the model and $\boldsymbol{\Sigma}\left(\boldsymbol{\theta}\right)$ is the covariance matrix as a function of $\boldsymbol{\theta}$ implying that each element of the covariance matrix is a function of one or more model parameters.

[83] An alternative is to set the variance of the unobservable variable η_t to one. However, setting one element of $\boldsymbol{\lambda}$ to an a priori value is often more convenient for economic interpretation and thus typically done [Dell'Anno and Schneider (2009)].

outlined in Sections 4.2 and 4.4 and to estimate three different MIMIC models, i.e., a MIMIC model for illegal goods smuggling, export misinvoicing as well as import misinvoicing. After model identification and determination of the latent variable's scale, the coefficients and model parameters are estimated and the hypothesized relationships between illegal and legal goods smuggling and the particular causes and indicators tested. The second step is to use the model's estimation results to calculate the latent variables scores for each point in time. Finally, a benchmarking procedure is applied to estimate "real world" figures of illegal and legal goods smuggling. The next section presents the theoretical reasoning for the selection of the indicators.

4.4 Measurement of Smuggling

In the measurement model, the indicators are regressed on a – per se undefined – unobservable (latent) variable. After defining each type of smuggling I select indicators to measure each type appropriately. Thus, the meaning of the latent variable depends on how well the indicators correspond to the operational definition.

Of course, indicators are often only imperfectly linked to the latent variable [Bollen (1989), p. 17], but it is obvious from equation (4.14) that all of them are alternative measures of the same latent variable, i.e., a change in the latent variable affects its indicators. This can be clarified further by taking the structural model into account. Within the theoretical framework from Section 4.2, I identify the microeconomic incentives that determine the profitability of each type of smuggling. If, for example, border enforcement is intensified, the cost for smugglers of illegal goods increases and the latent macroeconomic amount of illegal goods smuggled should decrease. Thus, a change in the microeconomic incentive structure transmits *uniformly* to the macroeconomic aggregate of all types of smugglers of illegal goods – be it smugglers of illegal drugs or illegal immigrants. The indicators discussed below all measure the total amount of each type of smuggling, as determined by the microeconomic incentive structure.

4.4.1 Indicators for Smuggling of Illegal Goods

The conceptual definition of illegal goods smuggling comprises the inflow of illegal drugs and illegal immigrants from Mexico to the United States. I do not consider smuggling in other types of illegal goods, for example, alcohol or bootlegs. The reasons for this are that, illegal drugs and immigrants are at the center of the political debate on whether to increase border patrol in the United States and estimates about the size of these types of smuggling – necessary to calculate the time trend in “real world” figures – are available.

To explain illegal goods smuggling, in particular illegal drugs and immigrants, in the measurement model, I use the following macroeconomic indicators: linewatch and non-linewatch apprehensions, real drug seizures, and the availability of drugs in the United States.

Smugglers of illegal drugs and illegal immigrants have in common that they have to cross the U.S.-Mexico border to bring their illegal “freight” to the United States. To stop this illegal inflow, the U.S. Border Patrol makes an enormous effort to apprehend smugglers crossing the border. One of the objectives of the National Border Patrol Strategy of 2004 is to “detect, apprehend, and deter smugglers of humans, drugs, and other contraband” [Office of Border Patrol (2004), p. 6]. If illegal goods smuggling increases the number of apprehensions should also increase, *ceteris paribus*. Thus, I expect that linewatch and non-linewatch apprehensions, i.e., the number of persons apprehended at the U.S.-Mexico border and inside the United States, are positively correlated with the smuggling of illegal goods.

Another indicator of illegal goods smuggling is drugs seized by the U.S. Border Patrol. Given the efforts of the United States to fortify the border against the inflow of illegal goods, I expect drug seizures to increase as illegal goods smuggling rises, *ceteris paribus*. Of course, several smugglers successfully cross the border and succeed in their smuggling activities. Thus, I also include the availability of drugs as another indicator in order to account for illegal goods that have been smuggled into the United States successfully (i.e., undetected). I expect drug availability to increase as illegal goods smuggling rises, *ceteris paribus*.

4.4.2 Indicators for Smuggling of Legal Goods

In contrast to smugglers of illegal goods, smugglers of legal goods break the law from their offices rather than at the border. As no data on convicted misinvoicers are available, I employ balance of payments data – in particular trade discrepancies and data on errors and omissions – to proxy legal goods smuggling as common in the literature. Assuming that industrialized countries like the United States correctly report trade figures, discrepancies between U.S. figures and Mexican figures result from misreporting by Mexican importers/exporters. Export underinvoicing by Mexican exporters is the difference between U.S. imports from Mexico (reported by the United States) and Mexican exports to the United States (reported by Mexico).[84] Import underinvoicing by Mexican importers is the difference between U.S. exports to Mexico (reported by the United States) and Mexican imports from the United States (reported by Mexico).

Data on errors and omissions are included in the Mexican balance of payments and are used as a second indicator of legal goods smuggling.[85] Unreported Mexican exports (export underinvoicing) lead to inflows of foreign exchange. These exports do not appear in the trade balance but rather increase the errors and omissions of the Mexican balance of payments by the amount of export underinvoicing. I therefore conclude that the higher the export underinvoicing, the higher the errors and omissions, *ceteris paribus*. Likewise, the lower the import underinvoicing, the higher the errors and omissions.

4.5 Empirical Analysis

This section presents the results of the MIMIC model estimations and the long-term trends in the smuggling of illegal goods and legal goods (export and import misinvoicing) across the U.S.-Mexico border. Recognizing these different types of smuggling as outlined in Section 4.2, I estimate three different MIMIC models. Table

[84] The export figures are in FOB (Free on Board) prices, and the import figures are in CIF (Cost, Insurance, and Freight) prices. In order to make them comparable, I multiply the export figures by a factor of 1.1 as suggested by the International Monetary Fund [IMF (1993), p. 8], in order to adjust for transportation and insurance costs.

[85] In addition to trade misinvoicing, errors and omissions reflect misreporting of capital flows and different schedules for reporting goods in transit [see, for example, Fausten and Pickett (2004)]. However, trade misinvoicing is a popular instrument to camouflage capital flight [Eggerstedt et al. (1995)]. Therefore, I assume the size of errors and omissions to be mainly driven by trade misinvoicing.

D.1 in Appendix D presents the empirical identification, data sources, and definitions of the variables.

The first model tests whether the microeconomic causal variables affect the smuggling of illegal goods as hypothesized in Section 4.2.1. Figure 4.1 illustrates the path diagram of illegal goods smuggling using the indicators explained in Section 4.4.1. The second and third models test the determinants of legal goods smuggling, also hypothesized in Section 4.2 using the indicators outlined in Section 4.4.2. Figures 4.2 and 4.3 display the path diagrams for export and import misinvoicing, respectively.

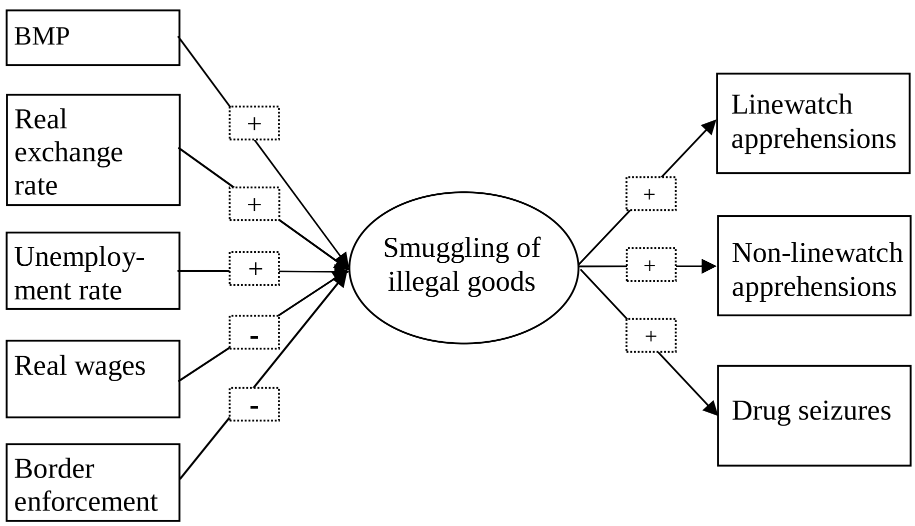

Figure 4.1 Path Diagram for Smuggling of Illegal Goods

Note: The squares attached to the arrows indicate the expected signs for the relationships between the causes (indicators) and the latent variable as hypothesized in Section 4.2.1 (Section 4.4.1).

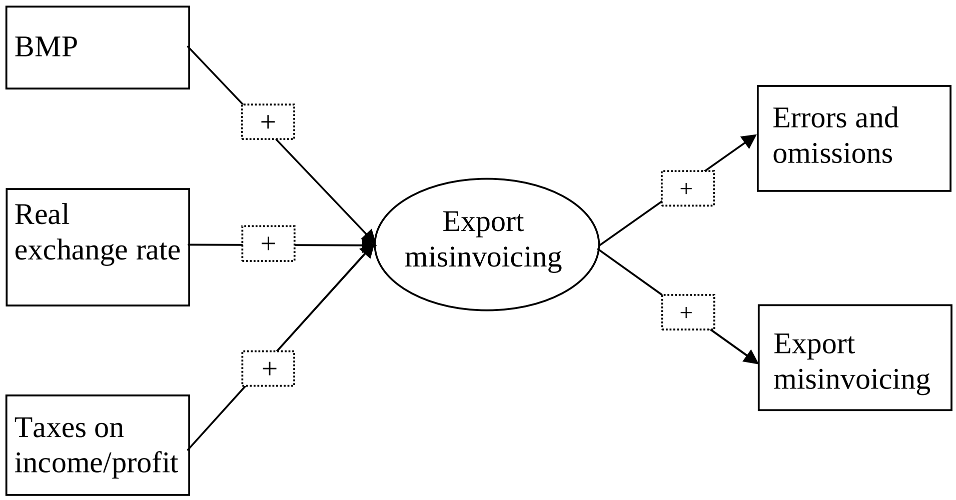

Figure 4.2 Path Diagram for Export Misinvoicing

Note: The squares attached to the arrows indicate the expected signs for the relationships between the causes (indicators) and the latent variable as hypothesized in Section 4.2.2 (Section 4.4.2).

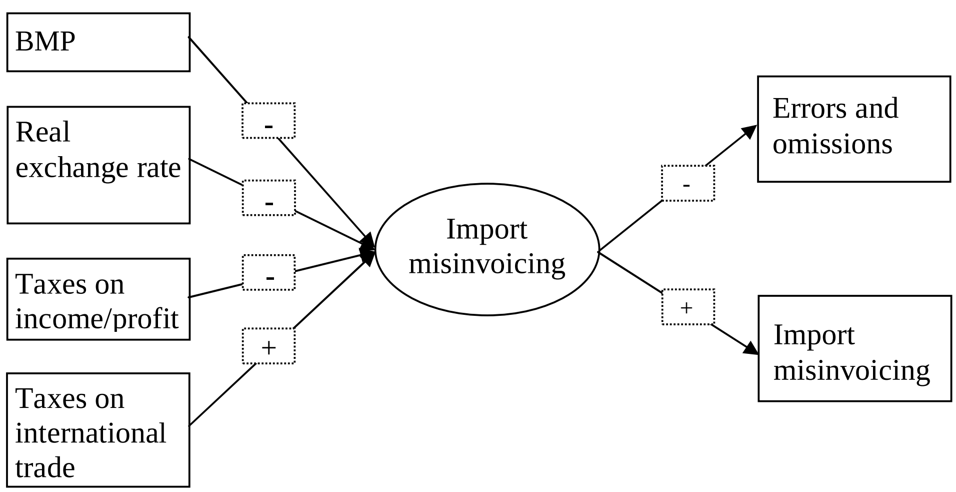

Figure 4.3 Path Diagram for Import Misinvoicing

Note: The squares attached to the arrows indicate the expected signs for the relationships between the causes (indicators) and the latent variable as hypothesized in Section 4.2.2 (Section 4.4.2).

4.5.1 Data

To estimate the MIMIC models, I use monthly data from 1975 to 2004. Because data on the BMP is only available through December 1998 (the date of the last issue of *Pick's World Currency Report*) and data on errors and omissions in the Mexican balance of payments is only available from January 1980, however, some of the estimations are limited to 1980-1998.

I test for unit roots as MIMIC models with nonstationary time series produce misleading estimates. I therefore examine each time series for those periods subsequently used in the estimations under the null hypothesis of a unit root against the alternative of stationarity using the ADF test. The KPSS test, which tests stationarity against the alternative of the presence of a unit root, is used to cross-check the ADF test's results.[86]
I find that most variables, except for the BMP and the real exchange rate 1975-1998 and 1975-2004, are not stationary in levels. However, for 1980-1998 and 1980-2004, I cannot reject the null hypothesis of a unit root for the BMP as both unit root tests produce conflicting results. Consequently, I use the BMP in first differences in the estimations covering these time periods. Other variables found nonstationary in levels are also transformed in this way and re-tested. As the null hypothesis of a unit root is now rejected, I use the first difference of all variables except for the BMP and real exchange rate 1975-1998 and 1975-2004 in the MIMIC model estimations. Tables 4.1 and 4.2 present the unit root tests for smuggling of illegal and smuggling of legal goods.

[86] Unit root tests have already been introduced in Section 2.4.2. See also the literature cited there.

Table 4.1 Analysis of Stationarity for Smuggling of Illegal Goods

Variable	Test statistics for variables in levels (first differences)							
	1975-1998		1975-2004		1980-1998		1980-2004	
	ADF	KPSS	ADF	KPSS	ADF	KPSS	ADF	KPSS
Causes								
BMP	-3.459**	0.386	-3.459**	0.386	-2.938*	0.862	-2.938*	0.862
	(--)	(--)	(--)	(--)	(-21.211***)	(0.033)	(-21.211***)	(0.033)
Real exchange rate	-2.948**	0.304	-3.053**	0.276	-2.838*	0.222	-2.849*	0.453
	(--)	(--)	(--)	(--)	(--)	(--)	(--)	(--)
Unemployment rate	-1.834	1.014	-2.149	1.247	-1.739	0.357	-1.975	0.518
	(-5.424***)	(0.069)	(-19.230***)	(0.111)	(-4.685***)	(0.062)	(-5.474***)	(0.064)
Real wages	-1.539	1.158	-1.859	1.050	-2.313	0.603	-2.706*	0.377
	(-4.711***)	(0.060)	(-5.252***)	(0.093)	(-3.554***)	(0.109)	(-4.076***)	(0.159)
Probability of apprehension	-0.246	0.740	0.004	1.382	-0.787	1.258	-0.098	1.539
	(-18.737***)	(0.117)	(-21.272***)	(0.187)	(-15.867***)	(0.369)	(-19.312***)	(0.386)

(continued on next page)

Table 4.1 (cont.)

Indicators	ADF	KPSS	ADF	KPSS	ADF	KPSS	ADF	KPSS
Linewatch	-2.131	1.578	-2.196	1.703	-2.047	1.301	-2.134	1.238
apprehensions	(-17.585***)	(0.036)	(-20.312***)	(0.062)	(-14.938***)	(0.037)	(-18.139***)	(0.053)
Non-linewatch	-2.093	0.215	-1.413	0.889	-1.834	0.361	-1.241	1.096
apprehensions	(-17.285***)	(0.050)	(-19.591***)	(0.065)	(-15.232***)	(0.053)	(-17.754***)	(0.050)
Drug seizures	-1.081	1.629	-1.562	1.737	-1.250	1.510	-1.719	1.280
	(-29.132***)	(0.058)	(-18.931***)	(0.085)	(-15.070***)	(0.059)	(-17.260***)	(0.107)
Drug availability	-0.817	0.450	-1.473	0.335	-1.640	0.428	-2.169	0.439
	(-29.138***)	(0.359)	(-4.092***)	(0.121)	(-2.420)	(0.630)	(-3.138**)	(0.218)

Note: *** Significance at the 1% level. ** Significance at the 5% level. * Significance at the 10% level. The order of the autoregressive correction for the unit root tests was chosen using the modified Akaike information criterion (ADF test). For the KPSS test, I use the Bartlett kernel estimator and the Newey-West (1994) data-based automatic bandwidth parameter method. The MacKinnon (1996) critical values for the ADF tests are: -3.64, -2.95, and -2.61 for the 1%, 5%, and 10% significance levels, respectively. The LM statistics critical values of the KPSS test – taken from Kwiatkowski et al. (1992) – are: 0.739, 0.463, and 0.347 for the 1%, 5%, and 10% significance levels, respectively.

Table 4.2 Analysis of Stationarity for Smuggling of Legal Goods

Variable	Levels				First differences			
	1980-1998		1980-2004		1980-1998		1980-2004	
	ADF	KPSS	ADF	KPSS	ADF	KPSS	ADF	KPSS
Causes								
BMP	-2.940*	0.862	-2.940*	0.862	-21.210***	0.033	-21.210***	0.033
Real exchange rate	-2.838*	0.222	-2.850*	0.453	--	--	--	--
Tax on income/ profit	-2.020	0.302	-2.070	0.384	-3.150**	0.142	-3.600**	0.106
Tax on international trade	-1.940	0.880	-2.050	1.384	-3.710***	0.105	-4.300***	0.100
Indicators								
Import misinvoicing	-0.160	1.459	-1.310	1.474	-26.590***	0.200	-28.340***	0.178
Export misinvoicing	-0.580	1.349	-0.690	1.792	-25.620***	0.222	-28.230***	0.134
Errors and omissions	-3.040**	0.312	-3.690***	0.170	--	--	--	--

Note: *** Significance at the 1% level. ** Significance at the 5% level. * Significance at the 10% level. The order of the autoregressive correction for the unit root tests was chosen using the modified Akaike information criterion (ADF test). For the KPSS test, I use the Bartlett kernel estimator and the Newey-West (1994) data-based automatic bandwidth parameter method. The MacKinnon (1996) critical values for the ADF tests are: -3.64, -2.95, and -2.61 for the 1%, 5%, and 10% significance levels, respectively. The LM statistics critical values of the KPSS test – taken from Kwiatkowski et al. (1992) – are: 0.739, 0.463, and 0.347 for the 1%, 5%, and 10% significance levels, respectively.

4.5.2 Estimation Results

Tables 4.3 and 4.4 present the results of the MIMIC model estimations for smuggling illegal and legal goods applying the maximum likelihood estimator.[87] As explained in Section 4.3, the estimation of a MIMIC model requires the normalization of one indicator for each latent variable that also determines the unit of measurement of the latent variable [Bollen (1989), pp. 91, 183].[88] In the illegal goods smuggling estimations, I set the coefficient of linewatch apprehensions to 1. In the case of legal goods smuggling, I set the coefficient for errors and omissions to 1 for export misinvoicing and to -1 for import misinvoicing.[89]

For the smuggling of illegal goods, I estimate seven different MIMIC model specifications by varying either the time period or the set of indicator variables. I include all causal variables considered in Section 4.2 except for the BMP, which is not included in estimations through 2004.[90] In the four model specifications for the smuggling of legal goods, I vary the time period only because alternative indicator variables are not available.

---

[87] All calculations have been carried out with LISREL® Version 8.80.

[88] The choice of the indicator to fix the scale of the latent variable does not affect the results because the maximum likelihood estimator is scale invariant [Swaminathan and Algina (1978)]. Typically, one selects the indicator that loads most on the unobservable variable.

[89] To calculate the smuggling indices, I use the fixed indicator as an index variable whose value is expressed relative to the base year value. Linewatch apprehensions are therefore used as an index variable equal to (linewatch apprehensions at t)/(linewatch apprehensions 2000) while errors and omissions are used as an index equal to (errors and omissions at t)/(errors and omissions 1984).

[90] The simple reason is that the last issue of *Pick's World Currency Report* appeared in 1998. Moreover, I could not estimate specification 3 by varying the set of indicators because the variable drug availability still exhibits a unit root for 1980-1998, even after taking the first difference.

Table 4.3 MIMIC Model Estimations for Illegal Goods Smuggling

Specification	1	2	3	4	5	6	7
Time period	1975 - 1998	1975 - 1998	1980 - 1998	1975 - 2004	1975 - 2004	1980 - 2004	1980 - 2004
Causes							
BMP (through 1998)	0.02	0.02	-0.01				
	(0.99)	(0.99)	(0.61)				
Real exchange rate	-0.02	-0.02	-0.02	0.02	0.02	0.03	0.02
	(0.80)	(0.57)	(0.68)	(0.65)	(0.44)	(0.67)	(0.43)
Unemployment rate	0.05**	0.05***	0.05**	0.05*	0.05*	0.06**	0.07**
	(2.20)	(2.34)	(2.24)	(1.69)	(1.73)	(2.00)	(2.05)
Real wages	-0.03**	-0.05***	-0.05***	-0.05*	-0.05**	-0.06***	-0.06***
	(2.26)	(3.25)	(3.18)	(1.91)	(2.20)	(2.36)	(2.67)
Border enforcement	-2.02***	-2.01***	-2.05***	-0.64***	-0.63***	0.63***	-0.61***
	(16.11)	(16.27)	(15.87)	(9.15)	(9.18)	(9.01)	(8.99)
Indicators							
Linewatch apprehensions (fixed)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Non-linewatch apprehensions	1.02***	1.03***	1.09***	0.49***	0.50***	0.48***	0.49***
	(9.33)	(9.23)	(9.57)	(13.66)	(13.34)	(13.34)	(12.95)
Drug seizures	0.12***		0.09*	0.00		0.00	
	(2.49)		(1.68)	(0.05)		(0.08)	
Drug availability		0.02			0.04		0.04
		(0.58)			(0.75)		(0.76)

(continued on next page)

Table 4.3 (cont.)

