

A Preliminary Attempt to Estimate the Financial Flows of Transnational Crime Using the MIMIC-Method

by

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and

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Summary:

This paper tries to meet two objectives: A first and preliminary calculation of the size and development of the proceeds of transnational organized crime (TOC) and a breakdown of the different types of crime proceeds, like the ones from drug-, human-, and arms trafficking. One conclusion is that a detailed analysis of the financial proceeds and their sources is crucial in order to reduce the basis of TOC operations.

Keywords: Transnational organized crime (TOC), financial flows of transnational crime, money laundering, Hawala banking, infiltration of transnational crime, financial proceeds of TOC.

JEL-Codes: C80, C82, H56, K42, O17, Y1

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1. Introduction

Until 2008, growth of the world economy was quite high and improved the economic well-being all over the globe, but this development was accompanied by some risks, too. One of them is transnational organized crime (TOC), which rose remarkably in the last 20 years¹. This raises the following two questions:

- (1) From where does transnational crime get its proceeds, and
- (2) What do we know about their size and development?

In this contribution question (1) will be briefly answered, the main focus lies on providing a more detailed answer on the size and development of the finances of transnational crime and their origin (question 2). A detailed analysis of the financial proceeds and their sources is crucial in order to reduce their possibilities, so that the basis of their operations is at least limited.

Our paper is structured as follows: section 2 provides a literature review on the kinds of transnational crime proceeds. Section 3 provides first estimates of the size and development of money laundering for 20 OECD countries over 1995 to 2006 using the MIMIC method, which is also explained in that section. In section 4 some conclusions and policy recommendations are drawn.

2. Transnational Crime Proceeds²

Dirty money from crime is earned through various underground activities, like drug, weapons and human trafficking. How much illicit crime money in all its forms can be observed?³ Baker (2005) estimates that these illicit money ranges between US\$ 1.0 and 1.6 trillion in 2000/2001, an estimate that has been adopted by the World Bank. Moreover, Baker estimates that half – US\$ 500 to 800 billion a year – comes out of developing and transitional economies. These are countries that often have the weakest legal and administrative structures, the largest criminal gangs of drug dealers, and, far too often, economic and political elites who want to take their money out of the country by any means possible. In table 2.1, Baker's global flows from illicit activities are shown. According to Baker, the proceeds of bribery and theft are the smallest quantities, at only perhaps three percent of the global total. Generated funds from classical crime activities (No 1-7) account for some 30 to 35 percent of the global total crime activities. Commercial criminal activities, like tax evasion, in particular driven by abusive transfer pricing and faked transactions, as well as mispricing, are by far the largest components, accounting for 60 to 65 percent of the global total crime activities.

¹ See for an example Walker and Unger (2009) and Masciandaro (2004).

² For a detailed analysis see Schneider (2008), Schneider and Windischbauer (2008), and Takats (2007).

³ Smith (2011) estimates that this amount is 1.5 trillion USD per year. However, no clear sources are given and even more important the procedure of calculation is not shown and critically discussed.

Table 2.1: Global Flows from Illicit Activities Worldwide, years 2000/2001

Number	Global Flows	Low (US\$ bn)	%	High (US\$ bn)	%
1.	Drugs	120	11%	200	12.5%
2.	Counterfeit goods	80	7.5%	120	7.5%
3.	Counterfeit currency	3	0.2%	3	0.2%
4.	Human trafficking	12	1.1%	15	0.9%
5.	Illegal arms trade	6	2.0%	10	0.6%
6.	Smuggling	60	5.6%	100	6.3%
7.	Racketeering	50	4.7%	100	6.3%
	Crime subtotal	331	31.2%	549	34.3%
8.	Mispricing	200	18.9%	250	15.6%
9.	Abusive transfer pricing	300	28.3%	500	31.2%
10.	Fake transactions	200	18.9%	250	15.6%
	Commercial subtotal	700	66.0%	1,000	62.5%
11.	Corruption	30	2.8%	50	5.1%
	Grand Total	1,061	100.0%	1,599	100.0%

Source: Baker (2005).

In table 2.2 the estimates of illicit flows out of developing countries and out of countries in transition over the period 2000 to 2006 are presented. As it is quite difficult to calculate exact figures, the table provides minimum and maximum values. Table 3.2 clearly shows that between 46.6 and 51.7 percent of all illicit financial outflows come from the “Asia and the Pacific” region, followed by Europe, where the share is between 18.1 and 21.7. In the year 2006 between 858.6 and 1,056.2 billion US dollars left the developing countries. This is a range between 6 and 7 percent of the GDP of the developing countries, quite a remarkable sum. It is also amazing that over time there is a strong increase in these illicit outflows. Whereas in the year 2002 the minimum value only amounted for 372.5 billion US dollars, it increased to 858.6 billion dollars in the year 2006, which means the value had more than doubled.

