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Clandestinity by the Structural Equation Approach**

Alexandra Rudolph
Friedrich Schneider

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Alexandra Rudolph

Ruprecht Karls University of Heidelberg

Friedrich Schneider

*Johannes Kepler University of Linz
and IZA*

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IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

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ABSTRACT

International Human Trafficking: Measuring Clandestinity by the Structural Equation Approach *

Worldwide human trafficking (HT) is the third most often registered international criminal activity, ranked only after drug and weapon trafficking. The aim of the paper is to measure the extent of HT inflows to destination countries. It proposes the application of the Multiple Indicators Multiple Causes (MIMIC) structural equation model in order to include potential causes and indicators in one model and generate an index of the intensity of HT in destination countries. Thus, we account for the unobservable nature of the crime as well as for visible aspects that both shape the extent of it. By including both dimensions of the trafficking process the model is applied over a period of ten years. The resulting measure orders 142 countries between 2000 and 2010 according to their potential of being a destination country based on characteristics of the trafficking process. The results are that OECD countries are the most likely destination countries while developing countries are less likely.

JEL Classification: C39, F22, K42, K49

Keywords: human trafficking, MIMIC models, latent variable, structural equation models

Corresponding author:

Friedrich Schneider
Department of Economics
Johannes Kepler University of Linz
Altenbergerstrasse 69
4040 Linz
Austria
E-mail: Friedrich.Schneider@jku.at

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1. Introduction

Human trafficking (HT) is the third largest illicit international commerce, after illegal drug and weapon smuggling (U.S. Department of State 2004). It creates an underground economy of illegal labor markets and businesses where both enormous profits and great suffering are made. Belser (2005) estimates that HT generates around one billion dollars every year in industrialized countries alone. It is estimated that annual global profits are approximately 31.61 billion dollars (Interpol 2012, ILO 2005); money that is generated on tax evasion and presumably used for illegal businesses that traffic individuals as well as other associated activities. The International Labour Organization (ILO) calculates that around 20.9 million people are victims of trafficking in persons (TIP)¹ at any point in time (ILO 2012). These victims are either exploited in the sex industry or work under forced exploitative conditions in the private sector (ibid 2012). HT is a crime against the human rights of each victim, because they are used as commodity. They are abused through exploitation and coercion and deprived of the freedom to move or choose their place of living (Gallagher 2009). Besides the suffering of its victims HT causes on the individual level, countries are also affected by the international cross border nature of HT that raises security concerns and threatens national sovereignty through international active criminal organization (Belser 2005). Thus, corruption of civil society is facilitated by transnational criminal activities, such as HT, as they bypass borders, undermine state sovereignty and threaten state governance and human security (Shelley 1999).

To render the clandestine phenomena HT visible, the aim of the paper is to suggest a new measure of HT addressing the extent of victim exploitation in destination countries. Based on observed causes and indicators the multiple causes multiple indicators (MIMIC) structural equation approach allows one to explore the structural relationship between the causes and indicators of HT which to the best of our knowledge has not been done in the literature. We estimate these relationships and derive an index of the degree of HT in destination countries. By applying this approach two strands of the literature are combined providing a twofold contribution. First, applying the single latent variable structural equation method (MIMIC) on the latent phenomenon HT, and second, providing a detailed analysis of HT which sheds further light on the mechanism behind the trafficking process. Constructing an index of the scale is one advantage of the approach together with the possibility to re-estimate the model on a yearly basis over the period of ten years (2000-2010) and thereby address the question of how

¹ Human trafficking (HT) and trafficking in persons (TIP) are two expressions for the same phenomenon and used interchangeably.

HT inflows developed in this decade. In addition, looking at the whole period since the implementation of the Palermo Protocol² allows one to examine the implications for policy approaches and other relevant topics in reference to the trafficking process. Given that the index offers not only a ranking of countries but also the possibility to interpret the relative difference between countries, future research will be able to build on this measure and test hypotheses with empirical analysis.

To foreshadow basic results the MIMIC estimates support the main hypothesis on the determinants and indicators of HT. Importantly richer countries see more intense inflows of HT. This is also driven by employment opportunities and existing trade routes. The indicators combine both aspects of the trafficking process, the criminal activity and the fight against it. The HT index shows the prevalence of HT inflows to destination countries for the 2000 to 2010 period for 142 countries. It is scaled between 0 and 100 with higher values indicating a greater prevalence of HT in the country. Not surprisingly, developed countries experience a greater volume and frequency of human trafficking into their national territory whereas less developed countries see less. The top ranking destination countries are the United Kingdom (UK) and Sweden for five out of eleven years. The UK is traditionally a destination country for migration and thus home to a vulnerable population prone to trafficking. The index is positively correlated with other measures of aspects of human trafficking, which shows the relevance of the HT measure in this field of research.