Goodness-of-fit statistics							
Observations	282	282	223	358	358	300	300
Degrees of freedom	25	25	25	18	18	18	18
Chi-square	5.27	14.88	2.79	5.22	9.96	4.91	9.34
(*p*-value)	(0.99)	(0.94)	(0.97)	(0.99)	(0.93)	(0.99)	(0.95)
RMSEA	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: *** Significance at the 1% level. ** Significance at the 5% level. * Significance at the 10% level. Absolute *z*-statistics in parentheses. The degrees of freedom are determined by 0.5 (p + q) (p + q + 1) – t; with p = number of indicators; q = number of causes; t = the number for free parameters. If the model fits the data perfectly and the parameter values are known, the sample covariance matrix equals the covariance matrix implied by the model. The null hypothesis of perfect fit corresponds to a *p*-value of 1. The root mean squared error of approximation (RMSEA) measures the model's fit based on the difference between the estimated and the actual covariance matrix. RMSEA values smaller than 0.05 indicate a good fit [Browne and Cudeck (1993)].

The MIMIC model estimations for the smuggling of illegal goods show that this kind of smuggling reacts only to changes in smuggling costs. Thus, the unemployment rate, real wages, and border enforcement are the major causes and have the theoretically expected impact on smuggling. Higher wages and lower unemployment increase opportunity costs during imprisonment and, thus, reduce smuggling in illegal goods. More intense border enforcement significantly deters illegal goods smuggling for all specifications estimated. This variable approximates the probability of being caught smuggling at the border. The higher this probability, the higher the expected costs for smugglers and, thus, the lower the smuggling of illegal goods, *ceteris paribus*. By contrast, changes in the variables affecting revenues from smuggling illegal goods do not significantly influence smuggling, i.e., the BMP and the real exchange rate are not significant for any specification. It seems that smugglers live at the subsistence level and have to smuggle illegal goods to earn a living for their families. The decision whether or not to engage in smuggling is then based on the opportunity cost, i.e., on the employment opportunities in the official economy and on the probability of being apprehended.

Turning to the indicators, I find a strongly significant, positive relationship between illegal goods smuggling and the number of apprehensions, which confirms my hypothesis that the number of failed smuggling attempts indicates the level of illegal goods smuggling. The relationship between drug seizures/drug availability and smuggling is only sometimes statistically significant. While I find the hypothesized positive sign for all specifications, drug seizures are significant for specifications 1 and 3 only while drug availability is not significant.

In the MIMIC models for the smuggling of legal goods, all causal variables except for the BMP are statistically significant at conventional significance levels and have the expected sign. Hence, the data confirms the theoretical hypotheses in Section 4.2. A real depreciation of the peso against the U.S. dollar leads to higher export underinvoicing as the competitiveness of Mexican goods increases. Moreover, the higher Mexican income/profit taxes are, the stronger the incentive to underinvoice exports as illegal/unreported Mexican exports are not taxed and thus more competitive. Again, an important motive to underinvoice exports is tax evasion. In the case of import misinvoicing, real peso depreciation against the U.S. dollar decreases the amount of import underinvoicing as Mexican products gain competitiveness over misinvoiced U.S. imports. A rise in Mexican income/profit taxes lowers import underinvoicing. Illegal/unreported Mexican imports cannot be claimed as tax exempt and thus lose profitability compared to legal/reported Mexican imports, which confirms the tax evasion argument. In contrast, a higher tariff rate increases import underinvoicing, supporting the common view that import underinvoicing is motivated by tariff evasion.

All estimated MIMIC models show satisfactory goodness-of-fit statistics, i.e., the models fit the data fairly well. While the main statistics are given in Tables 4.3 and 4.4, Tables D.2 and D.3 in Appendix D present additional goodness-of-fit statistics of the MIMIC models for illegal and legal goods smuggling.[91] I accept the validity of the estimated models and conclude that all specifications are suitable to calculate long-term trends in the smuggling of illegal and legal goods.

---

[91] For a description of the goodness-of-fit statistics, see Section A.3 in Appendix A.

Table 4.4 MIMIC Model Estimations for Legal Goods Smuggling

	Export misinvoicing		Import misinvoicing	
Specification	8	9	10	11
Time period	1980-1998	1980-2004	1980-1998	1980-2004
Causes				
BMP (through 1998)	-0.02		-0.01	
	(0.46)		(0.27)	
Real exchange rate	0.16***	0.17***	-0.13***	-0.16***
	(2.82)	(3.52)	(2.45)	(3.45)
Taxes on income/profit	0.11***	0.14***	-0.10***	-0.13***
	(2.54)	(3.15)	(2.79)	(3.24)
Taxes on international trade			0.06**	0.06*
			(1.96)	(1.68)
Indicators				
Errors and omissions (fixed)	1.00	1.00	-1.00	-1.00
Import misinvoicing			0.17	0.23
			(0.67)	(0.97)
Export misinvoicing	0.19	0.06		
	(0.52)	(0.19)		
Goodness-of-fit statistics				
Observations	228	305	228	305
Degrees of freedom	8	4	9	8
Chi-square	1.85	0.91	5.38	1.74
(*p*-value)	(0.98)	(0.92)	(0.80)	(0.98)
RMSEA	0.00	0.00	0.00	0.00

Note: *** Significance at the 1% level. ** Significance at the 5% level. * Significance at the 10% level. Absolute *z*-statistics in parentheses. The degrees of freedom are determined by 0.5 (p + q) (p + q + 1) – t; with p = number of indicators; q = number of causes; t = the number for free parameters. If the model fits the data perfectly and the parameter values are known, the sample covariance matrix equals the covariance matrix implied by the model. The null hypothesis of perfect fit corresponds to a *p*-value of 1. The RMSEA measures the model's fit based on the difference between the estimated and the actual covariance matrix. RMSEA values smaller than 0.05 indicate a good fit [Browne and Cudeck (1993)].

4.5.3 Long-term Trends in Illegal Goods Smuggling

The estimated MIMIC coefficients allow me to determine the dimensionless time pattern of smuggling only. To obtain the market value of smuggling over time, I convert the MIMIC index into "real world" figures measured in U.S. dollars. In the first step, I calculate an exogenous base value for illegal goods smuggling across the U.S.-Mexico border in 2000 using expert estimates. As mentioned in Section 4.4, I focus on the two types of smuggled illegal "goods" prominently discussed in the media: illegal immigrants and illegal drugs.[92] In the second step, this base value is used to calibrate a time series of smuggling by applying the benchmarking procedure promoted by Dell'Anno and Schneider (2006), Dell'Anno (2007), and Dell'Anno and Solomon (2008).

The average inflow of illegal (unauthorized) adult Mexican immigrants to the United States is estimated at about 330,000 per year between 2000 and 2007 [Hoefer et al. (2008), p. 4; Passel and Cohn (2008), p. 14]. Because I cannot assess the "market value" of these illegal immigrants, I calculate the average wage earned while working in the United States illegally using the Mexican Migration Project (MMP) database. Since 1982, the MMP has conducted annual surveys of (illegal) Mexican immigrants. Using data on the employment characteristics of Mexicans who entered the United States illegally, and their duration of stay, I calculate the average salary an illegal Mexican immigrant earns during her stay in the United States. Table 4.5 illustrates that illegal Mexican immigrants, on average, worked in the United States for 20.08 months and earned $26,325. Based on the underlying sub-sample of 270 survey respondents, I calculate that the 330,000 illegal Mexican immigrants earn wages amounting to $8.7 billion each year.

---

[92] Although the MIMIC index of illegal goods smuggling may include other types of illegal goods, the calculation of "real world figures" is limited to illegal immigrants and illegal drugs. The reason is that the political debate on whether to increase border patrol in the United States centers on these two types of illegal goods and estimates about the size of these types of smuggling – necessary to calculate the time trend in "real world" figures – are available.

Table 4.5 Employment Characteristics of an Average Illegal Mexican Immigrant During Her Stay in the United States.

Duration in the United States (in months)	Months worked per year	Hours worked per week	Hourly wage (in U.S. dollars)	Illegal wages earned in the United States (in U.S. dollars)
20.08	9.41	46.51	8.62	26,325

Source: Mexican Migration Project (MMP) database. The MMP data is available online at http://mmp.opr.princeton.edu.

Note: These average characteristics are drawn from a sub-sample of 270 survey respondents who entered the United States illegally, i.e., with or without false documents, between 2000 and 2006.

To calculate the base value of illegal drugs smuggled across the U.S.-Mexico border, I employ expert estimates as illustrated in Table 4.6. According to Rhodes et al. (2001, p. 31), Americans spent $61.2 billion on illegal drugs in 2000. Using the estimated "Mexican" share of these drugs,[93] I quantify the market value of drugs smuggled across the U.S.-Mexico border at $31.4 billion in 2000. Aggregating the calculated size of illegal immigration and illegal drugs smuggling, I obtain an exogenous estimate for illegal goods smuggling across the U.S.-Mexico border of $40.1 billion in 2000.

[93] According to expert estimates shown in Table 4.6, most of the cocaine and marijuana available in the United States is smuggled via the Mexican border.

Table 4.6 Base Value for Illegal Drugs Smuggled via the U.S.-Mexico Border in 2000

	Cocaine	Heroin	Marijuana	Metham-phetamine	Total
Total U.S. expenditures on illegal drugs in 2000 (in billion U.S. dollars) 1)	35.3	10.0	10.5	5.4	61.2
Estimated average percentage arriving in the United States via the U.S.-Mexico border	66% 2)	18% 3)	55.6% 4)	9.1% 5)	
Estimated value of illegal drugs smuggled through the U.S.-Mexico border in 2000 (in billion U.S. dollars)	23.3	1.8	5.8	0.5	31.4

1) Source: Rhodes et al. (2001, p. 31).

2) The Interagency Assessment of Cocaine Movement estimates that 66% of cocaine in the United States flows through Mexico [Ford (2008), p. 7].

3) According to the Drug Availability Steering Committee (2002, p. 61), 16% to 20% of heroin in the United States in 2000 originated in Mexico.

4) The Drug Availability Steering Committee (2002, pp. 106, 119) estimates that 4651 metric tons of Mexican marijuana arrived on the U.S. market in 2000. The total amount of marijuana in the United States in 2000 is estimated at between 5,577 and 16,731 metric tons, which corresponds to a Mexican market share of between 27.8% and 83.4%.

5) According to the Drug Availability Steering Committee (2002, pp. 82-85) 8.6%-9.6% of methamphetamines in 2000 came from Mexico.

This base value allows me to calculate a time series for illegal goods smuggling applying a benchmarking procedure. Unfortunately, no consensus exists in the literature about which benchmarking procedure to use. I use the methodology promoted by Dell'Anno and Schneider (2006), Dell'Anno (2007), and Dell'Anno and Solomon (2008). In the first step, the MIMIC model index of smuggling is calculated by multiplying the coefficients of the significant causal variables by the respective raw time series. For the numerical example of specification 4 the structural equation is given as:

$$\frac{\tilde{\eta}_t}{Smugglers_{2000}} = 0.05 \cdot x_{1t} - 0.05 \cdot x_{2t} - 0.64 \cdot x_{3t}, \text{[94]} \tag{4.16}$$

and measures illegal goods smuggling per apprehended smuggler in 2000 according to the MIMIC model's identification rule.[95] Next, this index is converted into a time series of illegal goods smuggling which takes up the base value of \$40.1 billion in 2000. Thus, the annual U.S. dollar amount of illegal goods smuggling $\hat{\eta}_t$ at time t is given as:

$$\frac{\tilde{\eta}_t}{Smugglers_{2000}} \frac{Smugglers_{2000}}{\tilde{\eta}_{2000}} \eta^*_{2000} = \frac{\tilde{\eta}_t}{\tilde{\eta}_{2000}} \eta^*_{2000} = \hat{\eta}_t, \tag{4.17}$$

where $\left(\tilde{\eta}_t / Smugglers_{2000}\right)$ denotes the value of the MIMIC index at t according to equation (4.16), $\left(\tilde{\eta}_{2000} / Smugglers_{2000}\right)$ is the base value of this index in 2000, and η^*_{2000} is the exogenous estimate of illegal goods smuggling amounting to \$40.1 billion in 2000.

The final estimates of illegal goods smuggling over the last three decades are calculated using specifications 4 through 7.[96] As shown in Figure 4.4, all calculated indices have a similar pattern.[97] Table D.4 in Appendix D presents selected annual estimates for illegal goods smuggling.

Illegal goods smuggling seems to be driven largely by macroeconomic conditions in Mexico and by changes in U.S. border enforcement policy. The two major Mexican recessions, triggered by a debt crisis in 1982/83 and by a currency crisis in 1994/95, resulted in a significant increase in the smuggling of illegal goods to \$113 billion in 1983 and \$87 billion in 1995. Both economic downturns were associated with rising unemployment and falling real wages in Mexico and were a push factor for Mexican

---

[94] x_{1t}, x_{2t}, and x_{3t} represent the unemployment rate, real wages, and border enforcement, respectively.

[95] As outlined in Section 4.5.2, linewatch apprehensions are used as an index variable where the denominator equals linewatch apprehensions in the base year 2000. As the latent variable is measured in units of the fixed indicator, illegal goods smuggling is measured per apprehended smuggler at the border in 2000.

[96] Specifications 1 to 3 cannot be used as they do not cover the base year 2000.

[97] The pattern of the illegal goods smuggling index is not dominated by one or two of the causes although the variable 'probability of apprehension' has a large coefficient and thus influences the dynamics mostly.

smugglers. As Mexican labor market conditions worsened, many Mexicans chose to engage in illegal smuggling activities as an alternative source of income.

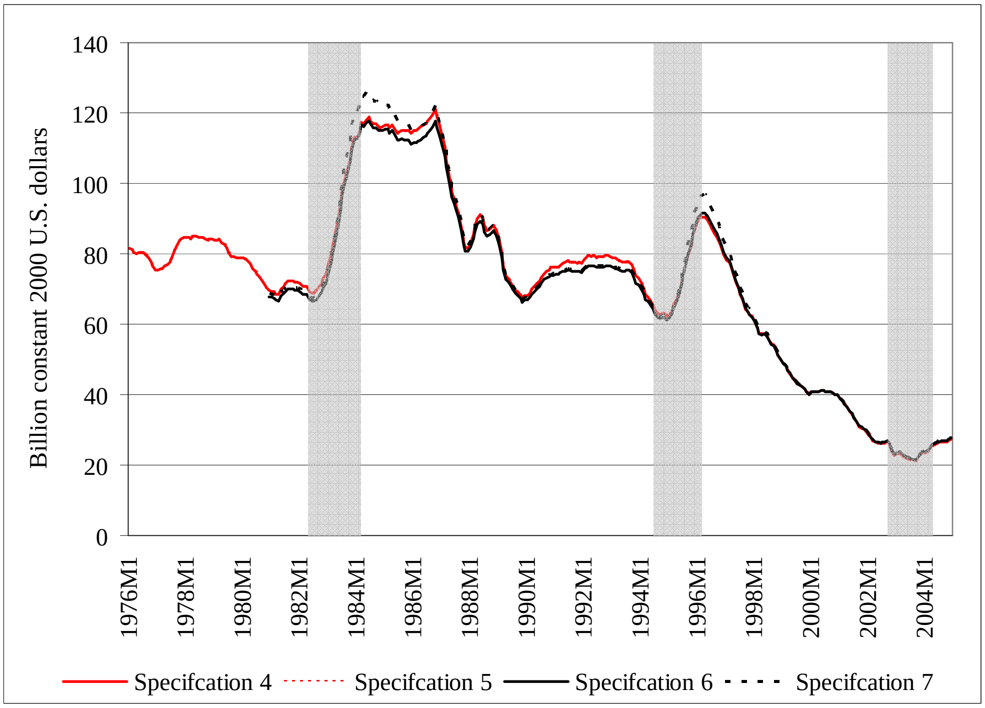

Figure 4.4 Smuggling of Illegal Goods

Note: The grey bars mark the Mexican recessions in 1982/83 and 1995 and changes in U.S. drug policy in 2003.

I also find evidence that a stricter U.S. border enforcement policy since the Immigration Reform and Control Act (IRCA) in 1986 may have contributed to a long-term decline in the smuggling of illegal goods, which fell from $116 billion in 1986 to $27 billion in 2004. The number of man-hours spent by the U.S. Border Patrol policing the U.S.-Mexico border increased from 2.7 million in 1986 to 9.7 million in 2004. This rise in border enforcement activities effectively raised the probability of apprehension, thereby reducing smuggling. In 2003, the pattern of illegal goods smuggling reversed as an unintended consequence of a change in U.S. drug policy [Carpenter (2005)]. U.S. officials believed that by focusing on the drug cartels' top figures, rather than on petty smugglers at the border, they could achieve huge decreases in drug trafficking. But the new policy only led to a decentralization of the drug trade: instead of the kingpins who had controlled it before, there are now more than three hundred small groups engaged in illegal drug smuggling [Carpenter (2005)].

4.5.4 Long-term Trends in Legal Goods Smuggling

As with illegal goods smuggling, equation (4.17) is applied to convert the MIMIC index into a time series of legal goods smuggling using the significant causal variables in specifications 9 (export misinvoicing) and 11 (import misinvoicing).[98] The base values for benchmarking are taken from Eggerstedt et al. (1995), who present estimates for misinvoicing in the U.S.-Mexican trade using U.S. Department of Commerce and Banco de Mexico data. I use the overinvoicing estimate of $588.3 million in 1984 as the base value for export misinvoicing and the underinvoicing value of $914.4 in 1984 for import misinvoicing.

Figure 4.5 shows the estimated time series for legal goods smuggling. While export misinvoicing exhibits temporary fluctuations but no time trend, import misinvoicing is permanently affected by U.S.-Mexican trade integration. The reduction of Mexican tariffs on U.S. imports after Mexico's accession to GATT in 1987 and to NAFTA in 1994 resulted in a permanent switch from import underinvoicing – motivated by tariff evasion – to import overinvoicing – motivated by tax evasion.

---

[98] Specifications 9 and 11 are selected because they cover the entire observation period 1980-2004.

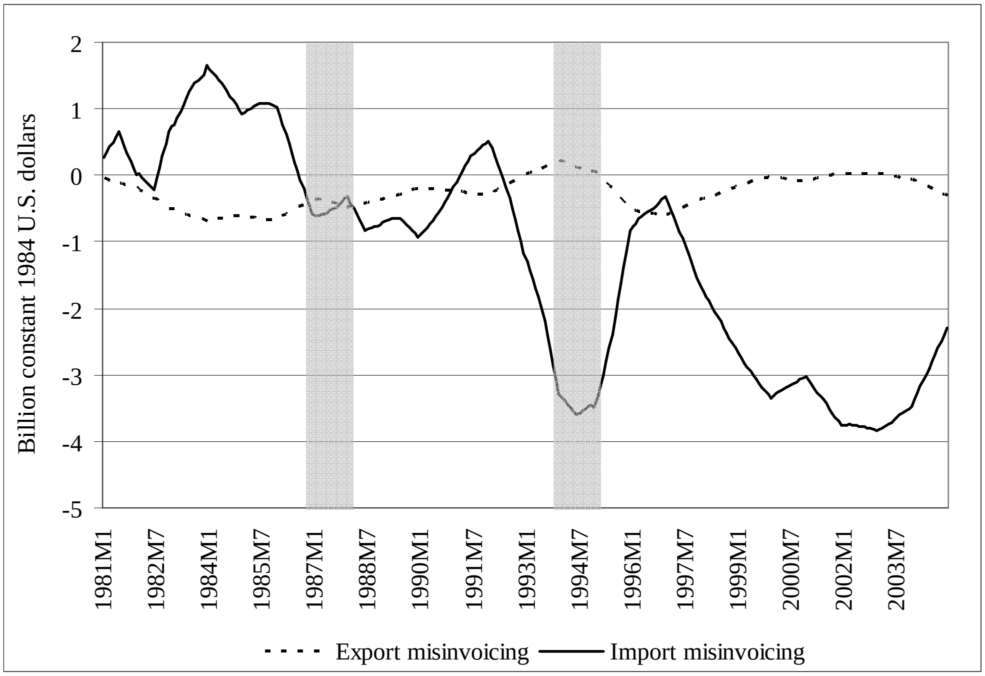

Figure 4.5 Smuggling of Legal Goods

Note: The grey bars mark Mexico's accession to GATT in 1987 and to NAFTA in 1994.

4.6 Summary and Conclusion

This chapter examines the determinants of and long-term trends in smuggling across the U.S.-Mexico border, distinguishing between the smuggling of illegal and legal goods. Working out the microeconomic incentives of the two types of smuggling, I hope to improve the understanding of this phenomenon. It seems reasonable to assume that smugglers who traffic illegal drugs or illegal immigrants respond to different incentives than trade misinvoicers. As smuggling is an informal (illegal) and, thus, unobservable activity, I use a MIMIC approach for the analyses of illegal and legal goods smuggling across the U.S.-Mexico border.

The results of the MIMIC model are robust and confirm most of the theoretical hypotheses. I find that illegal goods smuggling declines when Mexican labor market conditions improve or U.S. border enforcement activities are intensified as the cost of smuggling rises in this context. Confirming the competitiveness argument, export (import) misinvoicing is positively (negatively) correlated with real peso depreciation. Import misinvoicing is positively correlated with Mexican import tariffs, pointing to the incentive of tariff evasion. Export (import) misinvoicing is positively (negatively) correlated with Mexican taxes on income and profit, pointing to the incentive of tax evasion.