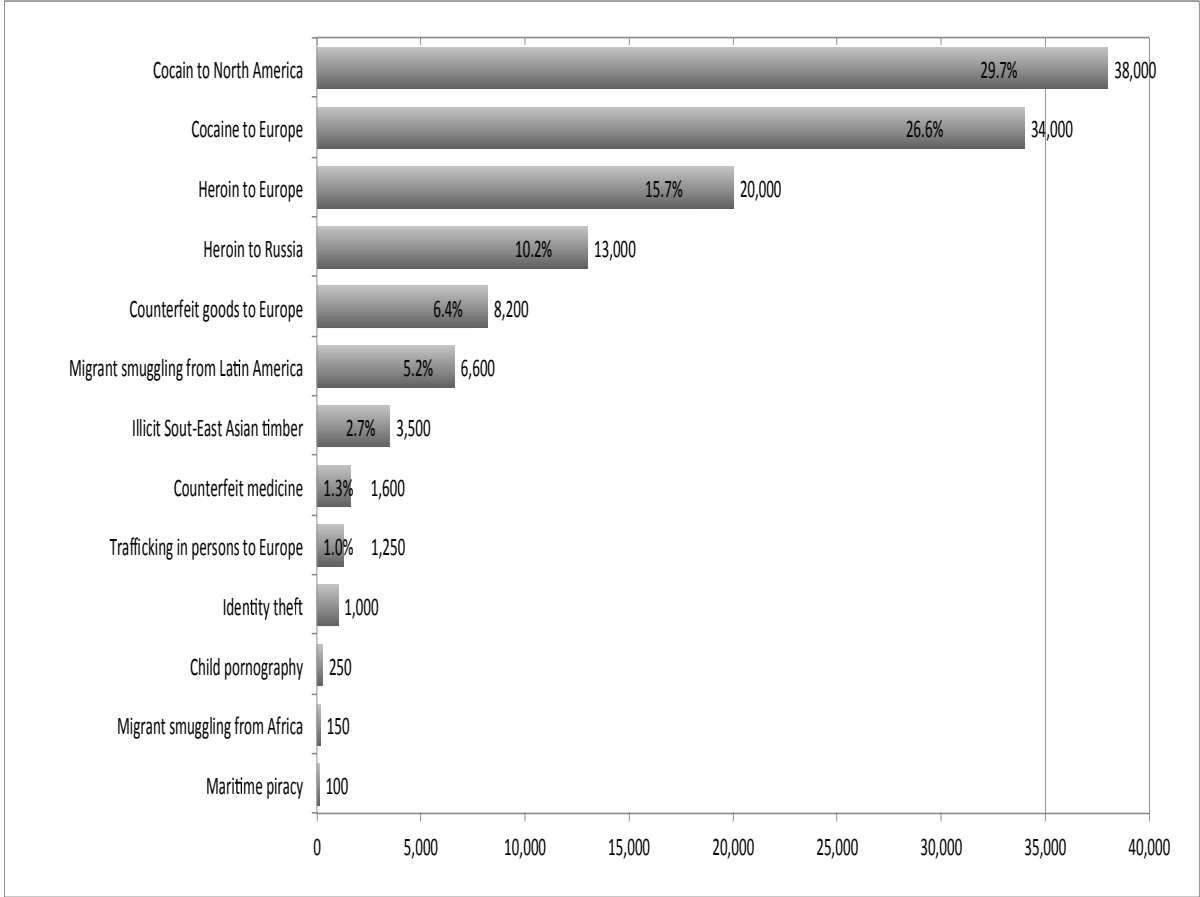
Table 2.2: Estimates of Out-of-country Illicit Financial Flows, in billion US \$

		2002	2005	2006	2006 in % of total illicit outflows	2006 in % of GDP
Developing countries of which	Min	372.5	674.9	858.6	100%	6%
	Max	435.4	805.8	1,056.2	100%	7%
Sub-Saharan Africa	Min	12.7	10.2	11.0	1.3%	1%
	Max	21.9	19.0	22.7	2.1%	3%
Asia and the Pacific	Min	192.9	364.0	400.0	46.6%	7%
	Max	219.1	448.9	546.3	51.7%	9%
Europe	Min	60.0	78.2	186.2	21.7%	7%
	Max	67.6	87.5	190.9	18.1%	7%
Middle East and North Africa	Min	22.1	125.3	164.8	19.2%	10%
	Max	25.1	143.1	187.4	17.7%	12%
Americas ('Western Hemisphere')	Min	84.8	97.2	97.3	11.3%	3%
	Max	101.7	107.2	108.9	10.3%	3%

Sources: Global Financial Integrity (Authors: Kar, D. and D. Cartwright-Smith), Illicit Financial Flows from Developing Countries, 2002-2006, Washington 2009 and World Bank Indicators (GDP current US dollars).

In Figure 2.1 an overview of the most important import crime types and their proceeds on a worldwide basis for the year 2008 is given. Drug trafficking to North America, to Europe and to Russia is the most profitable business. Cocaine to America has an estimated proceeds of 38 billion US dollars, cocaine to Europe of 34 billion dollars, heroine to Europe 20 billion and heroine to Russia 13 billion, followed by counterfeit goods to Europe with 8.2 billion and then migrant smuggling from Latin America with 6.6 billion and illicitly traded South Asian timber has a value of 3.5 billion US dollars.⁴ Figure 2.1 clearly demonstrates that the worldwide crime scene is a lively one, but also that drug trafficking is the most profitable business.

Figure 2.1: TOC Value Estimates in USD millions



Total sum 127,773 million US \$

Other crime types: Ivory to Asia 62 million (0.05%), Firearms from Eastern Europe 33 million (0.03%), Firearms to Mexico 20 million (0.02%), Rhino horn to Asia 8 million (0.01%).