The estimated long-term trends for both types of smuggling show the sensitivity of smuggling to major macroeconomic events. Import misinvoicing has switched from underinvoicing to overinvoicing over the last twenty years as a result of reduced import tariffs following Mexico's accession to GATT (1987) and NAFTA (1994). Illegal goods smuggling rose temporarily during the Mexican recessions in 1982/83 and 1995, but the overall trend is negative, decreasing by almost $90 billion from 1984 to 2004, which can be attributed to improved labor market conditions in Mexico and a successful U.S. border enforcement policy. Indeed, the increase in U.S. Border Patrol man-hours has increased the probability of apprehension and strengthened the deterrent to smuggle.

Analyzing smuggling using a MIMIC model has some shortcomings that are, however, widely accepted in other fields studying unobservable phenomena such as the shadow economy or corruption. First, although the model tracks the development of smuggling over time, the estimations for the volume of smuggling depends on the exogenous estimate used for calibration. Researchers can carefully check its size and reliability, but the final estimate remains an approximation. Second, other variables such as tax morality or socioeconomic factors may influence smuggling, for which data are not available.

Nevertheless, in this chapter I contribute to the understanding of smuggling and the results have important implications for the policy debate. The smuggling of illegal drugs and immigrants across the U.S.-Mexico border remains a major issue for U.S. national security. Illegal drug abuse leads to casualties, rising health care costs, and lower employment in the United States [French et al. (2001)]. Illegal immigration, as well, not only affects labor market conditions in the United States but is a serious humanitarian crisis. It is unbearable that myriad Mexicans die when attempting to cross the border illegally.[99]

Despite the successful border enforcement policy, several options are available to further reduce illegal goods smuggling. Increased bilateral trade, U.S. aid, and foreign direct investment to Mexico, for example, would improve Mexican labor market conditions, thereby reducing the incentive to smuggle. The United States could also further increase linewatch hours or invest in border patrol technologies. Finally, the United States could provide financial and/or technical support to intensify patrolling activities on the Mexican side of the border.

Trade misinvoicing seems to be a less serious problem given that it is a relatively small-scale financial crime with no loss of human life. Also, the scope for political intervention is limited. Tariffs have already been reduced significantly, and it is unlikely that exchange rate policy would be used to combat trade misinvoicing.

[99] The U.S.-Mexico case seems to be especially relevant in this context as illegal immigration is typically the more likely, the poorer and the less distant the source country [see, for example, Bratsberg (1995)].

CHAPTER FIVE

FINAL REMARKS

"Mixing one's wines may be a mistake, but old and new wisdom mix admirably."
Bertolt Brecht (1898-1956)

5.1 Summary and Conclusion

This dissertation has studied different types of economic activities: DIY, or household, activities, shadow economic activities, the smuggling of legal goods, and the smuggling of illegal goods. Although different, these activities are bound together by a common characteristic: they are all informal economic activities. The first chapter briefly explained two important concepts: the diversity of the informal economy and the attractiveness of informal economic activities as research topic for economists. Chapter 2 focused on DIY and shadow economic activities in Germany. Chapter 3 studied the smuggling of legal goods – often referred to as trade misinvoicing – in an international perspective. Chapter 4 widened the analysis of smuggling to include both the smuggling of legal and illegal goods within the U.S.-Mexican context.

Together, Chapters 2-4 examined the different types of informal economic activities using structural equation models (SEMs) with latent variables. Because of their informal character and because participants usually hide such activities, statistics on informal economic activities are not typically available. Instead, researchers must develop methods to *estimate* the informal economy. These techniques range from direct approaches, such as surveys, to indirect ones, such as the currency demand approach. This dissertation relies on SEMs with latent variables because they are able to determine the structural relationships between (unobservable) variables using the multiple causes and multiple indicators of each unobservable variable. These models thus avoid the problems of other macroeconomic approaches which often take into account only one cause or indicator, such as the burden of taxation or the amount of electricity consumed. SEMs consider the multiple causes leading to the existence and growth of informal economic activities as well as their multiple effects explicitly. This makes it a superior statistical methodology for the analysis of these types of activities. A minor drawback of using SEMs with unobservable variables is however that these models can track the development of informal economic activities over time but the estimation of “real world” figures depends on the exogenous estimate used for calibration.

Chapter 2 presented empirical evidence that the shadow economy makes up a significant portion of the German GDP. Many researchers have contributed to this analysis using a variety of methods: surveys, discrepancy methods, the physical input method, the currency demand approach, and latent estimation procedures such as the Multiple Indicators Multiple Causes (MIMIC) model. Estimates of the size of the German shadow economy vary depending on the methodology applied: they range from 1.0% (surveys) to 38.5% (discrepancy method) of official German GDP.

Although substantial research already exists, some questions have yet to be answered: makes the DIY economy up also a significant part of the German GDP or not? How have shadow economic and DIY activities developed over time? What effect did reunification have on these two parts of the informal economy? The models estimated in Chapter 2 provide new estimates of the size and development of shadow economic and DIY activities in Germany. They also show that the German shadow economy grew from around 1-2% to around 17% of official GDP between 1970 and 2005 while DIY activities grew only marginally from 4% to around 5% of official GDP during the same time. This suggests that DIY activities are not as dynamic a part of the hidden economy as shadow economic activities. Together, however, shadow economic and DIY activities comprised a remarkable 22% of official German GDP in 2005. With regard to the determinants of the shadow economy, statistically significant correlations exist for institutional variables such as the level of regulation and tax and social security contribution burdens. The DIY economy, on the other hand, appears to be driven by unemployment.

Although the results presented in Chapter 2 are only an additional step towards a comprehensive understanding of the dynamics of DIY and shadow economic activities, they nevertheless point to the fact that both types of activities have become a significant part of the German economy. To reduce the hidden economy and stimulate the official economy, German policymakers have two options. The empirical results suggest that fewer (business) regulations and lower tax and social security contribution burdens might be the two means of shifting more activity into the official economy. This would create more jobs – especially part-time work and specialty (craftsmen) trades – in the official economy and possibly reduce participation in the DIY economy.

A household runs most efficiently when some members invest in human capital by working in paid employment while others work at home and maximize their individual utility through, for example, rearing children [Becker (1993), pp. 30-55]. The relatively stable index of DIY activities calculated in Chapter 2 might be an indication of the relevance of this theory and the strong separation of responsibilities within a household. Although it is not clear if a reduction in DIY activities is a desirable policy goal, an effective policy measure might be the further deregulation of the labor market in Germany to increase the availability of low-skilled and/or part times jobs.

The dynamic growth of the shadow economy in Germany over the past 30 years suggests that minor policy reforms, by and large, have been ineffective. Major policy reforms, such as a comprehensive revision of the tax system and a substantial reduction of rules and regulations in the administrative procedure in Germany, are needed. It will be interesting to see whether the tax reforms the newly-elected German government wants to implement are suitable to reduce the size of the shadow economy in the future.

The smuggling index presented in Chapter 3 provides a ranking of smuggling for 54 countries during the 1990s. While previous research employs mostly trade discrepancies to estimate smuggling, I use an SEM that accounts both for the informal nature of smuggling as well as the smuggling's multiple causes and indicators. The empirical analyses show a highly statistically significant influence of the rule of law and the level of corruption on smuggling. Trade restrictions and high tariffs provide incentives to engage into smuggling. The cross-country analysis, however, indicates that the quality of institutions – measured by the rule of law and corruption – rather than high tariffs and trade restrictions drive smuggling, although the latter are also important determinants of smuggling. Overall, I conclude that legal goods smuggling is lowest in the high-income countries of the OECD and highest in the low-income countries of Latin America and Africa.

Two important policy conclusions may be drawn from the cross-country analysis of legal goods smuggling. First, like individuals who engage in shadow economic activities individuals who engage in the smuggling of legal goods are motivated by tax and tariff evasion. Reducing these barriers to trade may thus reduce smuggling in legal goods. Second, the analysis suggests that, even more so than barriers to trade, the rule of law and corruption are important determinants of smuggling. Thus, countries that wish to reduce the size of smuggling should strengthen their institutions, i.e., by strengthening the rule of law and reducing corruption. Ideally, a combination of lower taxes and tariffs and stronger institutions would best address the issue of smuggling.

Chapter 4 widened the analysis of smuggling to include the smuggling of both illegal and legal goods within the U.S.-Mexican context. The microeconomic model shows that traffickers of illegal goods, such as drugs and immigrants, respond to different incentives than smugglers of legal goods, i.e., trade misinvoicers. The robustness of the results confirms the theoretical hypotheses, from which two general conclusions may be drawn. First, illegal goods smuggling declines when Mexican labor market conditions improve and/or when U.S. border enforcement is intensified. This confirms previous findings that higher expected costs reduce illegal goods smuggling. Second, the smuggling of legal goods is strongly motivated by the incentive to evade taxes and tariffs. The estimated long-term trends for both types of smuggling show the sensitivity of smuggling to major macroeconomic events. Mexico’s accession to GATT (1987) and NAFTA (1994), for example, affected the smuggling of legal goods while the Mexican recessions in 1982/83 and 1995 and stricter U.S. border enforcement policies affected the smuggling of illegal goods. Indeed, the expansion of U.S. Border Patrol man-hours has increased the probability of apprehension and thus the expected costs for illegal goods smugglers, strengthening the deterrent to smuggle.

In general, the results of this dissertation show that the informal economy is significant and that growth of the informal economy is not exclusive to developing countries, although it is a more serious problem in these countries. Moreover, although the informal economy covers a wide range of rather diverse economic activities, a few similarities exist. These are important, especially for policymakers, in first understanding what drives informal economic activities and second designing appropriate policies to deter them.

Tax evasion is an important determinant of two types of informal economic activities: shadow economic activities and the smuggling of legal goods. Governments need to take this problem seriously as tax evasion places a disproportionate burden on the other members of society who do pay taxes. Since the government makes decisions about which goods and services to provide to its citizens, financed through taxes, tax evaders benefit twice. On the one hand, they benefit from the evasion of taxes as their profits increase. Second, they enjoy publicly provided goods and services – some of which are necessary to carry out their economic activities, such as infrastructure – for free. Tax evaders are thus free riding at the expense of the rest of the society. Reducing incentives for tax evasion, governments can not only lessen pure tax evasion but also informal shadow economic activities and the smuggling of legal goods.

The expected costs are important determinants of informal economic activities. Increasing the man-hours spent patrolling the U.S.-Mexico border, for example, raises the probability of apprehension and is thus a significant deterrent for smugglers of illegal goods. Strengthening institutions by encouraging the rule of law and reducing corruption also deter illegal activities.

Regulation – and its enforcement – is another determinant of informal economic activities. Societies regulate formal economic activities: licenses are required to undertake certain types of businesses (medicine, cooking, elderly care) and the way businesses operate is regulated according to environmental, health, and safety standards. These types of regulations are necessary to enforce minimum standards for consumers as well as employees. Individuals carrying out informal economic activities may impose a burden on society by using hazardous materials, providing unsafe working conditions, employing child labor, or exploiting workers. While stricter regulations drive individuals into informal economic activities, countries with a stronger rule of law and less corruption however have smaller informal economies. On the one hand, countries with greater economic regulation tend to have larger informal economies. On the other hand, enforcement of regulations by corrupt bureaucrats is a burden levied on businesses and individuals which drives them into the informal economy. This suggests that governments should put more emphasis on improving institutions and enforcing existing laws and regulations rather than creating new ones. Some governments, however, may choose to increase regulation to reduce informal economic activities because it increases bureaucratic power and creates jobs in the public sector.

Although none of the chapters presented a detailed microeconomic analysis, one can speculate on who participates in different informal economic activities. Entrepreneurs, for example, who seek to increase profits, are most likely to engage in shadow economic activities and the smuggling of legal goods. Households, which seek to maximize efficiency by assigning various activities according to the comparative advantages of the different household members, are most likely to engage in DIY activities. Individuals living at the subsistence level, trying to earn a living for their families, are most likely to engage in the smuggling of illegal goods. The decision whether or not to engage in informal economic activities is thus based on the opportunity cost, i.e., on employment opportunities in the official economy and on the probability of being caught.

The informal economy offers an escape from the burdens of participating in the formal economy. Informal economic activities however shed light on rules and regulations that are ineffective and which need to be reassessed. That is, determining the areas of growth in the informal economy may expose the weaknesses of current economic policies. In some cases, such as the smuggling of illegal drugs – which imposes costs on society in the form of higher health care expenditures, increased crime, and decreased productivity – an appropriate solution may be stricter law enforcement. Growth of the informal economy as a whole may be an indication that a combination of policy measures – including revising outdated and inefficient rules, regulations, and tax laws – is necessary.

5.2 Future Research

While this dissertation provides a plethora of previously unknown information about the informal economy, it also makes clear that there is still much to learn. Most of the literature focuses on the size and development of the shadow economy in a particular country or for a set of countries. What these papers fail to provide are disaggregated values for specific regions. Policymakers may be interested in breaking the shadow economy down according to region, level of urban development, or income. The relationship between the size of the shadow economy in the United States and the proportion of illegal immigrants from Mexico in the individual states may also be of value to U.S. lawmakers.

Various non-governmental organizations, such as the Institute for New Democracies, make their decisions based on the institutional environment of a particular country. The index of smuggling – a potential indicator of the general institutional quality in a particular country – outlined in Chapter 3 may help non-governmental organizations monitor the institutional environment over time. Another promising avenue for future empirical research is studying the impact of economic, political, and institutional reforms, such as the implementation of free trade zones or the improvement of institutional quality, on smuggling.

The smuggling of illicit drugs across the U.S.-Mexico border into Arizona, California, New Mexico, and Texas is a major challenge for the United States. Treating smuggling as an unobservable phenomenon, one can use several indicators of smuggling simultaneously to estimate the level of smuggling. Analyzing the determinants of smuggling at the state-level using state-specific determinants, these estimates can then be used to determine whether the illicit drug trade is in fact correlated with crime rates and violence, as the media often claims.

REFERENCES

Aigner, D.J., C. Hsiaz, A. Kapteyn, and T. Wansbeek (1984), “Latent variable models in econometrics,” pp. 1321-1393 in: Z. Griliches and M.D. Intriligator (eds.), *Handbook of Econometrics*, Vol. 2, North-Holland: Amsterdam.

Allingham, M.G. and A. Sandmo (1972), “Income tax evasion: A theoretical analysis,” *Journal of Public Economics*, 1, 323-338.

Alm, J. (1991), “A perspective on the experimental analysis of taxpayer reporting,” *The Accounting Review*, 66, 577-593.

Asea, P.K. (1996), “The Informal Sector: Baby or Bath Water?,” *Carnegie-Rochester Conference Series Public Policy*, 45, 163-171.

Askari, H. (2006), *Middle East Oil Exporters: What happened to Economic Development?*, Edward Elgar Publishing Limited: Cheltenham.

Bajada, C. and F. Schneider (2005), “The shadow economies of the Asia-Pacific,” *Pacific Economic Review*, 10, 379-401.

Banerjee, N. (1982), “Survival of the poor,” pp. 175-183 in: H.I. Safa (ed.), *Towards a Political Economy of Urbanization in Third World Countries*, Oxford University Press: Delhi.

Becker, G.S. (1993), *A Treatise on the Family*, Enlarged Edition, Harvard University Press: Cambridge, Massachusetts.

Bentler, P.M. and D.G. Bonett (1980), “Significance tests and goodness-of-fit in the analysis of covariance structures,” *Psychological Bulletin*, 88, 588-606.

– –; and C.P. Chou (1987), “Practical issues in structural modeling,” *Sociological Methods and Research*, 16, 78-117.

Beja, E.L. (2008), “Estimating trade mis-invoicing from China: 2000 – 2005,” *China & World Economy*, 16, 82-92.

Berger, H. and V. Nitsch (2008), “Gotcha! A profile of smuggling in international trade,” CESifo Working Paper No. 2475.

Bhagwati, J.N. (1964), “On the under-invoicing of imports,” *Bulletin of the Oxford University*, Institute of Economics and Statistics, 26, 389-397.

– –; and B. Hansen (1973), "A theoretical analysis of smuggling," *The Quarterly Journal of Economics*, 87, 172-187.

Biswas, A.K. and S. Marjit (2007), "Preferential trade and mis-invoicing: Some analytical implications," *International Review of Economics & Finance*, 16, 130-138.

Bollen, K.A. (1989), *Structural Equations with Latent Variables*, Wiley: New York.

– –; and J.S. Long (1993), *Testing Structural Equation Models*, Sage: Beverly Hills, CA.

Bosch, L. and S. Lehndorf (1998), „Arbeitszeitverkürzung und Beschäftigung: Erfahrungen in Europa und wirtschaftspolitische Empfehlungen," *Vierteljahreshefte zur Wirtschaftsforschung*, 67, 300-325.

Bratsberg, B. (1995), "Legal versus illegal U.S. immigration and source country characteristics," *Southern Economic Journal*, 61, 715-727.

Breusch, T. (2005a), "The Canadian underground economy: An examination of Giles and Tedds," *Canadian Tax Journal*, 53, 367-391.

– – (2005b), "Estimating the underground economy using MIMIC models," Working Paper, Available under: http://econwpa.wustl.edu/eps/em/papers/0507/0507003.pdf.

Brodersen, S. (2003), *Do-it-yourself Work in North-Western Europe. Maintenance and Improvement of Homes*, Study No. 11, The Rockwool Foundation Research Unit, Copenhagen.

Brodie, N., J. Doole, and P. Watson (2000), *Stealing History: The Illicit Trade in Cultural Material*, McDonald Institute for Archaeological Research, University of Cambridge: Cambridge, UK.

Bromley, R. and C. Gerry (1979), *Casual Work and Poverty in Third World Cities*, Wiley: Chichester.

Browne, M.W. and R. Cudeck (1993), "Alternative ways of assessing model fit," pp. 445-455 in: K.A. Bollen and J.S. Long (eds.), *Testing Structural Equation Models*, Sage Publications: Newbury Park, CA.

Buehn, A. and M.R. Farzanegan (2008), "Smuggling around the world: Evidence from a structural equation model," Working Paper, Faculty of Business and Economics, Technische Universität Dresden, Dresden.

– –; and F. Schneider (2008), "MIMIC models, cointegration and error correction: An application to the French shadow economy, CESifo Working Paper No. 2200.

– –; and S. Eichler (2009), “Smuggling illegal versus legal goods across the U.S.-Mexico border: A structural equations model approach,” *Southern Economic Journal*, 76, 328-350.

– –; and F. Schneider (2009), “Corruption and the shadow economy: A structural equation model approach,” IZA Discussion Papers 4182.

– –; A. Karmann, and F. Schneider (2009), “Shadow economy and do-it-yourself activities: The German case,” *Journal of Institutional and Theoretical Economics*, 165, 700-721.

Byrne, B.M. (1998), *Structural Equation Modelling with LISREL, PRELIS and SIMPLIS: Basic Concepts, Applications and Programming*, Lawrence Erlbaum Associates: Mahwah, NJ.

Capraro, R.M., G. Kulm, and M.M. Capraro (2002), “Investigating the complexity of middle grade students’ understandings of mathematical constructs: An example from graphic representation,” Paper presented at the Annual Meeting of the American Educational Research Association (New Orleans, LA, April 1-5, 2002), Downloadable from ERIC - the Education Resources Information Center.

Carpenter, T.G. (2005), “Mexico is becoming the next Colombia,” *Cato Institute Foreign Policy Briefing*, 87, 1-8.

Cassar, A. (2001), “An index of the underground economy in Malta,” *Bank of Valletta Review*, 23, 44-62.

Choi, I. (1994), “Residual-based tests for the null of stationary with application to U.S. macroeconomic time series,” *Econometric Theory*, 10, 720-746.

Cooley, W.W. (1978), “Explanatory observational studies,” *Educational Researcher*, 7, 9-15.

Cziraky, D. (2004), “LISREL 8.54: A program for structural equation modelling with latent variables,” *Journal of Applied Econometrics*, 19, 135-141.

– – (2005), “A unifying statistical framework for dynamic structural equation models with latent variables,” Available under: http://stats.lse.ac.uk/ciraki/framework.pdf.

– –; and M. Gillman (2003), “Inflation-growth causality with a latent underground economy model, research report, WIIW/GDN-SEE, *Research Field II: Enterprise Development, Informal Economy and Labour Markets*, The Vienna Institute for International Economic Studies, Vienna, available at: www.wiiw.ac.at/balkan/ files/ GDN_EnterpriseLabourInformal_InflationGrowthUnderground.pdf.

Deardorff, A. and W. Stolper (1990), “Effects of smuggling under African conditions: A factual, institutional and analytic discussion,” *Weltwirtschaftliches Archiv*, 126, 116-141.

De Macedo, J.B. (1987), “Currency inconvertibility, trade taxes and smuggling,” NBER Working Paper No. 2177.

De Soto, H. (1989), *The Other Path: The Invisible Revolution in the Third World*, Harper and Row: New York.

Dell’Anno, R. (2003), “Estimating the shadow economy in Italy: A structural equation approach,” Working Paper 2003-7, Department of Economics, University of Aarhus, Aarhus.

– – (2007), “The shadow economy in Portugal: An analysis with the MIMIC approach,” *Journal of Applied Economics*, 10, 253-277.

– –; and F. Schneider (2003), “The shadow economy of Italy and other OECD countries: What do we know?,” *Journal of Public Finance and Public Choice*, 21, 97-120.

– –; and – – (2006), “Estimating the underground economy: A response to T. Breusch’s critique,” Discussion Paper, Department of Economics, Johannes Kepler University Linz, Linz.

– –; and O.H. Solomon (2008), “Shadow economy and unemployment rate in USA: Is there a structural relationship? An empirical analysis,“ *Applied Economics*, 40, 2537-2555.

– –; and F. Schneider (2009), “A complex approach to estimate the shadow economy: The structural equation modelling,” pp. 110-130 in: M. Faggini and T. Lux (eds.), *Coping with the Complexity of Economics*, Springer: Heidelberg.

– –; M. Gomez-Antonio, and A. Alanon Pardo (2007), “Shadow economy in three different Mediterranean countries: France, Spain and Greece. A MIMIC approach,” *Empirical Economics*, 33, 51-84.

Department of Justice (2008), *National Drug Threat Assessment 2008*, U.S. Department of Justice, Washington, DC.

Deregulation Commission (1991), *Opening of Markets and Competition, Report presented to the German Federal Government*, Bonn.

Deutsche Bundesbank (2002), „Der DM-Bargeldumlauf – von der Währungsreform zur Währungsunion," pp. 21-35 in: Deutsche Bundesbank (ed.), *Monatsbericht März 2002*, Deutsche Bundesbank: Frankfurt/Main.

Diamantopoulos, A. and J.A. Siguaw (2000), *Introducing LISREL. A Guide for the Uninitiated*, Sage Publications Inc.: London.

DIW (Deutsches Institut für Wirtschaftsforschung) (1998), „Arbeitszeitpräferenzen in West- und Ostdeutschland 1997. Potential für Verkürzung der Arbeitszeit gesunken," *DIW-Wochenbericht*, 65 (37), 667-677.

Dreher, A. (2006), "Does globalization affect growth? Evidence from a new index of globalization," *Applied Economics*, 38, 1091-1110.

– –; C. Kotsogiannis, and S. McCorriston (2007), "Corruption around the world: Evidence from a structural model," *Journal of Comparative Economics*, 35, 443-466.

Drug Availability Steering Committee (2002), *Drug Availability Estimates in the United States*, Office of National Drug Control Policy, Washington, DC.

Easterly, W. and M. Sewadeh (2002), *Global Development Network Growth Database*, The World Bank, Washington, DC.

Eggerstedt, H., R.B. Hall, and S. van Wijnbergen (1995), "Measuring capital flight: A case study of Mexico," *World Development*, 23, 211-232.

Farzanegan, M.R. (2009), "Illegal trade in the Iranian economy: Evidence from a structural model," *European Journal of Political Economy*, 25, 489-507.

Fausten, D.K. and B. Pickett (2004), "Errors & omissions in the reporting of Australia's cross-border transactions," *Australian Economic Papers*, 43, 101-115.

Feige, E.L. (1981), "The UK's unobserved economy: A preliminary assessment," *Journal of Economic Affairs*, 1, 205-212.

– – (1989), *The Underground Economies. Tax Evasion and Information Distortion*, Cambridge University Press: Cambridge.

– – (1990), "Defining and estimating underground and informal economies: The new institutional economics approach," *World Development*, 18, 989-1002.

– – (1994), "The underground economy and the currency enigma," *Supplement to Public Finance/ Finances Publiques*, 49, 119-136.

– – (1996), "Overseas holdings of U.S. currency and the underground economy," pp. 5-62 in: S. Pozo (ed.), *Exploring the Underground Economy*, W. E. Upjohn Institute for Employment Research: Michigan.

– –; and I. Urban (2008), “Measuring underground (unobserved, non-observed, unrecorded) economies in transition countries: Can we trust GDP?,” *Journal of Comparative Economics*, 287-306.

Feld, L.P. and C. Larsen (2005), *Black Activities in Germany in 2001 and 2004: A Comparison based on Survey Data*, Study No. 12, The Rockwool Foundation Research Unit, Copenhagen.

Fisman, R. and S.-J. Wei (2004), “Tax rates and tax evasion: Evidence from “missing imports” in China,” *Journal of Political Economy*, 112, 471-496.

– –; and – – (2007), “The smuggling of art, and the art of smuggling: Uncovering the illicit trade in cultural property and antiques,” NBER Working Paper No. 13446.

– –; and – – (2009), “The smuggling of art, and the art of smuggling: Uncovering the illicit trade in cultural property and antiques,” *American Economic Journal: Applied Economics*, 1(3), 82-96.

Fleck, S. and C. Sorrentino (1994), “Employment and unemployment in Mexicos’ labor force,” *Monthly Labor Review*, 117, 3-31.

Fleming, M.H., J. Roman, and G. Farrel (2000), “The shadow economy,” *Journal of International Affairs*, 53, 64-89.

Folmer, H. and A. Karmann (1992), “The permanent income hypothesis revisited – a dynamic LISREL approach,” *Methods of Operations Research*, 64, 355-359.

Ford, J.T. (2008), *U.S. Assistance Has Helped Mexican Counternarcotics Efforts, but the Flow of Illicit Drugs into the United States Remains High*, U.S. Government Accountability Office, Washington, DC.

French, M.T., M.C. Roebuck, and P.K. Alexandre (2001), “Illicit drug use, employment, and labor force participation,” *Southern Economic Journal*, 68, 349-368.

Frey, B.S. (1989), “How large (or small) should the underground economy be?,” pp. 111-129 in: E.L. Feige (ed.), *The Underground Economy: Tax Evasion and Information Distortion*, Cambridge University Press: Cambridge, UK.

– –; and H. Weck (1983a), “Bureaucracy and the shadow economy: A macro-approach,” pp. 89-109 in: H. Hanusch (ed.), *Anatomy of Government Deficiencies*, Springer: Berlin.

– –; and – – (1983b), “Estimating the shadow economy: A ‘naive’ approach,” *Oxford Economic Papers*, 35, 23–44.

– –; and W. Pommerehne (1984), “The hidden economy: State and prospect for measurement,” *Review of Income and Wealth*, 30, 1-23.

– –; and H. Weck-Hannemann (1984), “The hidden economy as an “unobserved” variable,” *European Economic Review*, 26, 33-53.

– –; – –; and W.W. Pommerehne (1982), “Has the shadow economy grown in Germany? An exploratory study,” *Weltwirtschaftliches Archiv*, 118, 499-524.

Garson, D.G. (2005), “Statnotes: An online textbook,” Available under: http://www2.chass.ncsu.edu/garson/pa765 /structur.htm.

Gërxhani, K. (2004), “The informal sector in developed and less-developed countries: A literature survey,” *Public Choice*, 120, 267-300.

Giles, D.E.A. (1995), “Measuring the size of the hidden economy and the tax gap in New Zealand: An econometric analysis,” Working Paper on Monitoring the Health of the Tax System n.5a, Inland Revenue Department, Wellington, New Zealand.

– – (1999), “Modelling the hidden economy in the tax-gap in New Zealand,” *Empirical Economics*, 24, 621-640.

– –; and L.M. Tedds (2002), “Taxes and the Canadian underground economy,” *Canadian Tax Foundation*, Toronto.

– –; – –; and G. Werkneh (2002), “The Canadian underground and measured economies,” *Applied Economics*, 34, 2347-2352.

Goldberger, A. (1972), “Structural equation methods in the social sciences,” *Econometrica*, 40, 979-1001.

Granger, C.W.J. and P. Newbold (1974), “Spurious regressions in econometrics,” *Journal of Econometrics*, 2, 111-120.

Greene, W.H. (2008), *Econometric Analysis*, 6th edition, Pearson Prentice Hall: Upper Saddle River, NJ.

Hanson, G.H. (2006), “Illegal migration from Mexico to the United States,” *Journal of Economic Literature*, 44, 869-924.

– –; and A. Spilimbergo (1999), “Illegal immigration, border enforcement, and relative wages: Evidence from apprehensions at the U.S.-Mexico border,” *American Economic Review*, 89, 1337-1357.

Harding, P. and R. Jenkins (1989), *The Myth of the Hidden Economy: Towards a New Understanding of Informal Economic Activity*, Open University Press: Philadelphia.

Hart, K. (1970), “Small scale entrepreneurs in Ghana and development planning,” *Journal of Development Studies*, 6, 104-120.

– – (1973), “Informal income opportunities and urban employment in Ghana,” *Journal of Modern African Studies*, 11, 61-89.

Hauser, R.M. and A.S. Goldberger (1971), “The treatment of unobservable variable in path analysis,” pp. 81-177 in: H.L. Costner (ed.), *Sociological Methodology*, Jossey-Bass: San Francisco.

Hayduk, L.A. (1987), *Structural Equation Modelling with LISREL. Essential and Advances*, The Johns Hopkins University Press: London.

Helberger, C. and H. Knepel (1988), “How big is the shadow economy? A re-analysis of the unobserved-variable approach of B.S. Frey and H.Weck-Hannemann,” *European Economic Review*, 32, 965-976.

Hill, R. (2002), “The underground economy in Canada: Boom or bust?,” *Canadian Tax Journal*, 50, 1641-1654.

Hoefer, M., N. Rytina, and B.C. Baker (2008), *Estimates of the Unauthorized Immigrant Population Residing in the United States: January 2007*, U.S. Department of Homeland Security Office of Immigration Statistics, Washington, DC.

Holmes, K.R., E.J. Feulner, and M.A. O´Grady (2007), *2007 Index of Economic Freedom*, Washington, DC.

Hoyle, R.H. (ed.) (1995), *Structural Equation Modeling: Concepts, Issues, and Applications*, Sage Publications: Thousand Oaks, CA.

Hu, L., P.M. Bentler, and Y. Kano (1992), “Can test statistics in covariance structure analysis be trusted?,” *Psychological Bulletin*, 112, 351-362.

IfD (1975), *Freizeitarbeit 1974 – Eine Stichtagsuntersuchung*, Institut für Demoskopie: Allensbach.

IMF (1993), *A Guide to Direction of Trade Statistics*, International Monetary Fund, Washington, DC.

International Labour Organization (1972), *Employment, Income and Equality: A Strategy for Increasing Productivity in Kenya*, ILO: Geneva.

James, L.R., S.A. Mulaik, and J.M. Brett (1982), *Causal Analysis: Assumptions, Models, and Data*, Sage: Beverly Hills, CA.

Johansen, S. (1991), “Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models,” *Econometrica*, 59, 1551-1580.

– – (1995), *Likelihood-based Inference in Cointegrated Vector Autoregressive Models*, Oxford University Press: Oxford.

Johnson, S., D. Kaufmann, and A. Shleifer (1997), "The unofficial economy in transition," *Brookings Papers on Economic Activity*, 2, 159-221.

– –; – –; and P. Zoido-Lobatón (1998), "Corruption, public finances and the unofficial economy," Discussion paper, The World Bank, Washington, DC.

Johnston, L.D., P.M. O'Malley, J.G. Bachman, and J.E. Schulenberg (2007), *Monitoring the Future National Survey Results on Drug Use, 1975-2006*. Volume I: Secondary school students, NIH Publication No. 07-6205, National Institute on Drug Abuse: Bethesda, MD.

Jöreskog, K.G (1970), "A general method for analysis of covariance structures," *Biometrika*, 57, 239-251.

– – (1973), "A general method for estimating a linear structural equation system," pp. 85-112 in: A.S. Goldberger and O.D. Duncan (eds.), *Structural Equation Models in the Social Sciences*, Academic Press: New York.

– –; and A.S. Goldberger (1972), "Factor analysis by generalized least squares," *Psychometrika*, 37, 243-260.

– –; and – – (1975), "Estimation of a model with multiple indicators and multiple causes of a single latent variable," *Journal of the American Statistical Association*, 70, 631-639.

– –; and D. Sörbom (2001), *LISREL 8: User's Reference Guide*, Scientific Software International: Lincolnwood.

Karmann, A. (1986), „Monetäre Ansätze zur Erfassung der Schattenwirtschaft: Ein Vergleich verschiedener Messansätz," *Kredit und Kapitel*, 19, 233–247.

– – (1988), „Größe und Formen der Schattenwirtschaft und ihr Verhältnis zur Wirtschaft," S. 87-107 in: P. Gross und P. Friedrich (Hrsg.), *Positive Wirkungen der Schattenwirtschaft?*, Nomos Verlagsgesellschaft: Baden Baden.

– – (1990a), „Schattenwirtschaft und ihre Ursachen: Eine empirische Analyse zur Schwarzwirtschaft und Selbstversorgung in der Bundesrepublik Deutschland," *Zeitschrift für Wirtschafts- und Sozialwissenschaften (ZWS)*, 110, 185-206.

– – (1990b), „Kausalanalysen von Zeitreihendaten mittels LISREL. Zur Praktikabilität der Methode an zwei ausgewählten Beispielen," S. 41-54 in: G. Nakhaeizadeh und

K.-H. Vollmer (Hrsg.), *Neuere Entwicklungen in der angewandten Ökonometrie*, Physica-Verlag: Heidelberg.

Kaufmann, D., A. Kraay, and M. Mastruzzi (2007), "Governance matters VI: Governance indicators for 1996-2006," World Bank Policy Research Working Paper 4280.

Keesling, J.W. (1972), *Maximum Likelihood Approaches to Causal Analysis*, Ph.D. dissertation, Department of Education, University of Chicago, Chicago, IL.

Kendall, M.G. and A. Stuart (1973), *The Advanced Theory of Statistics. Inference and Relationship*, Vol. 2, 3rd Ed., Griffin: London.

Kirchgässner, G. (1983), "Size and development of West-German shadow economy 1955-1980," *Zeitschrift für die gesamte Staatswissenschaft*, 139, 197-214.

Kmenta, J. (1971), *Elements of Econometrics*, Macmillan: New York.

Kwiatkowski, D., P.C.B. Phillips, P. Schmidt, and Y. Shin (1992), "Testing the null hypothesis of stationarity against the alternative of a unit root," *Journal of Econometrics*, 54, 159-178.

Langfeldt, E. (1983), „Ursachen der Schattenwirtschaft und ihre Konsequenzen für die Wirtschaft, Finanz- und Gesellschaftspolitik," Universität Kiel, Kiel.

– – (1984), "The unobserved economy in the Federal Republic of Germany," pp. 236-60 in: E.L. Feige (ed.), *The Unobserved Economy*, Cambridge University Press: Cambridge, UK.

Le May, M.C. (2007), *Illegal Immigration: A Reference Handbook*, ABC-CLIO: Santa Barbara.

Lippert, O. and M. Walker (1997), *The Underground Economy: Global Evidences of its Size and Impact*, The Fraser Institute:Vancouver.

Loayza, N.V. (1996), "The economics of the informal sector: A simple model and some empirical evidence from Latin America," *Carnegie-Rochester Conference Series on Public Policy*, 45, 129-162.

Lomax, R. (1989), "Covariance structure analysis: Extensions and developments," pp. 170-204 in: B. Thompson (ed.), *Advances in Social Science Methodology*, JAI Press: Greenwich, CT.

Long, J.S. (1983a), *Confirmatory Factor Analysis*, Sage: Beverly Hills, CA.

– – (1983b), *Covariance Structure Models: An Introduction to LISREL*, Sage: Beverly Hills, CA.

MacCallum, R.C. (1995), “Model specification: Procedures, strategies, and related issues,” pp. 16-36 in: R.H. Hoyle (ed.), *Structural Equation Modeling: Concepts, Issues, and Applications*, Sage: Thousand Oaks, CA.

MacKinnon, J.G. (1996), “Numerical distribution functions for unit root and cointegration tests,” *Journal of Applied Econometrics*, 11, 601-618.

– –; A.A. Haug, and L. Michelis (1999), “Numerical distribution functions of likelihood ratio tests for cointegration,” *Journal of Applied Econometrics*, 14, 563-577.

Maddala, G.S. and I. Kim (1998), *Unit Roots, Cointegration, and Structural Change*, Cambridge University Press: Cambridge, UK.

Martin, L. and A. Panagariya (1984), “Smuggling, trade and price disparity: A crime theoretic approach,” *Journal of International Economics*, 17, 201-217.

Maruyama, G.M. (1997), *Basic of Structural Equation Modeling*, Sage Publications: Thousand Oaks, CA.

Mauro, P. (1995), “Corruption and growth,” *Quarterly Journal of Economics*, 110, 681-712.

McDonald, D.C. (1985), “Trade data discrepancies and the incentive to smuggle,” *IMF Staff paper*, 4, 668-692.

Merriman, D., A. Yurekli, and F. Chaloupka (2000), “How big is the worldwide cigarette-smuggling problem?,” pp. 365-392 in: P. Jha and F.J. Chaloupka (eds.), *Tobacco Control in Developing Countries*, Oxford University Press: London.

Merz, J. and K.G. Wolff (1993), “The shadow economy: Illicit work and household production: A mircoanalysis of West Germany,” *Review of Income and Wealth*, 39, 177-194.

Mummert, A. and F. Schneider (2002), “The German shadow economy: Parted in a united Germany?,” *Finanzarchiv*, 58, 286-316.

Mulaik, S.A., L.R. James, J. Van Alstine, N. Bennett, S. Lind, and C.D. Stilwell (1989), “Evaluation of goodness-of-fit indices for structural equation models,” *Psychological Bulletin*, 105, 430-445.

Muthen, B.O. (2002), “Beyond SEM: General latent variable modeling,” *Behaviormetrika*, 29, 81-117.

Neck, R., M. Hofreither, and F. Schneider (1989), “The consequences of progressive income taxation for the shadow economy: Some theoretical considerations,” pp. 149-

176 in: D. Boes and B. Felderer (eds.), *The Political Economy of Progressive Taxation*, Springer: Berlin.

Newey, W. and K. West (1994), "Automatic lag selection in covariance matrix estimation," *Review of Economic Studies*, 61, 631-653.

Niessen, H.-J. and R. Ollmann (1987), *Schattenwirtschaft in der Bundesrepublik*, VS Verlag: Opladen.

Ngai, R. and C.A. Pissarides (2008), "Trends in hours and economic growth," *Review of Economic Dynamics*, 11, 239-256.

Norton, D. (1988), "On the economic theory of smuggling," *Economica*, 55, 107-118.

Olssen, U.H., S.V. Troye, and R.D. Howell (1999), "Theoretic fit and empirical fit: The performance of Maximum Likelihood versus Generalized Least Squares estimation in Structural Equations Models," *Multivariate Behavioral Research*, 34, 31-58.

– –; T. Foss, – –; and – – (2000), "The performance of ML, GLS, and WLS estimation in structural equation modeling under conditions of misspecification and nonnormality," *Structural Equation Modeling*, 7, 557-595.

Office of Border Patrol (2004), "National border patrol strategy," available at http://www.cbp.gov, accessed: November 2008, U.S. Department of Homeland Security, Washington, DC.

Paldam, M. (2003), "The cross-country pattern of corruption: Economics, culture and the seesaw dynamics," *European Journal of Political Economy*, 18, 215-240.

Passel, J.S. (2007), "Unauthorized migrants in the United States: estimates, methods, and characteristics," OECD Social, Employment and Migration Working Papers No. 57.

– –; and D. Cohn (2008), *Trend in Unauthorized Immigration: Undocumented Inflow now Trails Legal Inflows*, Pew Hispanic Center, Washington, DC.

Pedersen, S. (2003), *The Shadow Economy in Germany, Great Britain and Scandinavia. A Measurement based on Questionnaire Surveys*, Study No. 10, The Rockwoll Foundation Research Unit, Copenhagen.

Pelzmann, L. (2006), *Wirtschaftspsychologie: Arbeitslosenforschung, Schattenwirtschaft, Steuerpsychologie*, 4. Auflage, Springer: Berlin.

Pick, F. (1955-1982), *Pick's Currency Yearbook*, various issues, Pick Publishing Corporation: New York, NY.

– – (1983-1998), *World Currency Reports*, various issues, International Currency

Analysis Inc.: New York, NY.

Pickhardt, M. and J. Sardà Pons (2006), "Size and scope of the underground economy in Germany," *Applied Economies*, 38, 1707-1713.

Pitt, M.M. (1981), "Smuggling and price disparity," *Journal of International Economics*, 11, 447-458.

– – (1984), "Smuggling and the black market for foreign exchange," *Journal of International Economics*, 16, 243-257.

Pohit, S. and N. Taneja (2003), "India's informal trade with Bangladesh: A qualitative assessment," *The World Economy*, 26, 1187-1214.

PWT (2002), A. Heston, R. Summers, and B. Aten, *Penn World Table Version 6.1*, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania.

Renooy, P.H. (1990), *The Informal Economy: Meaning, Measurement and Social Significance*, Netherlands Geographical Studies: Amsterdam.

Reinhart, C.M. and K.S. Rogoff (2004), "The modern history of exchange rate arrangements: A reinterpretation," *Quarterly Journal of Economics*, 69, 1-48, data set available at http://www.wam.umd.edu/~creinhar, accessed: May 13, 2008.

Rhodes, W., M. Layne, A. Bruen, P. Johnston, and L. Becchetti (2001), *What America's Users Spend on Illegal Drugs*, Office of National Drug Control Policy, Washington, DC.

Schneider, F. (1986), "Estimating the size of the Danish shadow economy using the currency demand approach: An attempt," *The Scandinavian Journal of Economics*, 88, 643-668.

– – (1994), "Can the shadow economy be reduced through major tax reforms? An empirical investigation for Austria," *Supplement to Public Finance/ Finances Publiques*, 49, 137-152.

– – (1997), "The shadow economies of Western Europe," *Economic Affairs*, 17, 42-48.

– – (2005), "Shadow economies around the world: What do we really know?," *European Journal of Political Economy*, 21, 598-642.