Source: UNODC, 2010, The Globalization of Crime, New York, p. 200.

⁴ Buehn and Eichler (2009) present an interesting application of a MIMIC model to study illegal immigration and drug smuggling across the U.S-Mexico border.

3. Money Laundering

3.1 Methods of Money Laundering

The main goal of money laundering is to make dirty money appear legal (Walker 1999). There are many methods of money laundering; in table 3.1 according to Unger and Walker (2007) the 12 most common methods are shown. Which method of those 12 mostly used is chosen, depends on the type of crime activity and on the specific institutional arrangements of the country the criminal money is “earned” in. For example, in the drug business method 8, i.e., business ownership is quite often used.⁵ In the drug business and in big cities smaller amounts of cash are earned by drug dealers in a lot of different places, which they infiltrate into cash intensive operations such as restaurants which are especially well suited for money laundering purposes. But also cash deposits the so-called smurfing method, or illegal gambling is quite often used.

Table 3.1: The Methods of Money Laundering¹⁾

1.	Wire transfers or electronic banking	The primary tool of money launderers to move funds through the banking system. These moves can conceal their illicit origins or just place the money where the launderers need it. Often the funds go through several banks and even different jurisdictions.
2.	Cash deposits	Money launderers need to deposit cash advances to bank accounts prior to wire transfers. Due to anti-money-laundering regulations they often ‘structure’ the payments, i.e. break down large to smaller amounts. This is also called ‘smurfing’.
3.	Informal value transfer systems (IVTS)	Money launderers need not rely on the banking sector, other transfer providers, such as the Hawala or Hindi are readily available to undertake fund transfers. These systems consist of shops (mainly selling groceries, phone cards or other similar items), which are also involved in transfer services. IVTSs enable international fund transfers, as these shops are present in several jurisdictions.
4.	Cash smuggling	Money launderers might mail, Fedex or simply carry cash with them from one region to another, or even to different jurisdictions.
5.	Gambling	Casinos, horse races and lotteries are ways of legalizing funds. The money launderer can buy (for ‘dirty’ cash) winning tickets – or in the case of casinos chips – and redeem the tickets or the chips in a ‘clean’ bank check. Afterwards, the check can be easily deposited in the banking sector.
6.	Insurance policies	Money launderers purchase single premium insurance (with dirty cash), redeem early (and pay some penalty) in order to receive clean checks to deposit. Longer-term premium payments might make laundering even harder to detect.
7.	Securities	Usually used to facilitate fund transfers, where underlying security deals provide cover (and legitimate looking reason) for transfers.
8.	Business ownership	Money might be laundered through legitimate businesses, where laundering funds can be added to legitimate revenues. Cash-intensive operations, such as restaurants, are especially well suited for laundering.
9.	Shell corporations	Money launderers might create companies exclusively to provide cover for fund moves without legitimate business activities.
10.	Purchases	Real estate or any durable good purchases can be used to launder monies. Typically, the item is bought for cash and resold for clean monies, like bank checks.
11.	Credit card advance payment	Money launderers pay money in advance with dirty money, and receive clean checks on the balance from the bank
12.	ATM operations	Banks might allow other firms to operate their ATMs, i.e. to maintain and fill them with cash. Money launderers fill ATMs with dirty cash, and receive clean checks (for the cash withdrawn) from the bank.

¹⁾ Source: Unger (2007, pp.195-196).

⁵ Compare Schneider (2004) and Masciandaro (2004).

3.2 Estimating Financial Flows of Transnational Crime Organizations

As the size of financial flows of the transnational crime organizations is an unknown (hidden) figure, a latent estimator approach using the MIMIC (i.e. **m**ultiple **i**ndicators, **m**ultiple **c**auses estimation) procedure is applied. This method has quite successfully been used to estimate the size of the shadow economy and is based on the statistical theory of unobserved variables. The statistical idea behind such a model 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.⁶ Using covariance information among the observable variables, the unobservable variable is in the first step linked to observable variables in a factor analytical model also called measurement model. Second, the relationships between the unobservable variable and observable variables are specified through a structural model. Therefore, a MIMIC model is the simultaneous specification of a factor and a structural model. In this sense, the MIMIC model tests the consistency of a “structural” theory through data and is thus a confirmatory, rather than an exploratory technique. An economic theory is thus tested examining the consistency of actual data with the hypothesized relationships between the unobservable (latent) variable or factor and the observable (measurable) variables.⁷ 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 TOC activities these two goals mean (i) to estimate the relationships between a set of observable variables, divided into causes and indicators, and the TOC activity (unobservable variable), and (ii) to test if the researcher’s theory or the derived hypotheses as a whole fit the data. MIMIC models are, compared to regression models, a rarely used method by economists what might be due to an under-evaluation of their capabilities with respect to the potential contribution for economic research.

The idea of the MIMIC model application is to examine the relationships between the latent variable size of financial flows of transnational organized crime (TOC), and observable variables in terms of the relationships among a set of observable variables by using their covariance

⁶ Estimation of a MIMIC model with a latent variable 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).

⁷ 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 the MIMIC model 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].

information. The observable variables are divided into causes and indicators of the latent variable (see Figure 3.1). The key benefits of the MIMIC model are that it allows modeling financial flows of TOC as an unobservable (latent) variable and that it takes into account its multiple determinants (causes) and multiple effects (indicators). A factor-analytic approach is used to measure the size of financial flows of transnational organized crime as an unobserved variable over time. The unknown coefficients are estimated in a set of structural equations, as the “unobserved” variable, i.e., the size of the financial flows of TOC cannot be measured directly. 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 $\mathbf{y}'_t = (y_{1t}, y_{2t}, \dots, y_{pt})'$ of indicators, i.e., observable variables that reflect the TOC flows, subject to a p vector of random error terms $\mathbf{\varepsilon}'_t = (\varepsilon_{1t}, \varepsilon_{2t}, \dots, \varepsilon_{pt})'$. The unobservable variable η_t is a scalar and λ is a p column vector of parameters that relates y_t to η_t . The measurement equation is given by:

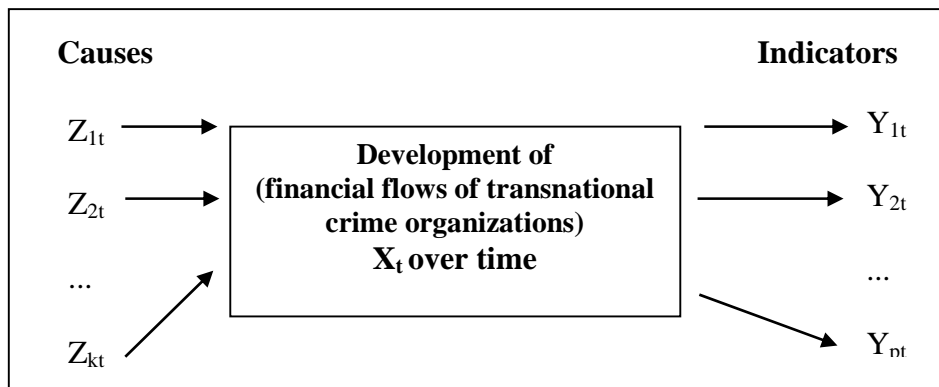
$$\mathbf{y}_t = \lambda \eta_t + \boldsymbol{\varepsilon}_t. \quad (1)$$

The structural model determines the unobservable variable η_t by a set of exogenous causes $\mathbf{x}'_t = (x_{1t}, x_{2t}, \dots, x_{qt})'$ that may be useful in predicting its movement and size, subject to a structural disturbance error term ζ_t . The structural equation is given by:

$$\eta_t = \boldsymbol{\gamma}' \mathbf{x}_t + \zeta_t, \quad (2)$$

where $\boldsymbol{\gamma}'$ is a q row vector of structural parameters.⁸ In equations (1) and (2) it is assumed that ζ_t and the elements of $\boldsymbol{\varepsilon}_t$ are normally, independently and identically distributed, the variance of the structural disturbance term ζ_t is denoted by ψ , and $\boldsymbol{\Theta}_\varepsilon = E(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}'_t)$ is the $(p \times p)$ covariance matrix of the measurement errors.⁹ Figure 3.1 shows the path diagram of the MIMIC model.

Figure 3.1: The MIMIC model



⁸ Without loss of generality, all variables are taken as standardized deviations from their means.

⁹ 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].

The MIMIC model of TOC flows estimated in this paper uses three indicators and nine causes. Hence, within this model, equations (1) and (2) are specified as follows:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{bmatrix} = \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \end{bmatrix} \cdot \eta_t + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}, \quad (3)$$

$$\eta_t = \begin{bmatrix} \gamma_1 & \gamma_2 & \gamma_3 & \gamma_4 & \gamma_5 & \gamma_6 & \gamma_7 & \gamma_8 & \gamma_9 \end{bmatrix} \cdot \begin{bmatrix} x_{1t} \\ x_{2t} \\ x_{3t} \\ x_{4t} \\ x_{5t} \\ x_{6t} \\ x_{7t} \\ x_{8t} \\ x_{9t} \end{bmatrix} + \zeta_t. \quad (4)$$

Substituting (1) into (2) yields a reduced form equation which expresses the relationships between the observed causes and indicators, i.e., between \mathbf{x}_t and \mathbf{y}_t . This is shown in equation (5):

$$\mathbf{y}_t = \mathbf{\Pi} \mathbf{x}_t + \mathbf{z}_t, \quad (5)$$

where: $\mathbf{\Pi} = \boldsymbol{\lambda} \boldsymbol{\gamma}'$ is a (3×9) reduced form coefficient matrix and $\mathbf{z}_t = \boldsymbol{\lambda} \zeta_t + \boldsymbol{\varepsilon}_t$ is a reduced form vector of a linear transformation of disturbances that has a (3×3) reduced form covariance matrix $\boldsymbol{\Omega}$ given as:

$$\boldsymbol{\Omega} = \text{Cov}(\mathbf{z}_t) = \text{E}[(\boldsymbol{\lambda} \zeta_t + \boldsymbol{\varepsilon}_t)(\boldsymbol{\lambda} \zeta_t + \boldsymbol{\varepsilon}_t)'] = \boldsymbol{\lambda} \boldsymbol{\psi} \boldsymbol{\lambda}' + \boldsymbol{\Theta}_\varepsilon. \quad (6)$$

In equation (6), $\boldsymbol{\psi} = \text{Var}(\zeta_t)$ and $\boldsymbol{\Theta}_\varepsilon = \text{E}(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t')$ is the measurement error's covariance matrix.