– – (2007a), "Shadow economies and corruption all over the world: New estimates for 145 countries," *Economics: The Open-Access, Open-Assessment E-Journal*, 1, 2007–9.

– – (2007b), “Shadow economy and corruption all over the world: What do we know?,” Discussion Paper, Johannes Kepler University of Linz, Department of Economics, Linz.

– –; and D. Enste (2000), “Shadow economies: Size, causes, and consequences,” *The Journal of Economic Literature*, 38, 77-114.

– –; and – – (2002), *The Shadow Economy: Theoretical Approaches, Empirical Studies, and Political Implications*, Cambridge University Press: Cambridge. UK.

Schwert, G.W. (1987), “Effects of model specification on tests for unit roots in macroeconomic data,” *Journal of Monetary Economics*, 20, 73-103.

Seitz, F. (1995), “Der DM-Umlauf im Ausland,“ Bundesbank Diskussionspapier No. 1, Deutsche Bundesbank, Frankfurt/Main.

Sheikh, M. (1974), “Smuggling, protection and welfare,” *Journal of International Economics*, 4, 355-364.

Smith, P. (1994), “Assessing the size of the underground economy: The Canadian statistical perspectives,” *Canadian Economic Observer*, 7, 3.16-3.33.

Smith, R.S. (2002), “The underground economy: Guidance for policy makers?,” *Canadian Tax Journal*, 50, 1655-1661.

Stapleton, D.C. (1978), “Analyzing political participation data with a MIMIC Model,” *Sociological Methodology*, 15, 52-74.

Stevens, J. (1996), *Applied Multivariate Statistics for the Social Sciences*, Lawrence Erlbaum Associates, Publishers: Mahwah, NJ.

Swaminathan, M. (1991), “Understanding the informal sector: A survey,” World Institute for Development Economics Research, Working Paper No. 95.

Swaminathan, H. and J. Algina (1978), “Scale freeness in factor analysis,” *Psychometrika*, 43, 581-583.

Tanzi, V. (ed.) (1982), *The Underground Economy in the United States and Abroad*, Heath: Lexington DC.

– – (1986), “The underground economy in the United States: Reply to comments by Feige, Thomas, and Zilberfarb,” *IMF-Staff Papers*, 33, 799-811.

– – (1999), “Uses and abuses of estimates of the underground economy,” *The Economic Journal*, 109, 338-340.

Thomas, J.J. (1992), *Informal Economic Activity*, Handbooks in Economics, London School of Economics, Harvester Wheatsheaf: London.

– – (1999), “Quantifying the black economy: ‘Measurement without theory’ yet again?,” *The Economic Journal*, 109, 381-389.

Thursby, M., R. Jensen, and J. Thursby (1991), “Smuggling, camouflaging, and market structure,” *Quarterly Journal of Economics*, 106, 789-814.

Transparency International (1999), *The 1999 Transparency International Corruption Perceptions Index (CPI)*, available at: http://www.transparency.org/policy_research/surveys_indices/cpi/previous_cpi/1999, accessed: May 17, 2008, Berlin.

United Nations (2009), *World Drug Report 2009*, United Nations Office on Drugs and Crime, Vienna.

Wacziarg, R.T. and K.H. Welch (2003), “Trade liberalization and growth: New evidence,” NBER Working Paper No. W10152.

Weck-Hannemann, H. (1983), *Schattenwirtschaft: Eine Möglichkeit zur Einschränkung der öffentlichen Verwaltung? Eine ökonomische Analyse*, Lang: Frankfurt/Main.

World Bank (2006), *World Development Indicators*, CD-Rom, Washington, DC

– – (2009a), Anticorruption, http://go.worldbank.org/K6AEEPROC0.

– – (2009b), *World Bank List of Economies*, July 2009, accessed: October 23, 2009, Washington, DC.

Zellner, A. (1970), “Estimation of regression relationships containing unobservable variables,” *International Economic Review*, 11, 441-454.

APPENDICES

APPENDIX A: STRUCTURAL EQUATION MODELS*

Structural equation models (SEMs) are used extensively in the social sciences, for example in sociology, psychology, and education. Such models take into account unobservable variables which can be defined or described by observable variables. SEMs are thus particularly suitable to analyze informal economic activities such as the shadow economy and smuggling. Cooley (1978) argues that SEMs allow one to establish a theoretical model in order to determine the degree to which the explanatory (observable) variables are related to unobservable variables. They are a generalization of many familiar techniques such as regression, path analysis, discriminant analysis, and confirmatory factor analysis. All of these methods can be treated as special cases of SEMs, and several authors give the SEM approach a high value. For Stevens (1996, p. 415) SEMs are "one of the most important advances in quantitative methodology in many years". Also Capraro et al. (2002, p.10) argue that SEMs "subsume all other parametric statistical analyses and provide some interesting options for the researcher". SEMs have been also termed "the single most important contribution of statistics to the social and behavioral sciences during the past twenty years" [Lomax (1989), p. 171].

The statistical idea behind SEMs is to compare a sample covariance matrix, i.e., a covariance matrix of observable variables, with the parametric structure imposed on this matrix by a hypothesized model.[100] The relationships among the observable variables are described in terms of their covariances and it is assumed that they are generated by

---

* I would like to thank Alexander Karmann for his suggestion to include this appendix.

[100] Estimation of an SEM with latent variables can be done by means of a computer program for the analysis of covariance structures, such as LISREL (Linear Structural Relations). A useful overview of the LISREL software package in an economics journal is Cziraky (2004). General overviews about the SEM approach are given in Hayduk (1987), Bollen (1989), Hoyle (1995), Maruyama (1997), Byrne (1998), Muthen (2002), and Cziraky (2005).

(usually a smaller number of) unobservable variables. To analyze the observable variables' covariance matrix, this matrix is decomposed into two steps. Firstly, the unobservable variables are linked to observable variables in a factor analytical model also called measurement model. Secondly, the relationships between the unobservable variables or between unobservable and observable variables are specified through a structural model. Therefore, an SEM is the simultaneous specification of a factor and a structural model. In this sense, SEMs test the consistency of a "structural" theory through data and are thus a confirmatory, rather than an exploratory technique. In fact, in a confirmatory factor analysis a model is constructed in advance, whether an unobservable (latent) variable or factor influences an observable variable is specified by the researcher, and parameter constraints are imposed. Thus, an economic theory is tested by examining the consistency of actual data with the hypothesized relationships between the unobservable (latent) variables or factors and the observable (measurable) variables.[101]

In general, a confirmatory factor analysis has two goals: (i) to estimate parameters such as coefficients and variances and (ii) to assess the fit of the model. For the analysis of informal economic activities these two goals mean (i) to estimate the relationships between a set of observable variables, divided into causes and indicators, and the respective informal economic activity (unobservable variable), and (ii) to test if the researcher's theory or the derived hypotheses as a whole fit the data. SEMs are, compared to regression models, a rarely used method by economists what might be due

---

[101] On the contrary, in an exploratory factor analysis a model is not specified in advance, i.e., beyond the specification of the number of latent variables (factors) and observed variables the researcher does not specify any structure of the model. This means that one assumes that all factors are correlated, all observable variables are directly influenced by all factors, and all measurement errors are uncorrelated with each other. In practice however, the distinction between a confirmatory and an exploratory factor analysis is less strong. Facing poorly fitting models, researchers using SEM techniques or a confirmatory factor analysis often modify their models in an exploratory way in order to improve the fit. Thus, most applications fall between the two extreme cases of exploratory (non-specified model structure) and confirmatory (ex-ante specified model structure) factor analysis [Long (1983a), pp. 11-17].

to an under-evaluation of their capabilities with respect to the potential contribution for economic research.[102]

Several authors however have applied Multiple Indicators Multiple Causes (MIMIC) models, a particular type of an SEM, to estimate the size and development of the shadow economy. One of the earliest studies was Frey and Weck-Hannemann (1984) who use a MIMIC model to analyze the shadow economy in 17 OECD countries, followed by other economists, who also use this approach to estimate the size of the shadow economy.[103] The analysis of other informal economic activities using an SEM or a MIMIC model has become an interesting area in the literature recently. For example, Dreher et al. (2007) use a MIMIC model to derive an index of corruption for approximately 100 countries over the period 1976-1997. Buehn and Farzanegan (2008) apply this type of model to analyze smuggling in 54 countries during the 1990s. Buehn et al. (2009) use two distinct MIMIC models and a more general SEM to analyze Do-it-yourself (DIY) and shadow economic activities in Germany. Farzanegan (2009) and Buehn and Eichler (2009) use MIMIC models to estimate the size and development of smuggling in Iran and across the U.S.-Mexico border, respectively. Buehn and Schneider (2009) use an SEM to shed more light on the relationship between corruption and the shadow economy.

Appendix A is organized as follows. First, Section A.1 explains the types of SEMs used in this dissertation. Section A.2 then shows how SEMs are estimated. Section A.3 describes how one can assess the fit of SEMs. Section A.4 critically evaluates the advantages and disadvantages of the application of SEMs in economics. Section A.5 finally summarizes and concludes.

---

[102] Seminal studies using an SEM and/or a Multiple Indicators Multiple Causes (MIMIC) model include Zellner (1970), Hauser and Goldberger (1971), Jöreskog and Goldberger (1975), and Aigner et al. (1984).

[103] Important studies on the shadow economy are Loayza (1996) for Latin American countries, Giles (1995; 1999) for New Zealand, Giles and Tedds (2002) for Canada, Dell'Anno (2003) for Italy, Dell'Anno and Schneider (2003) for OECD countries, Cziraky and Gillman (2003) for Romania, Croatia and Bulgaria, Bajada and Schneider (2005) for Asian-pacific countries, Schneider (2005) for 110 countries all over the world, Pickhardt and Sardà Pons (2006) for Germany, Dell'Anno (2007) for Portugal, Dell'Anno et al. (2007) for France, Greece, and Spain, and Dell'Anno and Solomon (2008) for the USA.

A.1 The Structural Equation Model Approach

A.1.1 The Multiple Indicators Multiple Causes Model

The main idea behind SEMs is to examine the relationships among unobservable variables and/or between unobservable and observable variables in terms of the relationships among a set of observable variables by using their covariance information. This section investigates a particular alternative of an SEM with one latent variable which can be the shadow economy, DIY activities, or smuggling, and a number of observable variables. The observable variables are divided into causes and indicators of the latent variable. The key benefits of this so-called MIMIC model are that it allows modeling the respective informal economic activity as an unobservable (latent) variable and that it takes into account its multiple determinants (causes) and multiple effects (indicators).

Formally, the MIMIC model consists of two parts: the structural equation model and the measurement model. In the measurement model, the unobservable variable η_t determines a p vector $\boldsymbol{y}_t' = \left(y_{1t}, y_{2t}, \ldots, y_{pt}\right)'$ of indicators subject to a p vector of random error terms $\boldsymbol{\varepsilon}_t' = \left(\varepsilon_{1t}, \varepsilon_{2t}, \ldots, \varepsilon_{pt}\right)'$.[104] The unobservable variable η_t is a scalar and $\boldsymbol{\lambda}$ is a p column vector of parameters that relates $\boldsymbol{y}_t$ to η_t. The measurement equation is given by:

$$\boldsymbol{y}_t = \boldsymbol{\lambda}\eta_t + \boldsymbol{\varepsilon}_t . \tag{A.1}$$

The structural model determines the unobservable variable η_t by a set of exogenous causes, $\boldsymbol{x}_t' = \left(x_{1t}, x_{2t}, \ldots, x_{qt}\right)'$, subject to a structural disturbance error term ς_t. The structural equation is given by:

$$\eta_t = \boldsymbol{\gamma}' \boldsymbol{x}_t + \varsigma_t , \tag{A.2}$$

---

[104] Appendix A follows the standard LISREL notation of Jöreskog and Sörbom (2001). The subscript *t* indicates the time series dimension of the variables. Except for Chapter 3 which is a cross-sectional analysis of smuggling in 54 countries, all applications presented in this dissertation analyze the size and development of informal economic activities over time.

where $\boldsymbol{\gamma}'$ is a q row vector of structural parameters. Without loss of generality, all variables are taken as standardized deviations from their means. In equations (A.1) and (A.2) it is assumed that ς_t and the elements of $\boldsymbol{\varepsilon_t}$ are normally, independently, and identically distributed,[105] the variance of the structural disturbance term ς_t is denoted by ψ, and $\boldsymbol{\Theta}_\varepsilon = \mathrm{E}\left(\boldsymbol{\varepsilon_t}\boldsymbol{\varepsilon_t}'\right)$ is the $(p \times p)$ covariance matrix of the measurement errors.[106] Figure A.1 shows the path diagram of the standard MIMIC model.

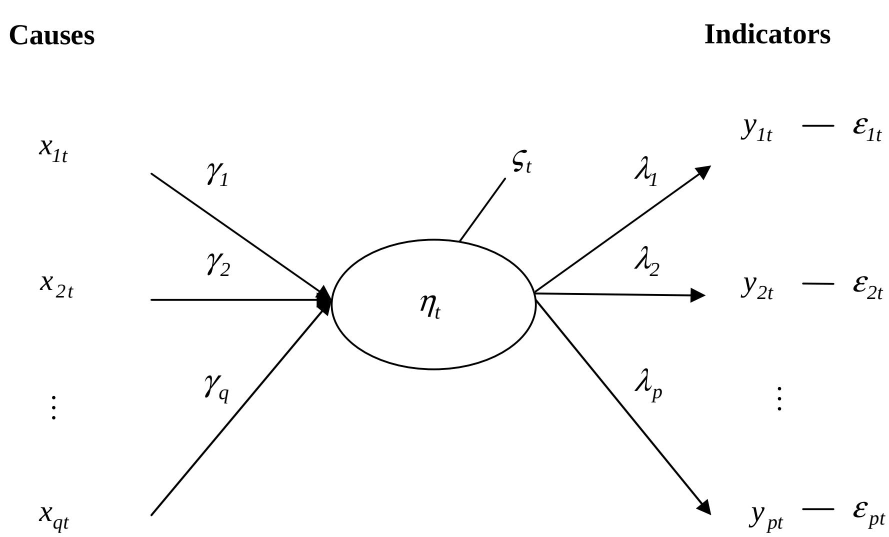

Figure A.1 Path Diagram of a Standard MIMIC Model

In the following, I use the S-DIY MIMIC model of Chapter 2, in particular the shadow economy (S) part of this model, as an example to further demonstrate the nomenclature

---

[105] The assumption of independence between the structural disturbance ς_t and each ε_{it}, $i = 1, \ldots,$ and p, could be considered as too restrictive, when mainly using an economic dataset and, consequently, espoused to question the validity of this approach. However, Hayduk (1987, p. 193) explains that this assumption "is purely a matter of arbitrary convention" for an SEM analysis.

[106] In the standard MIMIC model the measurement errors are assumed to be independent of each other, but this restriction could be relaxed [Stapleton (1978), p. 53].

of the MIMIC model. The S-DIY MIMIC model analyzes the shadow economy in Germany using 5 observable variables as causes and 3 observable variables as indicators (see Figure 2.3). Within this model, equations (A.1) and (A.2) are specified as follows:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{bmatrix} = \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \end{bmatrix} \cdot \eta_t + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}, \tag{A.3}$$

$$\eta_t = \begin{bmatrix} \gamma_1 & \gamma_2 & \gamma_3 & \gamma_4 & \gamma_5 \end{bmatrix} \cdot \begin{bmatrix} x_{1t} \\ x_{2t} \\ x_{3t} \\ x_{4t} \\ x_{5t} \end{bmatrix} + \varsigma_t . \tag{A.4}$$

Substituting equation (A.1) into (A.2) yields a reduced form equation which expresses the relationships between the observed causes and indicators, i.e., between $\boldsymbol{x_t}$ and $\boldsymbol{y_t}$. This is shown in equation (A.5):

$$\boldsymbol{y_t} = \boldsymbol{\Pi x_t} + \boldsymbol{z_t}, \tag{A.5}$$

where: $\boldsymbol{\Pi} = \boldsymbol{\lambda\gamma}'$ is a (3×5) reduced form coefficient matrix and $\boldsymbol{z_t} = \boldsymbol{\lambda}\varsigma_t + \boldsymbol{\varepsilon_t}$ is a reduced form vector of a linear transformation of disturbances that has a (3×3) reduced form covariance matrix $\boldsymbol{\Omega}$ given as:

$$\boldsymbol{\Omega} = \mathrm{Cov}(\boldsymbol{z_t}) = \mathrm{E}[(\boldsymbol{\lambda}\varsigma_t + \boldsymbol{\varepsilon_t})(\boldsymbol{\lambda}\varsigma_t + \boldsymbol{\varepsilon_t})'] = \boldsymbol{\lambda}\psi\boldsymbol{\lambda}' + \boldsymbol{\Theta}_\varepsilon . \tag{A.6}$$

In equation (A.6), $\psi = \mathrm{Var}(\varsigma_t)$ and $\boldsymbol{\Theta}_\varepsilon = \mathrm{E}\left(\boldsymbol{\varepsilon_t \varepsilon_t}'\right)$ is the covariance matrix of the measurement errors.

The models used in this dissertation to analyze the different types of informal economic activities, i.e., the S-DIY model of shadow economic and DIY activities in Germany (Chapter 2), the model analyzing smuggling in 54 countries (Chapter 3), and the models analyzing smuggling of illegal and legal goods across the U.S.-Mexico border (Chapter 4), are such MIMIC models.[107] Only the H-DIY model of Chapter 2 is a more general type of an SEM. This model is explained in the next section.

---

[107] Consequently, these models have the same formal structure as presented in equations (A.3) (measurement equation) and (A.4) (structural equation) although different numbers of causes and indicators may be used.

A.1.2 The H-DIY Structural Equation Model

The more general H-DIY SEM of Chapter 2 analyzes the hidden economy in Germany and models DIY activities as part of it using several causes and indicators for each of the two unobservable variables (see Figure 2.4). Formally, this SEM has also two parts: the measurement model and the structural equation model. The measurement model again links the latent variable to its observable indicators and is specified as:

$$\boldsymbol{y_t} = \boldsymbol{\Lambda\eta_t} + \boldsymbol{\varepsilon_t}. \tag{A.7}$$

The p vectors $\boldsymbol{y_t}$ and $\boldsymbol{\varepsilon_t}$ are defined as in equation (A.1). In equation (A.7) however, $\boldsymbol{\eta_t}$ is a column vector of two latent variables, $\boldsymbol{\eta_t}' = (\eta_{1t}, \eta_{2t})'$, and $\boldsymbol{\Lambda}$ is a $(p \times 2)$ matrix of parameters relating $\boldsymbol{y_t}$ to $\boldsymbol{\eta_t}$. The two main differences of this model compared to the standard MIMIC model are that it (i) explains two instead of one latent variable and (ii) the structural equation not only describes the relationships between the set of causes $\boldsymbol{x_t}$ and the unobservable variables $\boldsymbol{\eta_t}$ but additionally the relationship between the two unobservable variables η_{1t} and η_{2t}. Hence, the structural equation model is given by:

$$\boldsymbol{\eta_t} = \boldsymbol{B\eta_t} + \boldsymbol{\Gamma x_t} + \boldsymbol{\varsigma_t}, \tag{A.8}$$

where $\boldsymbol{x_t}$ is a q vector defined as in equation (A.2) and $\boldsymbol{\varsigma_t}' = (\varsigma_{1t}, \varsigma_{2t})'$ is a column vector of structural error terms. The $(2 \times q)$ matrix $\boldsymbol{\Gamma}$ describes the relationships between the latent variables and the observable causes and the (2×2) coefficient matrix $\boldsymbol{B}$ the link between the two unobservable variables, i.e., between the hidden economy and DIY activities. The precise nomenclatures of equations (A.7) and (A.8) in the H-DIY SEM are as follows:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \\ y_{4t} \end{bmatrix} = \begin{bmatrix} \lambda_1 & 0 \\ \lambda_2 & 0 \\ \lambda_3 & 0 \\ 0 & \lambda_4 \end{bmatrix} \cdot \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix}, \tag{A.9}$$

$$\begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ \beta_{21} & 0 \end{bmatrix} \cdot \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix} + \begin{bmatrix} \gamma_1 & \gamma_2 & \gamma_3 & \gamma_4 & \gamma_5 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} x_{1t} \\ x_{2t} \\ x_{3t} \\ x_{4t} \\ x_{5t} \end{bmatrix} + \begin{bmatrix} \varsigma_{1t} \\ \varsigma_{2t} \end{bmatrix}. \tag{A.10}$$

Equation (A.9) represents the measurement model equation and equation (A.10) is the structural model equation of the H-DIY SEM. The parameter β_{21} explains the relationship between the two latent variables η_{1t} and η_{2t}, i.e., between the hidden economy and DIY activities.