In general, estimation of a MIMIC model 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, the MIMIC model 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 that approach is that the covariance matrix of the observed variables is a function of a set of model parameters:

$$\boldsymbol{\Sigma} = \boldsymbol{\Sigma}(\boldsymbol{\theta}), \quad (7)$$

where $\boldsymbol{\Sigma}$ is the population covariance matrix of the observed variables, $\boldsymbol{\theta}$ 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., Σ will equal $\Sigma(\theta)$. 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)].

Estimation is thus performed by finding values for $\hat{\theta} = f(\hat{\lambda}, \hat{\gamma}, \hat{\psi}, \hat{\Phi}, \hat{\Theta}_\varepsilon)$ producing an estimate of the models covariance matrix $\hat{\Sigma}$ that most closely corresponds to the sample covariance matrix S . During this estimation procedure, all possible matrices that meet the imposed restrictions are considered. If an estimate Σ^* of $\hat{\Sigma}$ is close to S , one might conclude that θ^* is a reasonable estimate of the model's parameters. Hence, estimation of a MIMIC model is reduced to the problem of measuring how close Σ^* is to 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]. The covariance equation of the MIMIC model can be derived and has the following functional form:

$$\hat{\Sigma} = \left[\begin{array}{c|c} \hat{\lambda}(\hat{\gamma}'\hat{\Phi}\hat{\gamma} + \hat{\psi})\hat{\lambda}' + \hat{\Theta}_\varepsilon & \hat{\lambda}\hat{\gamma}'\hat{\Phi} \\ \hline \hat{\Phi}\hat{\gamma}\hat{\lambda}' & \hat{\Phi} \end{array} \right]. \quad (8)$$

The function measuring how close a given Σ^* is to the sample covariance matrix S is called fitting function $F(S; \Sigma^*)$. The θ^* of all possible θ^* that meets the imposed constraints on λ , γ , Φ , ψ , and Θ_ε and minimizes the fitting function, given the sample covariance matrix S , is the sample estimate $\hat{\theta}$ of the population parameters. This means that if one set of estimates θ_1^* produces the matrix Σ_1^* and a second set θ_2^* produces the matrix Σ_2^* and if $F(S; \Sigma_1^*) < F(S; \Sigma_2^*)$, Σ_1^* is then considered to be closer to S than Σ_2^* [Long (1983a), p. 56].

The most widely used fitting function is the Maximum Likelihood (ML) function.¹⁰ Under the assumption that $\Sigma(\theta)$ and S are positive definite, i.e., nonsingular, and S has a Wishart distribution, the following fitting function is minimized:

$$F_{ML} = \log|\Sigma(\theta)| + tr[S\Sigma^{-1}(\theta)] - \log|S| - (p + q), \quad (9)$$

¹⁰ 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 θ and that F_{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, F_{GLS} accepts the wrong model more often than ML and parameter estimates tend to suffer when using F_{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].

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 F_{ML} exists. Hence, the values of λ , γ , Φ , ψ and Θ_ε that minimize the fitting function are estimated applying iterative numerical procedures.¹¹ The ML estimator is widely used because of its desirable properties.¹² First, the ML estimator is asymptotically unbiased. Second, the ML estimator is consistent, i.e., $\text{plim } \hat{\theta} = \theta$ ($\hat{\theta}$ is the ML estimator and θ 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 $\hat{\lambda}$, $\hat{\gamma}$, $\hat{\Phi}$, $\hat{\psi}$ and $\hat{\Theta}_\varepsilon$ are the same for any change of scale.

It is widely accepted by most scholars who estimate the size and development of informal economic activities such as the shadow economy using the MIMIC model or more general Structural Equation Models (SEMs) with more than one unobservable variable, 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 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, they are increasingly used for estimating the shadow economy and other informal economic activities.

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,

¹¹ See Appendix 4C in Bollen (1989) for details.

¹² The properties are briefly reviewed only. For a detailed discussion see Bollen (1989, pp. 107-123).

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)]. Schneider and Enste (2000) 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 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 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) The most common objection estimating informal economic activities using SEMs concerns the meaning of the latent variable [e.g. Helberger and Knepel (1988); 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 data availability.
- (2) Helberger and Knepel (1988) 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)].¹³

¹³ Especially the assumptions $E(\zeta_{ik}^2) = \text{Var}(\zeta_i)$ for all k (homoscedasticity assumption) and $\text{Cov}(\zeta_{ik}, \zeta_{il}) = 0$ 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 is Folmer and Karmann (1992).

(3) Criticism is also related to the benchmarking procedure used to derive “real world” figures of informal economic activities [Breusch (2005a; 2005b)]. 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.¹⁴

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.