Re-arranging equation (A.8), $\boldsymbol{\eta_t} = (\boldsymbol{I} - \boldsymbol{B})^{-1} \boldsymbol{\Gamma x_t} + (\boldsymbol{I} - \boldsymbol{B})^{-1} \boldsymbol{\varsigma_t}$, and substituting it into equation (A.7) yields a reduced form equation which expresses the relationships between the observed variables $\boldsymbol{x_t}$ and $\boldsymbol{y_t}$. This is shown in equation (A.11):

$$\boldsymbol{y_t} = \boldsymbol{\Pi x_t} + \boldsymbol{z_t}, \tag{A.11}$$

where $\boldsymbol{\Pi} = \boldsymbol{\Lambda}(\boldsymbol{I} - \boldsymbol{B})^{-1} \boldsymbol{\Gamma}$ is a (4×5) reduced form coefficient matrix and $\boldsymbol{z_t} = \boldsymbol{\Lambda}(\boldsymbol{I} - \boldsymbol{B})^{-1} \boldsymbol{\varsigma_t} + \boldsymbol{\varepsilon_t}$ is a reduced form vector of disturbances that has a (4×4) reduced form covariance matrix $\boldsymbol{\Omega}$ given by:

$$\begin{aligned} \boldsymbol{\Omega} &= \mathrm{Cov}(\boldsymbol{z_t}) = \mathrm{E}\left[\left(\boldsymbol{\Lambda}(\boldsymbol{I} - \boldsymbol{B})^{-1} \boldsymbol{\varsigma_t} + \boldsymbol{\varepsilon_t}\right)\left(\boldsymbol{\Lambda}(\boldsymbol{I} - \boldsymbol{B})^{-1} \boldsymbol{\varsigma_t} + \boldsymbol{\varepsilon_t}\right)'\right] \\ &= \boldsymbol{\Lambda}(\boldsymbol{I} - \boldsymbol{B})^{-1} \boldsymbol{\Psi} (\boldsymbol{I} - \boldsymbol{B}')^{-1} \boldsymbol{\Lambda}' + \boldsymbol{\Theta}_{\varepsilon}, \end{aligned} \tag{A.12}$$

where $\boldsymbol{\Psi} = \mathrm{E}\left(\boldsymbol{\varsigma_t \varsigma_t'}\right)$ is the (2×2) covariance matrix of the structural equation disturbances and $\boldsymbol{\Theta}_{\varepsilon} = \mathrm{E}\left(\boldsymbol{\varepsilon_t \varepsilon_t'}\right)$ is the (4×4) covariance matrix of the measurement errors $\boldsymbol{\varepsilon_t}$. The next section explains how the information contained in the covariance matrix of causes and indicators is used to estimate an SEM.

A.2 Application of Structural Equation Models

In general, estimation of an SEM uses covariance information of sample data to derive estimates of population parameters. Instead of minimizing the distance between observed and predicted individual values as in standard econometrics, SEMs minimize the distance between an observed (sample) covariance matrix and the covariance matrix predicted by the model the researcher imposes on the data.

The idea behind the SEM approach is that the covariance matrix of the observed variables is a function of a set of model parameters:

$$\boldsymbol{\Sigma} = \boldsymbol{\Sigma}(\boldsymbol{\theta}), \tag{A.13}$$

where $\boldsymbol{\Sigma}$ is the population covariance matrix of the observed variables $\boldsymbol{y_t}$ and $\boldsymbol{x_t}$, $\boldsymbol{\theta}$ is a vector that contains the parameters of the model, and $\boldsymbol{\Sigma}(\boldsymbol{\theta})$ is the covariance matrix as a function of $\boldsymbol{\theta}$ implying that each element of the covariance matrix is a function of one or more model parameters. If the hypothesized model is correct and the parameters are known, the population covariance matrix would be exactly reproduced, i.e., $\boldsymbol{\Sigma}$ will equal $\boldsymbol{\Sigma}(\boldsymbol{\theta})$. In practice, however, one does not know either the population variances and covariances, or the parameters but instead uses the sample covariance matrix and sample estimates of the unknown parameters for estimation [Bollen (1989, p. 256]. However, before an SEM can be estimated, its identification must be verified.

A.2.1 Identification

An SEM is said to be identified if a unique solution for each parameter in $\boldsymbol{\theta}$ exists. This means sufficient information to obtain a unique solution for the parameters to be estimated. In other words, it must be possible to solve each parameter of the model in terms of the variances and covariances of the observed variables [Long (1983a), pp. 34-36].

If the information is not sufficient, the model is said to be unidentified or under-identified. In this case, a unique solution cannot be obtained and, as a consequence, one can find an infinite number of values for the parameters to be estimated and fit any covariance matrix to the model.[108] For a model to be identified it is thus necessary that the number of independent parameters being estimated is less than or equal to the number of non-redundant, i.e., unique, elements of the sample covariance matrix $\boldsymbol{S}$ of the observed causes and indicators. To determine if the model meets this condition one can use the following formula: $t \leq s$. This so called *t*-rule tests if the number of parameters to be estimated in $\boldsymbol{\theta}$, *t*, i.e., the number of independent parameters, is less than or equal to the number of unique elements in the variance-covariance matrix of the observed variables calculated as $s = (p+q)(p+q+1)/2$ [Bollen (1989), pp. 93-94].

---

[108] This problem is similar to the one that arises if one were asked to find a unique solution for the equation $A \cdot B = 20$. Being faced with two unknowns and one equation one can find infinite solutions for $A, B \in \mathbb{R}$ [Diamantopoulos and Siguaw (2000), p. 49].

If $t > s$, the *t*-rule is violated and the model is thus under-identified. This problem can be corrected by the researcher by modifying the model. A solution to the identification problem is to impose more constraints on the model by (i) including more observable variables (i.e. indicators) in the model, (ii) fixing additional parameters to zero, and (iii) setting parameters equal to each other [Bollen (1989), p. 91; Diamantopoulos and Siguaw (2000), p. 49]. Of course, such model modifications should not be randomly established to achieve identification but theoretically justified.

A model is said to be identified if $t = s$ or $t < s$. If $t = s$, the model is said to be just identified and a single unique solution for the parameter estimates can be obtained. All information available is used to derive the parameter estimates and the degrees of freedom are zero.[109] If $t < s$, the model is over-identified and more than one estimate of each parameter can be obtained. Consequently, the degrees of freedom are positive and equal to $s - t$. In over-identified models, it is possible for the sample covariance matrix $\boldsymbol{S}$ of the observed causes and indicators to differ from the estimated covariance matrix $\hat{\boldsymbol{\Sigma}}$. This means, that one can test if the restrictions imposed on the model leading to over-identification, are valid. Over-identification of at least one parameter thus provides the possibility to test the model as models containing over-identified parameters will generally not fit the data exactly [MacCallum (1995)]. Thus, with over-identified models one can find that the model fits the observed data poorly providing evidence that it is incorrect.

The fact that the model satisfies the condition $t \leq s$ does not, however, guarantee that the model is in fact identified because this condition is only necessary and not sufficient. Unfortunately, no easily applicable sufficient or necessary and sufficient conditions are available [Long (1983b), p. 66]. To demonstrate through algebraic manipulations that a model is identified and each of its parameters can be solved in terms of the variances and covariances of the observed variables is often, in even moderately complex models, virtually impossible [Bollen (1989), p. 247]. There are, however, a few steps one can use

[109] With exactly identified models, the sample covariance matrix $\boldsymbol{S}$ of the observed variables is always equal to the estimated covariance matrix $\hat{\boldsymbol{\Sigma}}$ and no information remains to test the model. In other words, the model has always perfect fit that in no way indicates the scientific usefulness of a model [James et al. (1982), p. 135]. For this reason, the overall goodness-of-fit measures described in Section A.3 are not applicable in exactly identified models.

to make reasonably sure that the model is indeed identified.[110] The first step is to ensure that each unobservable variable in the model has been assigned a measurable scale which can be done by either setting one of the coefficients of the indicators to a constant, usually 1 or -1 [Bollen (1989), p. 91]. An alternative is to fix the variance of the unobservable variable η_t to 1 but the former is more convenient for economic interpretation and thus typically used [Dell'Anno and Schneider (2009)]. The second step is to check that $t < s$ is satisfied and the degrees of freedom are positive. A third possibility is to use results of previous research, i.e., to scan the literature whether the particular model used has already proven to be identified. Finally, the LISREL program itself provides a very handy diagnostic facility for detecting identification problems. If identification problems are detected the program will provide a warning message that certain parameters "may not be identified".[111] All models estimated in this dissertation have been carefully checked and proven to be identified using each of the four steps.

A.2.2 Estimation

Estimation of an SEM can be thought of as follows. The starting point is the sample covariance matrix $\boldsymbol{S}$ of the observed causes and indicators because the population covariance matrix $\boldsymbol{\Sigma}$ is unknown. The diagonal elements of $\boldsymbol{S}$ are the variances of causes and indicators, the off-diagonal elements are their covariances. Thus, $\boldsymbol{S}$ can be thought of as the following partitioned matrix:

$$\boldsymbol{S} = \left[\begin{array}{c|c} \mathrm{Cov}(\boldsymbol{y}_t) & \mathrm{Cov}(\boldsymbol{y}_t, \boldsymbol{x}_t) \\ \hline \mathrm{Cov}(\boldsymbol{x}_t, \boldsymbol{y}_t) & \mathrm{Cov}(\boldsymbol{x}_t) \end{array}\right]. \tag{A.14}$$

---

[110] For a discussion of further identification rules see Bollen (1989, pp. 93-103).

[111] This assessment is based on the so called information matrix which is almost certainly positive definite if the model is identified [Jöreskog and Sörbom (2001), pp. 24, 326]. The advantage of this approach is that it can even detect empirical under-identification problems. Such problems can occur if the calculations of the model parameters involve division of covariances which are zero or almost zero. While it is theoretically possible to express all parameters as functions of sample variances and covariances, their actual calculation will fail because division by zero is not defined.

An estimate of the population covariance matrix $\boldsymbol{\Sigma}$, $\hat{\boldsymbol{\Sigma}} = \boldsymbol{\Sigma}(\hat{\boldsymbol{\theta}})$, is then defined in terms of estimates of $\ddot{\boldsymbol{B}} := (\boldsymbol{I} - \boldsymbol{B})$, $\boldsymbol{\Lambda}$, $\boldsymbol{\Gamma}$, $\boldsymbol{\Psi}$, $\boldsymbol{\Theta}_{\varepsilon}$, and $\boldsymbol{\Phi}$, the covariance matrix of the causes. These estimates are contained in the vector $\hat{\boldsymbol{\theta}}$, i.e., $\hat{\boldsymbol{\theta}} = f\left(\hat{\ddot{\boldsymbol{B}}}, \hat{\boldsymbol{\Lambda}}, \hat{\boldsymbol{\Gamma}}, \hat{\boldsymbol{\Psi}}, \hat{\boldsymbol{\Phi}}, \hat{\boldsymbol{\Theta}}_{\varepsilon}\right)$:

$$
\begin{aligned}
\hat{\boldsymbol{\Sigma}} &= \left[\begin{array}{c|c} \widehat{\mathrm{Cov}}(\boldsymbol{y}_t) & \widehat{\mathrm{Cov}}(\boldsymbol{y}_t, \boldsymbol{x}_t) \\ \hline \widehat{\mathrm{Cov}}(\boldsymbol{x}_t, \boldsymbol{y}_t) & \widehat{\mathrm{Cov}}(\boldsymbol{x}_t) \end{array}\right] \\
&= \mathrm{E}\left[\begin{array}{c|c} \boldsymbol{y}_t \boldsymbol{y}_t' & \boldsymbol{y}_t \boldsymbol{x}_t' \\ \hline \boldsymbol{x}_t \boldsymbol{y}_t' & \boldsymbol{x}_t \boldsymbol{x}_t' \end{array}\right] \\
&= \mathrm{E}\left[\begin{array}{c|c} (\boldsymbol{\Lambda}\boldsymbol{\eta}_t + \boldsymbol{\varepsilon}_t)(\boldsymbol{\Lambda}\boldsymbol{\eta}_t + \boldsymbol{\varepsilon}_t)' & \boldsymbol{x}_t (\boldsymbol{\Lambda}\boldsymbol{\eta}_t + \boldsymbol{\varepsilon}_t)' \\ \hline \boldsymbol{x}_t (\boldsymbol{\Lambda}\boldsymbol{\eta}_t + \boldsymbol{\varepsilon}_t)' & \boldsymbol{x}_t \boldsymbol{x}_t' \end{array}\right].
\end{aligned}
$$

After multiplication, distribution of the expectation operator, making use of the assumptions that

1. the variables are measured as deviations from mean, i.e., $\mathrm{E}(\boldsymbol{\eta}_t) = \mathrm{E}(\boldsymbol{x}_t) = \mathrm{E}(\boldsymbol{\varsigma}_t) = \mathrm{E}(\boldsymbol{y}_t) = \mathrm{E}(\boldsymbol{\varepsilon}_t) = 0$,
2. the error terms do not correlate to the causes, i.e., $\mathrm{E}(\boldsymbol{x}_t \boldsymbol{\varsigma}_t') = \mathrm{E}(\boldsymbol{\varsigma}_t \boldsymbol{x}_t') = 0$ and $\mathrm{E}(\boldsymbol{x}_t \boldsymbol{\varepsilon}_t') = \mathrm{E}(\boldsymbol{\varepsilon}_t \boldsymbol{x}_t') = 0$,
3. the error terms do not correlate across equations, $\mathrm{E}(\boldsymbol{\varepsilon}_t \boldsymbol{\varsigma}_t') = \mathrm{E}(\boldsymbol{\varsigma}_t \boldsymbol{\varepsilon}_t') = 0$,
4. the errors of the measurement model do not correlate to the latent variable, i.e., $\mathrm{E}(\boldsymbol{\eta}_t \boldsymbol{\varepsilon}_t') = \mathrm{E}(\boldsymbol{\varepsilon}_t \boldsymbol{\eta}_t') = 0$, and
5. $(\boldsymbol{I} - \boldsymbol{B})^{-1}$ exists, i.e., $(\boldsymbol{I} - \boldsymbol{B})$ is nonsingular meaning that non of the structural equation is redundant,

the covariance matrix can be derived [Long (1983b), pp. 42-59]. In the following I demonstrate calculation of the covariance matrix using the H-DIY SEM of Chapter 2. For this SEM, the covariance matrix is obtained as follows:

$$
\begin{aligned}
\mathrm{E}\left(\boldsymbol{y}_t\boldsymbol{y}_t'\right) &= \mathrm{E}\left[\left(\boldsymbol{\Lambda\eta}_t+\boldsymbol{\varepsilon}_t\right)\left(\boldsymbol{\Lambda\eta}_t+\boldsymbol{\varepsilon}_t\right)'\right]\\
&= \boldsymbol{\Lambda}\mathrm{E}\left(\boldsymbol{\eta}_t\boldsymbol{\eta}_t'\right)\boldsymbol{\Lambda}'+\boldsymbol{\Theta}_\varepsilon\\
&= \boldsymbol{\Lambda}\mathrm{E}\left[\left(\ddot{\boldsymbol{B}}^{-1}\boldsymbol{\Gamma}\boldsymbol{x}_t+\ddot{\boldsymbol{B}}^{-1}\varsigma_t\right)\left(\ddot{\boldsymbol{B}}^{-1}\boldsymbol{\Gamma}\boldsymbol{x}_t+\ddot{\boldsymbol{B}}^{-1}\varsigma_t\right)'\right]\boldsymbol{\Lambda}'+\boldsymbol{\Theta}_\varepsilon\\
&= \boldsymbol{\Lambda}\ddot{\boldsymbol{B}}^{-1}\left(\boldsymbol{\Gamma\Phi\Gamma}'+\boldsymbol{\Psi}\right)\ddot{\boldsymbol{B}}'^{-1}\boldsymbol{\Lambda}'+\boldsymbol{\Theta}_\varepsilon\ ,\\
\mathrm{E}\left(\boldsymbol{x}_t\boldsymbol{y}_t'\right) &= \mathrm{E}\left[\boldsymbol{x}_t\left(\boldsymbol{\Lambda\eta}_t+\boldsymbol{\varepsilon}_t\right)'\right]\\
&= \mathrm{E}\left(\boldsymbol{x}_t\boldsymbol{\eta}_t'\right)\boldsymbol{\Lambda}'\\
&= \mathrm{E}\left[\left(\boldsymbol{x}_t\right)\left(\ddot{\boldsymbol{B}}^{-1}\boldsymbol{\Gamma}\boldsymbol{x}_t+\ddot{\boldsymbol{B}}^{-1}\varsigma_t\right)'\right]\boldsymbol{\Lambda}'\\
&= \boldsymbol{\Phi\Gamma}'\ddot{\boldsymbol{B}}'^{-1}\boldsymbol{\Lambda}'\ ,\\
\mathrm{E}\left(\boldsymbol{y}_t\boldsymbol{x}_t'\right) &= \mathrm{E}\left[\left(\boldsymbol{\Lambda\eta}_t+\boldsymbol{\varepsilon}_t\right)\boldsymbol{x}_t'\right]\\
&= \boldsymbol{\Lambda}\ddot{\boldsymbol{B}}^{-1}\boldsymbol{\Gamma\Phi}\ ,\\
\mathrm{E}\left(\boldsymbol{x}_t\boldsymbol{x}_t'\right) &= \boldsymbol{\Phi}\ .
\end{aligned}
$$

The estimate of the population covariance matrix $\boldsymbol{\Sigma}$, $\hat{\boldsymbol{\Sigma}}$, defined in terms of the estimated parameters contained in the vector $\hat{\boldsymbol{\theta}}$ is thus given by:

$$
\hat{\boldsymbol{\Sigma}} = \left[\begin{array}{c|c}
\hat{\boldsymbol{\Lambda}}\hat{\ddot{\boldsymbol{B}}}^{-1}\left(\hat{\boldsymbol{\Gamma}}\hat{\boldsymbol{\Phi}}\hat{\boldsymbol{\Gamma}}'+\hat{\boldsymbol{\Psi}}\right)\hat{\ddot{\boldsymbol{B}}}'^{-1}\hat{\boldsymbol{\Lambda}}'+\hat{\boldsymbol{\Theta}}_\varepsilon & \hat{\boldsymbol{\Lambda}}\hat{\ddot{\boldsymbol{B}}}^{-1}\hat{\boldsymbol{\Gamma}}\hat{\boldsymbol{\Phi}}\\
\hline
\hat{\boldsymbol{\Phi}}\hat{\boldsymbol{\Gamma}}'\hat{\ddot{\boldsymbol{B}}}'^{-1}\hat{\boldsymbol{\Lambda}}' & \hat{\boldsymbol{\Phi}}
\end{array}\right], \tag{A.15}
$$

where ‘ ^ ’ indicates that the matrices contain estimates of the population parameters. Of course, these estimates must satisfy all constraints imposed on the model by the researcher. Equation (A.15) is called covariance equation. Estimation is performed by finding values for $\hat{\boldsymbol{\theta}} = f\left(\hat{\ddot{\boldsymbol{B}}},\hat{\boldsymbol{\Lambda}},\hat{\boldsymbol{\Gamma}},\hat{\boldsymbol{\Psi}},\hat{\boldsymbol{\Phi}},\hat{\boldsymbol{\Theta}}_\varepsilon\right)$ that produce an estimate of the models covariance matrix $\hat{\boldsymbol{\Sigma}}$ that most closely corresponds to the sample covariance matrix $\boldsymbol{S}$. During this estimation procedure, all possible matrices that meet the imposed restrictions are considered. If an estimate $\boldsymbol{\Sigma}^*$ of $\hat{\boldsymbol{\Sigma}}$ is close to $\boldsymbol{S}$, one might conclude that $\boldsymbol{\theta}^* = f\left(\ddot{\boldsymbol{B}}^*,\boldsymbol{\Lambda}^*,\boldsymbol{\Gamma}^*,\boldsymbol{\Psi}^*,\boldsymbol{\Phi}^*,\boldsymbol{\Theta}_\varepsilon^*\right)$ is a reasonable estimate of the model’s parameters. Hence, estimation of an SEM is reduced to the problem of measuring how close $\boldsymbol{\Sigma}^*$ is to $\boldsymbol{S}$ and if this estimate is the most accurate, i.e., if it is the best estimate given the set of all possible estimates that meet the imposed restrictions [Long (1983b), pp. 42-45].

Estimation of a MIMIC model proceeds accordingly although less parameters must be estimated, i.e., only estimates for $\boldsymbol{\lambda}$, $\boldsymbol{\gamma}$, $\boldsymbol{\Phi}$, ψ, and $\boldsymbol{\Theta}_{\varepsilon}$ must be found to produce an estimate of $\boldsymbol{\Sigma}$ that most closely corresponds to $\boldsymbol{S}$. That is, $\hat{\boldsymbol{\Sigma}} = \boldsymbol{\Sigma}\left(\hat{\boldsymbol{\theta}}\right)$ and $\hat{\boldsymbol{\theta}} = f\left(\hat{\boldsymbol{\lambda}}, \hat{\boldsymbol{\gamma}}, \hat{\psi}, \hat{\boldsymbol{\Phi}}, \hat{\boldsymbol{\Theta}}_{\varepsilon}\right)$. Going through the same algebraic steps as shown for the H-DIY SEM, the covariance equation of the MIMIC model can be derived. It has the following functional form:

$$\hat{\boldsymbol{\Sigma}} = \left[\begin{array}{c|c} \hat{\boldsymbol{\lambda}}\left(\hat{\boldsymbol{\gamma}}'\hat{\boldsymbol{\Phi}}\hat{\boldsymbol{\gamma}} + \hat{\psi}\right)\hat{\boldsymbol{\lambda}}' + \hat{\boldsymbol{\Theta}}_{\varepsilon} & \hat{\boldsymbol{\lambda}}\hat{\boldsymbol{\gamma}}'\hat{\boldsymbol{\Phi}} \\ \hline \hat{\boldsymbol{\Phi}}\hat{\boldsymbol{\gamma}}\hat{\boldsymbol{\lambda}}' & \hat{\boldsymbol{\Phi}} \end{array}\right]. \tag{A.16}$$

The function that measures how close a given $\boldsymbol{\Sigma}^*$ is to the sample covariance matrix $\boldsymbol{S}$ is called fitting function $\mathrm{F}\left(\boldsymbol{S};\boldsymbol{\Sigma}^*\right)$. The $\boldsymbol{\theta}^*$ of all possible $\boldsymbol{\theta}^*$ that meets the imposed constraints on $\ddot{\boldsymbol{B}}$, $\boldsymbol{\Lambda}$, $\boldsymbol{\Gamma}$, $\boldsymbol{\Psi}$, $\boldsymbol{\Phi}$, and $\boldsymbol{\Theta}_{\varepsilon}$ ($\boldsymbol{\lambda}$, $\boldsymbol{\gamma}$, $\boldsymbol{\Phi}$, ψ, and $\boldsymbol{\Theta}_{\varepsilon}$ in the case of the MIMIC model) and minimizes the fitting function, given the sample covariance matrix $\boldsymbol{S}$, is the sample estimate $\hat{\boldsymbol{\theta}}$ of the population parameters. This means that if one set of estimates $\boldsymbol{\theta}_1^*$ produces the matrix $\boldsymbol{\Sigma}_1^*$ and a second set $\boldsymbol{\theta}_2^*$ produces the matrix $\boldsymbol{\Sigma}_2^*$ and if $\mathrm{F}\left(\boldsymbol{S};\boldsymbol{\Sigma}_1^*\right) < \mathrm{F}\left(\boldsymbol{S};\boldsymbol{\Sigma}_2^*\right)$, $\boldsymbol{\Sigma}_1^*$ then is considered to be closer to $\boldsymbol{S}$ than $\boldsymbol{\Sigma}_2^*$ [Long (1983a), pp. 56-57].