In Figure 3.2, the MIMIC estimation results of the turnover of transnational crime for 20 highly developed OECD countries over the period 1994/95 to 2005/06 are shown. Figure 3.2 clearly shows the amount of criminal activities: amount of illegal weapon selling, amount of criminal activities of illegal drug selling, and amount of criminal activities of illegal trade with human beings has the expected positive and highly statistically significant influence on the turnover of transnational crime activities. The amount of criminal activities of fake products, the functioning of the legal system, and real police expenditures per capita per country are statistically significant as well. If we switch to the indicator variables, the amount of confiscated money has the expected positive sign and is highly statistically significant. The amount of prosecuted persons has the expected negative sign, but is not statistically significant using a strict measure. In general, this MIMIC estimation shows that the single crime types like illegal weapon selling, drug selling, trade with human beings have highly statistically significant influence on the financial turnover of transnational criminal activities.

If we discuss the econometric result of the MIMIC estimation in detail, we clearly see that seven out of the nine cause variables have statistically significant influence on the turnover of transnational criminal activities. The amount of criminal activities of illegal drug selling has the largest and most significant influence followed by the amount of criminal activities of illegal trade

¹⁴ See Dell’Anno and Schneider (2009) for a detailed discussion on different benchmarking procedures.

with human beings and the amount of criminal activities of illegal weapon selling. Also the real police expenditures have the expected negative and highly statistically significant influence together with the per capita income and the functioning of the legal system. The amount of criminal activities of fraud, computer crime turns out not to be significant as well as the amount of domestic crime activities. If we consider the indicators confiscated money has a strongly positive significant influence and the variable “prosecuted persons” is not statistically significant, but has the predicted negative sign.

Table 3.2: Estimated Turnover of Transnational Crime using the MIMIC Model

Year	Volume of money laundering (billion USD for 20 OECD countries)	Volume of money laundering in % of GDP1	20 OECD countries
1995	273	1.33%	Australia, Austria, Belgium, Canada, Denmark, Germany, Finland, France, Greece, Great Britain, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Switzerland, Spain and USA.
1996	294	1.37%	
1997	315	1.40%	
1998	332	1.42%	
1999	359	1.46%	
2000	384	1.47%	
2001	412	1.52%	
2002	436	1.56%	
2003	475	1.63%	
2004	512	1.66%	
2005	561	1.72%	
2006	603	1.74%	

Source: Own calculations, calibrated figures from the MIMIC estimations.

With the help of the MIMIC estimation procedure (compare figure 3.2) Schneider (2008) estimates that money laundering and/or financial turnover from transnational crime has increased from USD 273 billion (1,33% of the total official GDP) in 1995 to USD 603 billion (or 1,74% of the official GDP) in 2006 for 20 OECD countries (Australia, Austria, Belgium, Canada, Denmark, Germany, Finland, France, Greece, Great Britain, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Switzerland, Spain and the United States). These figures are presented in Table 3.2, which nicely shows the steady increase of the volume of laundered money over 1995 to 2006. On a worldwide basis in 2006 the IMF estimates USD 600 billion to be laundered coming only from the drug (crime) business.

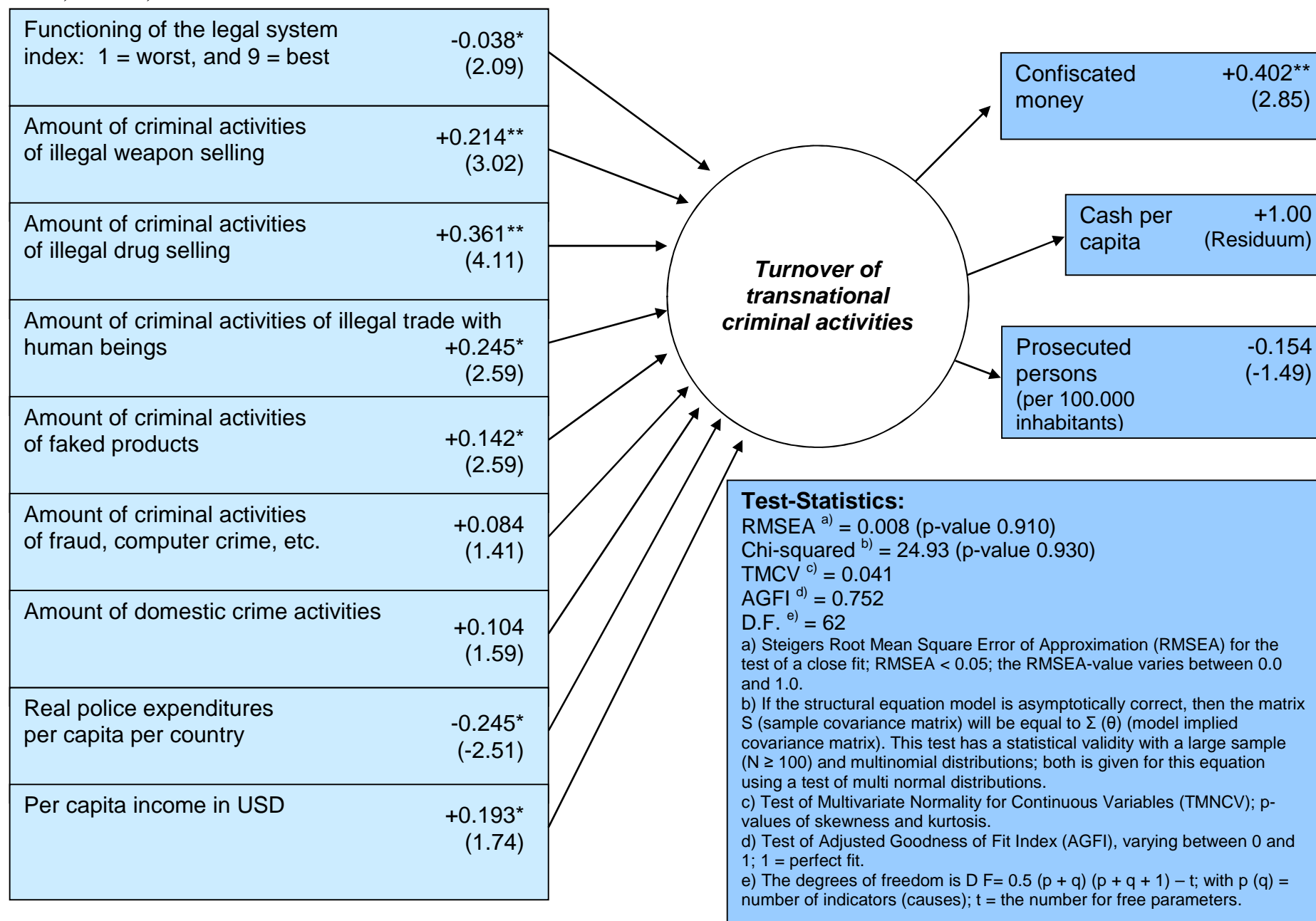
Unger (2007) estimates the amount of laundered money and its top 20 destination countries; these figures are shown in table 3.3 covering the time span 1997-2005. In this table two estimates are presented, one by Walker (1999, 2007) and one by the IMF. The Walker figure of 2.850 billion USD is much larger than the IMF figure of 1.500 billion USD (both figures are for the year

2005). Walker's figures have been criticized as much too high, which is one reason why the IMF estimates are shown, too. Table 3.3 clearly demonstrates that two thirds of worldwide money laundering was sent to the top 20 countries listed. One should realize that most of these countries are highly developed and have quite sizeable legal/official economies. What is also amazing is, that there are only a few microstate offshore countries and tax heavens among them (Cayman Islands, Vatican City, Bermuda and Liechtenstein)¹⁵. The majority of countries that attract money laundering flows are economically big players. The United States has the largest worldwide share of money laundering of almost 19%, followed by the Cayman Islands (4,9%), Russia (4,2%), Italy (3,7%), but also smaller countries like Switzerland (2,1% of worldwide money laundering), Liechtenstein (1,7%) and Austria (1,7%) are quite attractive. If one takes the lower IMF value for Austria, Switzerland and the United Kingdom, roughly 5.5 % of the total amount is laundered, which comes close to roughly 10% of official GDP of the three countries. However, it needs to be emphasized that it is not clear whether this money is "only" laundered in these countries or remains in these countries; it may well leave these countries after the laundering process. In general, table 3.8 demonstrates how substantial the amount of laundered money is and that two thirds of these funds are concentrated in only 20 countries.

Bagella, Busato and Argentiero (2009, pp.881) use a two-sector dynamic general equilibrium model to measure money laundering for the United States and the EU-15 macro areas over the sample 2000:01-2007:01 at a quarterly data basis. Their series are generated through a fully micro-founded dynamic model, which is appropriately calibrated to replicate selected stochastic properties of the two economies. Their model (and the analysis) has a short run perspective. Bagella et al. (2009, pp.881) got the following results: First the simulations show that money laundering accounts for approximately 19 percent of the GDP measured for the EU-15, while it accounts for 13 percent in the US economy, over the sample 2000:01-2007:04. Second, the simulated money laundering appears less volatile than the corresponding GDP. As regards the EU-15 macro area, the simulated statistics suggest that money laundering volatility is one-third of the GDP volatility; for the US economy, the same statistics produce a figure of two-fifths. Considering these estimates we admit that they are pretty high.

¹⁵ See also Masciandaro (2005), Zdanowicz (2009), Truman and Reuter (2004), and Walker and Unger (2009):

Figure 3.2: MIMIC estimation of the turnover of transnational crime for 20 highly developed OECD countries over the periods 1994/95, 1997/98, 2000/01, 2002/03, 2003/04 and 2004/05.



From a global perspective for 2000, the IMF (2003, 2001) as well as the World Bank estimate that 2-4% of the world gross domestic product (GDP) stem from illicit (criminal) sources. Agarwal and Agarwal (2006) estimate from economic intelligence units that global money laundering amounts to more than 2.0 to 2.5 trillion US\$ annually or about 5-6% of World GDP in 2006 (4,444 trillion US\$ in 2006) to be contrasted against an observed figure of US\$ 500 billion to one trillion in 2004 from the same authors (Agarwal and Agarwal (2004)). Recent IMF estimates on money laundering by drug traffickers who “introduce” the proceeds gained through the selling of drugs into the legitimate financial market, amount to 600 billion US\$ annually. The IDB (2004) reaches the conclusion that for Latin America a rough estimate of illicit flows appears to be somewhere between 2.5 and 6.3 % of annual GDP of Latin American countries. Besides the figures from Agarwal and Agarwal which are much higher, the others seem to be plausible considering their size.