The most widely used fitting function for SEMs is the Maximum Likelihood (ML) function.[112] Under the assumption that $\boldsymbol{\Sigma}(\boldsymbol{\theta})$ and $\boldsymbol{S}$ are positive definite, i.e.,

---

[112] Other estimation procedures such as Unweighted Least Squares (ULS) and Generalized Least Squares (GLS) are also available. ULS has the advantage that it is easier to compute, leads to a consistent estimator without the assumption that the observed variables have a particular distribution. Important disadvantages of ULS are however, that ULS does not lead to the asymptotically most efficient estimator of $\boldsymbol{\theta}$ and that $\mathrm{F}_{\mathrm{ULS}}$ is not scale invariant. The GLS estimator has similar statistical properties like the ML estimator but the significance tests are no longer accurate if the distribution of the observed variables has very "fat" or "thin" tails. Moreover, $\mathrm{F}_{\mathrm{GLS}}$ accepts the wrong model more often than ML and parameter estimates tend to suffer when using $\mathrm{F}_{\mathrm{GLS}}$. Thus, ML seems to be superior [see, for example, Bollen (1989), pp. 111-115; Olsson et al. (1999); Olsson et al. (2000); Jöreskog and Sörbom (2001), pp. 20-24].

nonsingular, and $\boldsymbol{S}$ has a Wishart distribution, the following fitting function is minimized:

$$\mathrm{F_{ML}} = \log\left|\boldsymbol{\Sigma}(\boldsymbol{\theta})\right| + tr\left[\boldsymbol{S\Sigma}^{-1}(\boldsymbol{\theta})\right] - \log\left|\boldsymbol{S}\right| - (p+q), \tag{A.17}$$

where $\log|\;|$ is the log of the determinant of the respective matrix and $(p+q)$ is the number of observed variables. In general, no closed form or explicit solution for the structural parameters that minimize $\mathrm{F_{ML}}$ exists. Hence, the values of $\boldsymbol{B}$, $\boldsymbol{\Lambda}$, $\boldsymbol{\Gamma}$, $\boldsymbol{\Psi}$, $\boldsymbol{\Phi}$, and $\boldsymbol{\Theta}_\varepsilon$ ($\boldsymbol{\lambda}$, $\boldsymbol{\gamma}$, $\boldsymbol{\Phi}$, ψ, and $\boldsymbol{\Theta}_\varepsilon$ in the case of the MIMIC model) that minimize the fitting function are estimated applying iterative numerical procedures.[113]

The ML estimator is widely used because of its desirable properties.[114] First, the ML estimator is asymptotically unbiased. Second, the ML estimator is consistent, i.e., $\operatorname{plim}\hat{\boldsymbol{\theta}} = \boldsymbol{\theta}$ ($\hat{\boldsymbol{\theta}}$ is the ML estimator and $\boldsymbol{\theta}$ is the population parameter). Third, the ML estimator is asymptotically efficient, i.e., among all consistent estimators no other has a smaller asymptotic variance. Fourth, the ML estimator is asymptotically normally distributed, meaning that the ratio of the estimated parameter and its standard error approximate a *z*-distribution in large samples. Fifth, a final important characteristic of the ML estimator is scale invariance [Swaminathan and Algina (1978)]. The scale invariance property implies that changes of the measurement unit of one or more of the observed variables do not change the value of the fitting function. This means that $\hat{\boldsymbol{B}}$, $\hat{\boldsymbol{\Lambda}}$, $\hat{\boldsymbol{\Gamma}}$, $\hat{\boldsymbol{\Psi}}$, $\hat{\boldsymbol{\Phi}}$, and $\hat{\boldsymbol{\Theta}}_\varepsilon$ ($\hat{\boldsymbol{\lambda}}$, $\hat{\boldsymbol{\gamma}}$, $\hat{\boldsymbol{\Phi}}$, $\hat{\psi}$, and $\hat{\boldsymbol{\Theta}}_\varepsilon$ in the case of the MIMIC model) are the same for any change of scale.

The ML and GLS estimation procedures assume multivariate normal data and a reasonable sample size.[115] If non-normality and excessive kurtosis threaten the validity

---

[113] See Appendix 4C in Bollen (1989) for details.

[114] This appendix briefly reviews these properties. For a detailed discussion see Bollen (1989, pp. 107-123).

[115] There are several rules of thumb about the sample size in the literature: the sample size should at least contain 50 observations or have more than 8 times the number of observations then are independent variables in the model [Garson (2005)]. Bentler and Chou (1987) recommend at least 5 observations per parameter estimate (including error terms as well as path coefficients). If possible, one should go beyond these minimum sample size recommendations

of the ML significance tests, corrections are helpful. A convenient approach is to find transformations that lead to better approximate multi-normality or remove excessive kurtosis. After successful transformation, one can apply F_{GLS} or F_{ML} to the data as usual. If the data are continuous but not normally distributed, an alternative method is an asymptotically distribution free estimation procedure, known as Weighted Least Squares (WLS). Although this estimator allows for non-normality, it is asymptotically efficient in large samples only.[116] If transformations do not lead to sufficient normality or WLS is not applicable because of a to small sample size, ML is still justified but the statistical tests need to be interpreted with caution [Jöreskog and Sörbom (2001), p. 170; Kmenta (1971), p. 579].

To summarize, the first step in the estimation procedure is thus to translate the underlying economic theory into a structural model. In the second step, it is necessary to check identification of the model and to fix one coefficient to an *a priori* value in order to give the latent variable an interpretable scale. In a third step the estimation method has to be chosen which defines the fitting function for the estimation of an SEM and finally provides estimates for the population parameters.

A.3 Assessing the Fit of Structural Equation Models

This section briefly reviews selected statistics for assessing an SEM's overall goodness-of-fit.[117] In general, these statistics assess the hypothesis that $\boldsymbol{\Sigma}$ equals $\boldsymbol{\Sigma}(\boldsymbol{\theta})$ by using their sample counterparts $\boldsymbol{S}$ and $\hat{\boldsymbol{\Sigma}}$. They are all a function of the sample size and the degrees of freedom and often take into account not only the fit of the model but also its complexity. When the model's fit is not adequate, it has become common practice to modify the model by excluding the non-significant parameters in order to improve the fit

particularly when the data are not normally distributed or are incomplete.

[116] Hu et al. (1992) and Olsson et al. (2000) find that the WLS method has a tendency to overestimate the true goodness-of-fit. The interval of the overestimation bias is however moderate in samples with more than 250 observations.

[117] See Bollen (1989, pp. 256-281) for a detailed description.

and to find the most suitable model.[118] Before evaluating the overall fit of a model, one should also carefully examine the estimated coefficients. Questions such as whether the estimated coefficients are significant and have the expected (correct) sign, whether their magnitudes correspond to previous research (and why they differ if they do) need to be addressed before turning to the evaluation of the model's overall fit.

Measures assessing the overall fit of an SEM determine the degree to which the model as a whole is consistent with the analyzed data. A widely used overall goodness-of-fit test is the chi-square goodness-of-fit measure:[119]

$$\chi^2 = (N-1)\,\mathrm{F}\left(\boldsymbol{S}, \hat{\boldsymbol{\Sigma}}\right), \tag{A.18}$$

where N is the sample size and $\mathrm{F}\left(\boldsymbol{S}, \hat{\boldsymbol{\Sigma}}\right)$ is the value of the fitting function at convergence. This statistic directly assesses how well the predicted covariance matrix reproduces the sample covariance matrix of the observed variables, i.e., it tests how close $\hat{\boldsymbol{\Sigma}}$ is to $\boldsymbol{S}$. In particular, it tests the null hypothesis $\mathrm{H}_0 : \hat{\boldsymbol{\Sigma}} = \boldsymbol{S}$, i.e., that a given model estimated by the covariance equation $\hat{\boldsymbol{\Sigma}}$ reproduces $\boldsymbol{S}$ as well as possible [Bollen (1989), p. 256].[120] Typically, the predicted covariance matrix $\hat{\boldsymbol{\Sigma}}$ does not reproduce $\boldsymbol{S}$ perfectly, due to the constraints imposed on the model's parameters. The chi-square goodness-of-fit test thus tests the imperfect, though acceptable, fit under H_0 against the

---

[118] As mentioned above (see footnote 100), in practice researchers often modify their ex-ante hypothesized model in an exploratory way to achieve a better fit, although SEMs are rather a confirmatory technique.

[119] Although this statistic is the most widely used overall goodness-of-fit measure, its application is seldom justified because one of the assumptions (that the observed variables are normally distributed, that the analysis is based on the covariance rather than the correlation matrix, and that the sample is large enough to ensure the asymptotic properties of the chi-square test) is often violated [Bentler and Bonett (1980); Jöreskog und Sörbom (2001), pp. 28-29]. Jörekog and Sörbom therefore suggest using the chi-square as a goodness-of-fit measure in the sense that large (small) values, relative to the degrees of freedom, indicate a bad (good) fit, rather than as formal hypothesis test.

[120] In this sense, the chi-square goodness-of-fit test is a simultaneous test that all residuals are zero because the null hypothesis is equivalent to $\boldsymbol{S} - \hat{\boldsymbol{\Sigma}} = 0$ [Diamantopoulos and Siguaw (2000), p. 83].

alternative hypothesis H_1 that $\hat{\boldsymbol{\Sigma}}$ is any positive definite unrestricted matrix. That is, "the standard of comparison is the perfect fit of $\hat{\boldsymbol{\Sigma}}$ equal to $\boldsymbol{S}$" [Bollen (1989), p. 266].

The higher the chi-square's probability, the closer is the fit of $\hat{\boldsymbol{\Sigma}}$ under H_0 to the perfect fit. Hence, the larger the difference between the two matrices, the larger is the chi-square and the lower is its probability. Large, statistically significant, values of the chi-square indicate an imperfect model fit and result in the rejection of H_0 leading to the conclusion that the hypothesized model did not generate the data.[121] Thus, in contrast to standard hypothesis testing the aim is not to reject H_0. Unfortunately, the chi-square is affected by the sample size in the sense that in large samples even very small discrepancies between $\boldsymbol{S}$ and $\hat{\boldsymbol{\Sigma}}$ become significant and thus point to a rejection of the model. On the contrary, in a small sample the null hypothesis might not be rejected although the model fits the data rather poorly.[122]

For this reason, alternative measures of fit were developed and are additionally used in the literature. One of the most important alternative overall fit measures is the root mean squared error of approximation (RMSEA):

$$\mathrm{RMSEA} = \sqrt{\frac{\chi^2 - df}{df\,(N-1)}}\,. \tag{A.19}$$

Again, N denotes the sample size, while df is the degrees of freedom calculated as $\frac{1}{2}(p+q)(p+q+1)-t$, where t is the number of parameters to be estimated. The RMSEA also focuses on the discrepancy between $\boldsymbol{S}$ and $\hat{\boldsymbol{\Sigma}}$ but controls for the number

---

[121] In other words, smaller values of the chi-square indicate a better fit, i.e., a smaller chi-square does not reject the null hypothesis that the model reproduces the sample covariance matrix $\boldsymbol{S}$ of causes and indicators [Long (1983b), p. 74].

[122] Because $\chi^2 = (N-1)\mathrm{F}_{\mathrm{ML}}$, the estimate of the chi-square is in direct proportion to the sample size N and the power of the test increases as N increases. In large samples, the statistical test will almost certainly be significant and researchers face the problem of whether a statistically significant chi-square indicates a serious specification error or whether the test has excessively high power. Alternatively, in a very small sample the test has low power and a non-significant chi-square can occur although the model is mis-specified [Bollen (1989), pp. 268, 338-349].

of observations and takes the complexity of the model (i.e., the number of observed variables and parameters to be estimated) into account. Of course, it also measures the model's fit based on the difference between the estimated and the sample covariance matrix. The literature considers models with a RMSEA of 0.05 or less, between 0.05 and 0.08, and above 0.08 as having a good, acceptable, and poor fit [Browne and Cudeck (1993)].

Other popular measures are the following absolute fit indices: the goodness-of-fit index (GFI), the adjusted goodness-of-fit index (AGFI), and the parsimony goodness-of-fit index (PGFI) [Bollen (1989), p. 276; Diamantopoulos and Siguaw (2000), p. 87]. These indices are shown in equations (A.20)-(A.22) with respect to the ML fitting function $\mathrm{F_{ML}}$:[123]

$$\mathrm{GFI_{ML}} = 1 - \frac{tr\left[\left(\boldsymbol{\Sigma}^{-1} - \boldsymbol{S} - \boldsymbol{I}\right)^2\right]}{tr\left[\left(\boldsymbol{\Sigma}^{-1} - \boldsymbol{S}\right)\right]}, \tag{A.20}$$

$$\mathrm{AGFI_{ML}} = 1 - \left[\frac{p+q(p+q+1)}{2df}\right](1 - \mathrm{GFI}), \tag{A.21}$$

$$\mathrm{PGFI_{ML}} = \frac{df}{df_0}\mathrm{GFI}. \tag{A.22}$$

The GFI measures how much of the relative amount of the variances and covariances in $\boldsymbol{S}$ is accounted for by the model, i.e., the GFI shows how well $\hat{\boldsymbol{\Sigma}}$ (in other words the model) predicts the observed covariance matrix. Unfortunately, the GFI does not take the number of model parameters, i.e., the complexity of the model, into account. This problem is solved by the AGFI which additionally adjusts according to the degrees of freedom relative to the number of variables in the model. Hence, the AGFI rewards simpler models with fewer variables for any number of variables $p+q$ and given GFI. The parsimony goodness-of-fit index (PGFI) makes a different type of adjustment for the model's complexity. It multiplies the GFI by the so called parsimony index df/df_0, where df and df_0 are the degrees of freedom of the estimated and the null model,

[123] For a discussion of these indices with respect to the $\mathrm{F_{ULS}}$, $\mathrm{F_{GLS}}$, and $\mathrm{F_{WLS}}$ fitting functions, see Bollen (1989, p. 277) and Mulaik et al. (1989).

respectively.[124] The PGFI thus compensates for the increase in fit of a less restricted model.[125] The GFI, AGFI, and PGFI indices are maximal when $\boldsymbol{S}$ equals $\hat{\boldsymbol{\Sigma}}$. Models are considered to have a good fit if their GFI and AGFI values are larger than 0.90. Values of the PGFI are usually much smaller and reflect a good fit if they are above 0.50 [Mulaik et al. (1989)].

Another useful indicator for the evaluation of a model's overall fit is the expected cross validation index (ECVI). The ECVI measures the discrepancy between the fitted covariance matrix and the expected covariance matrix of another sample of equivalent size, i.e., this measure assesses how valid a model is across samples of the same size from the same population. To assess a model's fit the ECVI is usually compared to the ECVIs of the independence and the saturated model (denoted as the independence and saturated models ECVI). The former is a model of complete independence among the variables (the null model), while in the latter the number of parameters is exactly equal to the number of variances and covariances among the observed variables. This means that the saturated model is just identified. The fit of the hypothesized model is acceptable if its ECVI is below the ECVIs of the independent and saturated models [Byrne (1998), p. 113; Diamantopoulos and Siguaw (2000), p. 86].

The final fit measure I use in this dissertation is the Akaike information criterion (AIC) for which smaller values indicate a better fit of the hypothesized model. As in the case of the ECVI, the model's AIC is compared to the independence and saturated models' AIC (denoted as the independence and saturated models AIC). An estimated model has a good fit if its AIC is smaller than the independence and saturated models' AIC [Diamantopoulos and Siguaw (2000), p.86].

---

[124] The null or independence model is a model of complete independence among all variables, i.e., all observed variables are uncorrelated. This model – being the most restrictive model – has $p+q$ parameters and $(p+q)(p+q-1)/2$ degrees of freedom [Diamantopoulos and Siguaw (2000), p. 86].

[125] Estimation of less restrictive models, i.e., freeing more parameters, improves the model's fit to the observed covariance matrix as removing constraints on the final solution allows for a better fit of the model-reproduced covariance matrix $\hat{\boldsymbol{\Sigma}}$ to the sample covariance matrix $\boldsymbol{S}$ [Mulaik et al. (1989)]. While the model's fit improves, the degrees of freedom reduce. Consequently, the parsimony index df/df_0 decreases.

A.4 Advantages and Disadvantages of Structural Equation Models

It is widely accepted by most scholars who estimate the size and development of informal economic activities using the SEM approach that such an empirical exercise is a “minefield” regardless which method is used. For example, in evaluating the currently available shadow economy estimates of different scholars, one should keep in mind, that already Schneider (1997) and Schneider and Enste (2000) warned that there is no best or commonly accepted method. Each approach has its strengths and weaknesses and can provide specific insights and results. Although SEM/MIMIC model applications in economics are “accompanied” by criticisms,[126] they are increasingly used for estimating the shadow economy and other informal economic activities.[127]

In comparison to other statistical methods, SEMs/MIMIC models offer several advantages for the estimation of informal economic activities. According to Giles and Tedds (2002), the MIMIC approach is a wider approach than most other competing methods, since it allows one to take multiple indicator and causal variables into consideration at the same time. Moreover, it is quite flexible, allowing one to vary the choice of causal and indicator variables according to the particular features of the informal economic activity studied, the period in question, and the availability of data. SEMs/MIMIC models lead to a formal estimation and to testing procedures, such as those based on the method of maximum likelihood. These procedures are well known and are generally “optimal”, if the sample is sufficiently large [Giles and Tedds (2002)].

A further advantage of SEMs/MIMIC models has been stressed by Schneider and Enste (2000). They emphasize that these models lead to some progress in estimation techniques for the size and development of the shadow economy, because this methodology allows a wide flexibility in its application. Therefore, they consider it potentially superior over all other estimation methods. Cassar (2001) argues that, when compared to other methods, SEMs/MIMIC models do not need restrictive assumptions to operate. Analogously, Thomas (1992, p. 168) argues that the only real constraint of this approach is not in its conceptual structure but the choice of variables. These positive

[126] Compare, for example, the criticism by Helberger and Knepel (1988) with respect to the pioneering work of Frey and Weck-Hannemann (1984).

[127] Compare the studies quoted at the beginning of Appendix A and in footnote 102.

aspects of the SEM approach in general and the MIMIC model in particular do not only apply in its application to the shadow economy but to all informal economic activities.

Of course this method has its disadvantages or limitations which are identified in the literature. The three most important points of criticism focus on the model's implementations, the sample used, and the reliability of the estimates:

(1) When estimating informal economic activities using SEMs the most common objection concerns the meaning of the latent variable [Helberger and Knepel (1988); Giles and Tedds (2002); Smith (2002); Hill (2002); Dell'Anno (2003)]. The confirmatory rather than exploratory nature of this approach means that one is more likely to determine whether a certain model is valid than to "find" a suitable model. Therefore, it is possible that the specified model includes potential definitions or informal economic activities other than the one studied. For example, it is difficult for a researcher to ensure that traditional crime activities such as drug dealing are completely excluded from the analysis of the shadow economy. This criticism which is probably the most common in the literature remains difficult to overcome as it goes back to the theoretical assumptions behind the choice of variables and empirical limitations on the availability of data. In this dissertation however, I hope to have provided a sound reasoning, based on previous theoretical and empirical findings of the literature (Chapters 2 and 3) and a (simple) microeconomic model (Chapter 4), for the choice of causes and indicators of the respective informal economic activity.

(2) Another objection is expressed by Helberger and Knepel (1988). They argue that SEM/MIMIC model estimations lead to instable coefficients with respect to changes of the sample size and alternative model specifications. Dell'Anno (2003) shows however that instability disappears asymptotically as the sample size increases. Another issue is the application of SEMs to time series data because only simple analytical tools such as q- and stemleaf plots are available to analyze the properties of the residuals [Dell'Anno (2003)]. Time series applications of the SEM/MIMIC approach are nevertheless common practice in economics and had already been used in Karmann (1990b).[128]

[128] Moreover, with respect to time series applications the assumptions $\mathrm{E}\left(\varsigma_{ik}^{2}\right) = \mathrm{Var}\left(\varsigma_{i}\right)$ for

(3) Criticism is also related to the benchmarking procedure used to derive "real world" figures of informal economic activities [Breusch (2005a; 2005b)]. It has its origin in the complications one faces when converting the index estimated by an SEM or MIMIC model into meaningful estimates. This is not an easy task, as the latent variable and its unit of measurement are not observed. SEMs just provide a set of estimated coefficients from which one can calculate an index that shows the dynamics of the unobservable variable.

Application of the so called calibration or benchmarking procedure, regardless which one is used, requires experimentation, and a comparison of the calibrated values in a wide academic debate. Unfortunately, at this stage of research on the application of the SEM/MIMIC approach in economics it is not clear which benchmarking method is the best or the most reliable. In which way to proceed is still extensively discussed in the literature.[129]

The economic literature using SEMs is well aware of these limitations. Consequently, it acknowledges that it is not an easy task to apply this methodology to an economic dataset but also argues that this does not mean one should abandon the SEM approach. On the contrary, following an interdisciplinary approach to economics, SEMs are valuable tools for economic analysis, particularly when studying informal (unobservable) economic activities. However, the mentioned objections should be considered as an incentive for further (economic) research in this field rather than as a suggestion to abandon this method.

---

all k (homoscedasticity assumption) and $\mathrm{Cov}(\varsigma_{ik}, \varsigma_{il}) = 0$ for all $k \neq l$ (no autocorrelation in the error terms) are critical. Unfortunately, corrections for autocorrelated and heteroscedastic error terms have yet received insufficient attention in models with unobservable variables [Bollen (1989), p. 58]. An interesting exception, dealing with the problem of autocorrelated observation, is Folmer and Karmann (1992).

[129] See Dell'Anno and Schneider (2009) for a detailed discussion and comparison of different benchmarking procedures.

A.5 Summary

This appendix presented a summary of SEMs, their application to economic activities, esp. macroeconomic informal ones, and discusses advantages as well as disadvantages. Although economic theory has become increasingly open to methodologies of the social sciences (e.g. in behavioral and experimental economics), SEMs are not widely used in empirical economic research. Opening empirical economics further towards methodologies of other social sciences can help economists to improve empirical methodologies to analyze informal economic activities such as the shadow economy and smuggling.

The advice to use methods of other disciplines in economics more often is not a new one. Unfortunately, it seems discouraging to observe that, after more than thirty years, Goldberger's advice on "numerous incentives for econometricians to break through those fences which still separate the social sciences" is still largely unheard [Goldberger (1972), p. 999]. The application of SEMs to different informal economic activities as undertaken in this dissertation is a small step forward in this direction showing that SEMs are appropriate econometric tools to study informal, unobservable economic activities.

The growth of human knowledge gains from problems and from attempts to solve them. These attempts require the formulation of theories which must go beyond existing knowledge and therefore require creativity and imagination. In the empirical analysis of informal economic activities, where the estimation step is particularly challenging, researchers are often forced to use "imagination" because existing estimation procedures have limitations and complications still exist.

For this reason, Appendix A also discusses the weaknesses of SEM applications in economics. These difficulties go back to the properties of SEMs being a quantitative method in the social sciences. This means that time series analysis using this method and conversion of the estimated index into "real world" figures are subject to controversial debate. Further attempts to improve this procedure are certainly necessary.

In applied economics, the measurement of the size and trend of an informal economic activity is just one important aspect in the context of a broader economic analysis. Economists are at least as interested to understand the economic determinants behind informal economic activities as they are eager to measure their actual size. In fact, for policymakers and economists it is just as appealing to be aware of the main causes for the dynamics of informal economic activities as it is to have a detailed knowledge of their size and development over time. This, bearing in mind the lack of other reliable methods and the additional information provided by the SEM approach, leads me to the conclusion that this approach is a valuable tool for the analysis of informal economic activities. Given the current state of the art, it is still one of the best approaches to analyze informal economic activities and a good example for the advantages of an open-minded, multidisciplinary approach to economic research. A greater opening and a broader interdisciplinary debate may create further fruitful discussions among researchers in order to overcome the existing difficulties regarding the SEM approach.

APPENDIX B: SHADOW ECONOMIC AND DO-IT-YOURSELF ACTIVITIES

Table B.1 Variable Definitions and Sources

Variable	Definition	Source
Causes		
Dummy	one for 1991 and 1992, null else	
Income	natural logarithm of the per capita real disposable income	Deutsche Bundesbank
Inflation	inflation rate	Federal Statistical Office of Germany, own calculations
Regulation	number of employed in public service (% of total population) excluding individuals employed by railways and the postal service, which were previously state-run	Federal Statistical Office of Germany, own calculations
Tax burden	public revenues (% of GDP)	OECD
Unemploy-ment	natural logarithm of the number of unemployed	Federal Statistical Office of Germany
Wages	natural logarithm of the average gross hourly earnings of male workers in the small business sector	Federal Statistical Office of Germany, own calculations

(continued on next page)

Table B.1 (cont.)

Indicators		
M0	natural logarithm of real domestic M0	Deutsche Bundesbank, own calculations
Growth rate GDP	growth rate of real GDP	Federal Statistical Office of Germany
Working hours	natural logarithm of the average hours worked per week	Federal Statistical Office of Germany
Turnovers	natural logarithm of real turnovers in DIY stores	A.C. Nielsen Company GmbH, own calculations

Table B.2 Further Goodness-of-fit Statistics of the Estimated Models

Goodness-of-fit statistics	Full model	
	S-DIY	H-DIY
AGFI	0.80	0.78
PGFI	0.64	0.62
ECVI	2.34	1.63
ECVI independence model	4.12	2.90
ECVI saturated model	3.77	2.57
AIC	66.87	54.19
AIC independence model	144.21	101.56
AIC saturated model	132.00	90.00

Table B.3 Robustness Checks S-DIY Model

	1971-2005		1972-2005		1973-2005		1970-2004		1970-2003		1970-2002		Parsimonious model [1)] (1970-2005)	
	S	DIY	S	DIY	S	DIY	S	DIY	S	DIY	S	DIY	S	DIY
Causes														
Regulation	12.12***		12.17***		12.48***		11.83***		12.08***		13.08***		11.94***	
	(2.63)		(2.59)		(2.55)		(2.55)		(2.59)		(2.63)		(2.64)	
Income	1.34***		1.34***		1.41***		1.34***		1.25***		1.45***		1.28***	
	(3.22)		(3.11)		(3.02)		(3.16)		(2.97)		(3.23)		(3.12)	
Inflation	-0.25	-0.62**	-0.24	-0.59**	-0.35	-0.58**	-0.27	-0.57**	-0.11	-0.55**	-0.49	-0.54**		-0.53**
	(0.39)	(2.33)	(0.35)	(2.21)	(0.49)	(2.09)	(0.42)	(2.15)	(0.18)	(2.03)	(0.72)	(2.08)		(2.28)
Dummy	0.09***	0.05***	0.09**	0.05***	0.09**	0.04***	0.09***	0.05***	0.09**	0.05***	0.10***	0.05***	0.09**	0.04***
	(2.38)	(4.01)	(2.33)	(3.86)	(2.34)	(3.63)	(2.41)	(3.92)	(2.29)	(3.77)	(2.45)	(4.08)	(2.37)	(4.25)
Tax burden	0.11**	-0.01	0.11**	-0.01	0.11**	-0.01	0.11**	-0.00	0.12***	-0.01	0.12**	0.00	0.09**	
	(2.34)	(0.35)	(2.28)	(0.35)	(2.22)	(0.35)	(2.29)	(0.27)	(2.43)	(0.44)	(2.18)	(0.08)	(2.12)	
Unemploy-ment		0.03**		0.03**		0.03*		0.03**		0.03**		0.03***		0.04***
		(2.11)		(2.04)		(1.86)		(2.19)		(2.15)		(2.44)		(2.75)
Wages		0.15		0.16		0.17		0.11		0.11		0.09		
		(0.78)		(0.78)		(0.68)		(0.58)		(0.56)		(0.46)		

(continued on next page)

Table B.3 (cont.)

Indicators							
M0 (fixed)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Growth rate GDP	0.27^{***} (3.25)	0.27^{***} (3.17)	0.26^{***} (3.06)	0.27^{***} (3.19)	0.30^{***} (3.13)	0.25^{***} (3.07)	0.28^{***} (3.29)
Working hours	-0.02 (1.31)	-0.02 (1.16)	-0.02 (1.12)	-0.02 (1.17)	-0.02 (1.04)	-0.01 (0.77)	
Turnovers (fixed)	2.00	2.00	2.00	2.00	2.00	2.00	2.00
Goodness-of-fit statistics							
Observations	35	34	33	35	34	33	36
Degrees of freedom	50	50	50	50	50	50	34
Chi-square	33.48	33.97	35.42	35.15	34.28	33.66	24.92
(*p*-value)	(0.96)	(0.96)	(0.94)	(0.94)	(0.96)	(0.96)	(0.97)
RMSEA	0.00	0.00	0.00	0.00	0.00	0.00	0.00

1) The parsimonious model excludes all insignificant variables.

Note: ***, **, * Significance at 1%, 5%, and 10% levels, respectively. Absolute *z*-statistics in parentheses. The degrees of freedom are determined by 0.5 (p + q) (p + q + 1) – t; with p = number of indicators; q = number of causes; t = the number for free parameters. If the model fits the data perfectly and the parameter values are known, the sample covariance matrix equals the covariance matrix implied by the model. The null hypothesis of perfect fit corresponds to a *p*-value of 1. The root mean squared error of approximation (RMSEA) measures the model's fit based on the difference between the estimated and the actual covariance matrix. RMSEA values smaller than 0.05 indicate a good fit [Browne and Cudeck (1993)].

Table B.4 Robustness Checks H-DIY Model

													Parsimonious model 1)	
	1971-2005		1972-2005		1973-2005		1970-2004		1970-2003		1970-2002		1970-2005	
	H	DIY	H	DIY	H	DIY	H	DIY	H	DIY	H	DIY	H	DIY
Causes														
Regulation	11.59***		11.46***		11.61***		11.17***		11.90***		11.71***		10.59***	
	(2.55)		(2.45)		(2.40)		(2.44)		(2.54)		(2.43)		(2.47)	
Income	1.40***		1.43***		1.48***		1.39***		1.38***		1.43***		1.18***	
	(3.42)		(3.36)		(3.23)		(3.33)		(3.23)		(3.29)		(3.01)	
Inflation	-0.86		-1.18		-1.70***		-0.85		-0.68		-1.00			
	(1.31)		(1.63)		(2.52)		(1.29)		(1.03)		(1.44)			
Dummy	0.12***		0.13***		0.13***		0.13***		0.12***		0.14***		0.11***	
	(3.13)		(3.22)		(3.20)		(3.15)		(2.96)		(3.21)		(2.81)	
Tax burden	0.09**		0.09*		0.09*		0.09*		0.11**		0.10*		0.09**	
	(2.06)		(1.90)		(1.83)		(2.02)		(2.18)		(1.96)		(2.04)	

(continued on next page)

Table B.4 (cont.)

Indicators							
M0 (fixed)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Growth rate GDP	0.23*** (3.17)	0.21*** (3.00)	0.20*** (2.84)	0.23*** (3.11)	0.25*** (3.15)	0.22*** (2.95)	0.29*** (3.26)
Working hours	-0.01 (1.10)	-0.01 (0.95)	-0.01 (0.91)	-0.01 (0.96)	-0.01 (0.83)	-0.01 (0.59)	
Turnovers (fixed)	2.00	2.00	2.00	2.00	2.00	2.00	2.00
Latent variable							
H → DIY	0.13* (1.96)	0.13** (2.00)	0.13** (1.98)	0.13* (1.88)	0.11 (1.58)	0.14** (2.00)	0.14* (1.84)
Goodness-of-fit statistics							
Observations	35	34	33	35	34	33	36
Degrees of freedom	33	33	33	33	33	33	19
Chi-square (p-value)	28.87 (0.67)	29.09 (0.66)	27.79 (0.72)	30.22 (0.61)	29.56 (0.64)	27.71 (0.73)	11.35 (0.91)
RMSEA	0.00	0.00	0.00	0.00	0.00	0.00	0.00

1) The parsimonious model excludes all insignificant variables.

Note: ***, **, * Significance at 1%, 5%, and 10% levels, respectively. Absolute *z*-statistics in parentheses. The degrees of freedom are determined by 0.5 (p + q) (p + q + 1) – t; with p = number of indicators; q = number of causes; t = the number for free parameters. If the model fits the data perfectly and the parameter values are known, the sample covariance matrix equals the covariance matrix implied by the model. The null hypothesis of perfect fit corresponds to a *p*-value of 1. The root mean squared error of approximation (RMSEA) measures the model's fit based on the difference between the estimated and the actual covariance matrix. RMSEA values smaller than 0.05 indicate a good fit [Browne and Cudeck (1993)].

Table B.5 Further Goodness-of-fit Statistics for the Parsimonious Models [1)]

Goodness-of-fit statistics	S-DIY parsimonious model (1970-2005)	H-DIY parsimonious model (1970-2005)
AGFI	0.79	0.88
PGFI	0.64	0.62
ECVI	1.60	1.06
ECVI independence model	2.95	2.18
ECVI saturated model	2.57	1.60
AIC	46.92	29.35
AIC independence model	103.39	76.18
AIC saturated model	90.00	56.00

1) The parsimonious models refer to the specifications excluding all insignificant variables [see last columns of Tables B.2 (S-DIY model) and B.3 (H-DIY model)].

APPENDIX C: SMUGGLING AROUND THE WORLD

Table C.1 Data Sources and Definitions

Name of variable	Definition	Sources
Causes		
Tariff burden	average tariff rate (%)	Wacziarg and Welch (2003)
Trade restrictions index	index of trade restrictions	Index of globalization, KOF Swiss Economic Institute [Dreher (2006)]
Openness	openness index defined as sum of exports and imports over GDP	PWT (2002)
Black market premium	difference between the parallel exchange rate and the official exchange rate divided by the official exchange rate (The exchange rate is defined as number of units of domestic currency per U.S. dollar.)	Easterly and Sewadeh (2002)
Lack of corruption index	perception of corruption in the business environment, including levels of governmental legal, judicial, and administrative corruption	1) Index of Economic Freedom, Heritage Foundation [Holmes et al. (2007)] 2) WGI, World Bank, [Kaufmann et al. (2007)]

(continued on next page)

Table C.1 (cont.)

Rule of law	agents' confidence in and abidance by the rules of society, in particular the quality of contract enforcement, the police, and the courts, as well as the likelihood of crime and violence	WGI, World Bank, [Kaufmann et al. (2007)]
Indicators		
Real GDP per capita		PWT (2002)
Tax revenues		World Bank (2006)
Trade discrepancy	calculated according to equation (4.7) and (4.8)	IMF Directions of Trade Statistics (DOTS)

Table C.2 Further Goodness-of-fit Statistics

Goodness-of-fit statistics	Specification									
	1	2	3	4	5	6	7	8	9	10
AGFI	0.85	0.86	0.91	0.84	0.86	0.90	0.89	0.79	0.79	0.88
PGFI	0.53	0.53	0.55	0.53	0.53	0.55	0.50	0.51	0.51	0.56
ECVI	0.96	0.96	0.96	0.97	0.96	0.96	1.06	1.13	1.12	0.94
ECVI independence model	8.36	8.45	7.97	8.88	5.68	8.19	7.87	8.36	5.68	5.68
ECVI saturated model	1.36	1.36	1.36	1.36	1.36	1.36	1.05	1.36	1.36	1.36
AIC	50.11	49.40	41.95	51.20	49.52	42.64	37.88	59.68	59.20	45.09
AIC independence model	442.96	447.86	422.53	470.61	300.96	434.12	417.21	442.96	300.96	300.96
AIC saturated model	72.00	72.00	72.00	72.00	72.00	72.00	56.00	72.00	72.00	72.00

APPENDIX D: SMUGGLING ILLEGAL AND LEGAL GOODS ACROSS THE U.S.-MEXICO BORDER

Table D.1 Data Sources and Definitions

Variable	Definition	Source
BMP (black market premium)	(black market exchange rate - official exchange rate) / official exchange rate	1975-1982: Pick (1955-1982), various issues; 1983-1998: Pick (1983-1998), various issues
Real exchange rate	nominal official exchange rate (peso/U.S. dollar)*U.S. Consumer Price Index (CPI) /MX CPI	nominal exchange rate: International Monetary Fund (IMF) International Financial Statistics; Mexican (MX) CPI: Banco de Mexico; U.S. CPI: Bureau of Labor Statistics
MX unemployment rate	unemployed persons as % of total labor force, seasonally adjusted	1975-84: Fleck and Sorrentino (1994); 1985-2004: Organization for Economic Cooperation and Development (OECD) Main Economic Indicators

(continued on next page)

Table D.1 (cont.)

MX real wages	nominal wage in manufacturing deflated with Mexican CPI, seasonally adjusted	1975M1-1998M5: Hanson and Spilimbergo (1999); 1998M6-2004M4: Instituto Nacional de Estadística, Geografía e Informática (INEGI)
U.S. border enforcement	number of person-hours spent by the U.S Customs and Border Protection (CBP) for border patrols / total apprehensions, seasonally adjusted	unpublished records of the U.S. Immigration and Naturalization Service (INS); Hanson (2006)
U.S. linewatch apprehensions	individuals apprehended by the CBP at international boundaries of the United States, seasonally adjusted	unpublished records of the INS; Hanson (2006)
U.S. non-linewatch apprehensions	individuals apprehended by the CBP inside the United States at traffic checkpoints, raids on businesses or interior patrols, seasonally adjusted	unpublished records of the INS; Hanson (2006)
U.S. real drug seizures	illegal drugs seized by the CBP, in million U.S. dollars, deflated by U.S. CPI	Department of Homeland Security; Hanson (2006)
U.S. drug availability	% of U.S. 12th-graders reporting that "marijuana is fairly or very easy" to get	Johnston et al. (2007)

(continued on next page)

Table D.1 (cont.)

MX taxes on income/profit	% of GDP	1975-2000 IMF Government Statistics; 2001-2004 OECD Revenue Statistics
MX taxes on international trade	% of imports	1975-2000 IMF Government Statistics; 2001-2004 OECD Revenue Statistics
MX errors and omissions	balance of payments position, million U.S. dollars	IMF, International Financial Statistics
Import misinvoicing	[U.S. exports (Cost, Insurance and Freight; Free on Board adjusted) – MX imports]	1975-1980: IMF Directions of Trade Statistics (DOTS) Historical; 1981-2004: IMF DOTS
Export misinvoicing	[U.S. imports – MX exports (Cost, Insurance and Freight; Free on Board adjusted)]	1975-1980: IMF DOTS Historical, 1981-2004: IMF DOTS

Table D.2 Further Goodness-of-fit Statistics (Illegal Goods Smuggling Estimations)

Goodness-of-fit statistics	Specification						
	1	2	3	4	5	6	7
AGFI	0.96	0.92	0.93	0.97	0.90	0.97	0.89
PGFI	0.54	0.53	0.53	0.49	0.47	0.49	0.47
ECVI	0.19	0.29	0.23	0.12	0.13	0.14	0.15
ECVI independence model	0.43	0.38	0.38	0.19	0.18	0.23	0.23
ECVI saturated model	0.26	0.26	0.32	0.16	0.16	0.19	0.19
AIC	41.57	50.27	45.20	33.42	45.02	33.02	46.08
AIC independence model	120.12	144.94	84.36	67.20	66.14	69.95	68.11
AIC saturated model	72.00	72.00	72.00	56.00	56.00	56.00	56.00

Table D.3 Further Goodness-of-fit Statistics (Legal Goods Smuggling Estimations)

Goodness-of-fit statistics	Specification			
	8	9	10	11
AGFI	0.97	0.98	0.99	0.99
PGFI	0.42	0.53	0.53	0.40
ECVI	0.15	0.07	0.10	0.05
ECVI independence model	0.14	0.10	0.11	0.09
ECVI saturated model	0.19	0.10	0.13	0.07
AIC	29.38	15.74	15.85	12.91
AIC independence model	32.61	30.26	25.73	26.38
AIC saturated model	42.00	30.00	30.00	20.00

Table D.4 Estimates for Illegal and Legal Goods Smuggling

Year	Illegal goods smuggling (billions U.S. dollars)	Export misinvoicing (billions U.S. dollars) [1)]	Import misinvoicing (billions U.S. dollars) [1)]
1976	75.52		
1977	84.68		
1978	84.16		
1979	78.81		
1980	69.45	-0.03	0.19
1981	71.99	-0.18	0.00
1982	74.24	-0.51	0.73
1983	113.11	-0.69	1.66
1984	115.99	-0.59	0.91
1985	114.36	-0.66	1.03
1986	116.36	-0.36	-0.59
1987	81.69	-0.47	-0.31
1988	86.58	-0.36	-0.71
1989	68.11	-0.19	-0.93
1990	76.20	-0.23	-0.18
1991	77.28	-0.29	0.52
1992	79.42	0.00	-1.17
1993	73.16	0.22	-3.30
1994	62.32	0.06	-3.50
1995	87.23	-0.51	-0.83
1996	79.77	-0.61	-0.32
1997	62.12	-0.36	-1.66
1998	50.07	-0.18	-2.59
1999	39.92	-0.02	-3.36
2000	40.10	-0.08	-3.03
2001	29.61	0.04	-3.77
2002	22.86	0.03	-3.83
2003	23.43	-0.06	-3.47
2004	27.36	-0.30	-2.28

1) Positive values indicate underinvoicing; negative values indicate overinvoicing.

Note: The indices for illegal goods smuggling, export misinvoicing, and import misinvoicing are calculated using specifications 4, 9, and 11 respectively.