In their latest study, Walker and Unger (2009, page 821) again undertake an attempt to measure global money laundering and/or the proceeds from transnational crime that are pumped through the financial system worldwide. They criticize methods such as case studies, proxy variables, or models for measuring the crime economy, arguing that they all tend to under- or overestimate money laundering. They present a model, which is a gravity model and which makes it possible to estimate the flows of illicit funds from and to each jurisdiction in the world and worldwide. This “Walker Model” was first developed in 1994, and was recently updated. The authors show that it belongs to the group of gravity models, which have recently become popular in international trade theory. The authors demonstrate that the original Walker Model estimates are compatible with recent findings on money laundering. Once the scale of money laundering is known, its macroeconomic effects and the impact of crime prevention, regulation and law enforcement effects on money laundering and transnational crime can also be measured. Walker and Unger (2009, p. 849-850) conclude that their model still seems to be the most reliable and robust method to estimate global money laundering, and thereby the important effects of transnational crime on economic, social and political institutions. Rightly they argue that the attractiveness of the distance indicator in the Walker model is a first approximation, but is still quite ad hoc. A better micro-foundation for the Walker Model will be needed in the future. A micro foundation means that, the behavior of money launderers is analyzed, and in particular what makes them send their money to a specific country. Hence, Walker and Unger (2009, p. 850) argue that an economics of crime micro-foundation for the Walker Model would mean that, similarly to international trade theory, behavioral assumptions about money launderers have to be

made. Their gravity model must be the (reduced form) outcome of the money launderer's rational calculus of sending their money to a certain country and potentially making large profits.

Table 3.3: The Amount of Laundered Money and Top 20 Destinations of Laundered Money, Year 2005¹⁾

Rank	Destination	% of worldwide money laundering	Walker estimate 2.85 trillion US\$ Amount in billion US\$	IMF estimate of 1.5 trillion worldwide Amount in billion US\$
1	United States	18.9%	538,145	283,500
2	Cayman Islands	4.9%	138,329	73,500
3	Russia	4.2%	120,493	63,000
4	Italy	3.7%	105,688	55,500
5	China	3.3%	94,726	49,500
6	Romania	3.1%	89,595	46,500
7	Canada	3.0%	85,444	45,000
8	Vatican City	2.8%	80,596	42,000
9	Luxembourg	2.8%	78,468	42,000
10	France	2.4%	68,471	36,000
11	Bahamas	2.3%	66,398	34,500
12	Germany	2.2%	61,315	33,000
13	Switzerland	2.1%	58,993	31,500
14	Bermuda	1.9%	52,887	28,500
15	Netherlands	1.7%	49,591	25,500
16	Liechtenstein	1.7%	48,949	25,500
17	Austria	1.7%	48,376	25,500
18	Hong Kong	1.6%	44,519	24,000
19	United Kingdom	1.6%	44,478	24,000
20	Spain	1.2%	35,461	18,000
	SUM	67.1%	1,910,922	1,006,500

1) Source Unger (2007: 80).

4. Summary and Conclusions

In our paper an attempt is made to estimate the finances of transnational organized crime (TOC).

Our paper reaches the following results:

First, the necessity of money laundering is obvious as a great number of illegal (criminal) transactions are done by cash. Hence, this amount of cash from criminal activities must be laundered in order to have some "legal" profit, to do some investment or consumption in the legal world.

Second, to get an estimate of the extent and development of the amount of the financial means of transnational crime over time is even more difficult¹⁶. This paper collects some

¹⁶ All estimated figures have a large error; the estimation procedures are very difficult to use. Hence the published figures should be interpreted with great care. Compare also conclusion 1.

findings and demonstrates that money laundering from transnational crime has increased from 273 billion USD (or 1,33% of official GDP) in 1995 to 603 billion USD (or 1,74% of official GDP) in 2006 for 20 OECD countries (Australia, Austria, Belgium, Canada, Denmark, Germany, Finland, France, Greece, Great Britain, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Switzerland, Spain and the United States). On a worldwide basis 600 billion USD are estimated to be laundered in 2006 coming only from the total drug (crime) business. These figures are very preliminary with a quite large margin of error, but give a clear indication how important money laundering and the turnover of transnational crime is.

From these preliminary results we draw three conclusions:

- (1) The revenues of transnational crime are scientifically extremely difficult to estimate. They are defined differently in almost every country, the measures taken against it are different and vary from country to country and it is not so all clear how large are the revenues of transnational crime.¹⁷ Moreover, we have little empirical evidence, where these dirty or “white-washed” financial means stay or are transferred to.
- (2) Fighting transnational crime is extremely difficult, as there are no efficient and powerful international organizations, which can effectively fight against transnational crime¹⁸.
- (3) Hence, this paper should be seen as a first start/attempt in order to shed some light on the grey area of the revenues of transnational crime and to provide some better empirical knowledge.

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¹⁷ Money laundering definitions considerably vary from country to country; also there are no international organized and harmonized effects to fight money laundering with the result that little has been done so far.

¹⁸ Some first attempts have been made, like the FATF, or some sub organizations of the U.N., compare e.g. UNO DC (2005), FATF (2005) and FATF-GAFI (2006).

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