The paper is organized as follows. The next section defines human trafficking and presents theoretical considerations in the causes and consequences of HT. Section 3 shows the value of using the MIMIC approach on the extent of HT and presents a baseline model. In section 4 the data used is described and the empirical results as well as the measure of HT is presented and discussed. The final section 5 concludes the paper.

2. Dynamics of human trafficking: Some theoretical considerations

This paper understands human trafficking in accordance with the international definition of trafficking in persons.³ It is not only the first successful international agreement on common elements and implications, but it also provides an important working basis for the present re-

² The official title of the Palermo Protocol is United Nations (UN) Protocol to Prevent, Suppress and Punish Trafficking in Persons especially Woman and Children which supplements the United Nations Convention against Transnational Organized Crime and was adopted and opened for signature in Palermo, Italy in 2000.

³ The Definition is presented in the Palermo Protocol Article 3.

search.⁴ The main elements are the incorporation of all forms of enslavement and the focus on the exploitation of victims through coercion or deception. These components acknowledge that most of HT's victims are vulnerable through migration, not willingly enslaved, and that it is a clandestine business of internationally-active criminal networks. These elements are two sides of the same coin: individuals that are vulnerable and prone to traffickers and criminal networks that make use of their circumstances. Both aspects have to be considered when measuring HT.

The focus of the paper is on the extent of human trafficking inflows not on push factors that force people to take high risks leading to their being trafficked.⁵ Important to identify is what drives people to exploit exposed individuals, i.e. the demand structure; and what puts people in this vulnerable position, i.e. the potential supply. In economic terms, HT is located in a market setting where demand and supply are met on the shoulders of vulnerable people. The main reason for the abuse and exploitation of people is global income disparity. Emigration is propelled by economic factors that drive people to migrate and take risks in searching for more prosperous living conditions. In particular, traffickers use their victims' vulnerability and bring them to countries where both the demand for cheap labor and exploitation profits are high. These are the key factors that help identify the indicators and causes of HT to destination countries.

2.1 Indicators of human trafficking

The extent of HT is not measurable directly, therefore we indicators have to be identified, that reflect HT in destination countries. The literature does not offer extensive guidance with respect to appropriate indicators of HT. However, one can think of many aspects that are correlated with human trafficking that can help show the prevalence of HT across the countries. What is important to acknowledge is the two-sided nature of HT. Some aspects are visible, but its illegal nature requires most of the action to be covert. Trafficking victims are exposed to life threatening conditions such as health risk, under-nutrition and physical and psychologi-

⁴ Article 3 of the protocol states that "human trafficking is the recruitment, transportation, transfer, harboring or receipt of persons, by means of the threat or use of force or other forms of coercion, of abduction, of fraud, of deception, of the abuse of power or of a position of vulnerability or of the giving or receiving of payments or benefits to achieve the consent of a person having control over another person, for the purpose of exploitation. Exploitation shall include, at a minimum, the exploitation or the prostitution of others or other forms of sexual exploitation, forced labor or services, slavery or practices similar to slavery, servitude or the removal of organs" (UN 2000).

⁵ Since October 2013 a measure of the prevalence of population in slavery for 162 countries is provided by the Walk Free Foundation (2013). This approach is based on risk characteristics of countries at one point in time. In contrast to the HT intensity measure provided here, the measure does not take into account development over time, which restricts analysis to the recent year rather than analysis of the last decade and makes a comparison difficult.

cal stress. One major indication of HT in the country is the number of identified victims in these countries. Although it is important to be aware that identification of victims, prosecution of traffickers and prevention of the crime largely depend on the awareness of the existence of HT by the broader public as well as by legal institutions (Tyldum and Brunovskis 2005), this number is a principal sign of the existence of trafficking in persons. The number of identified victims would thus be an indicator of HT at the lower limit of the real problem. This suggests testing the first hypothesis using the number of identified victims as percentage of the population:

H1: A high number of identified victims in a country increases the extent of human trafficking, *ceteris paribus*.

The extent of HT is also reflected in the legal fight against the crime. Fighting HT through prosecution of traffickers, protection of victims and prevention of the crime and other approaches taken within countries are thus another indication of its magnitude. All three elements of the legal fight against HT (protection, prosecution and prevention) increase the awareness within the judicial system and the police forces of the human trafficking problem, increasing the possibility to identify victims and prosecute traffickers. Protection policies, for instance, target victims of human trafficking and address their vulnerability, facilitating their identification. Prevention encompasses governmental efforts in promoting awareness about trafficking in persons within the country by means of campaigns, training, information exchange and monitoring of locations prone to trafficking. Information on the application of the three policy instruments is provided by the 3P-index of anti-trafficking policies (Cho et al. forthcoming). Countries with a high HT prevalence fight more rigorously against the crime, because they need to further curtail spread of this criminal activity. The line of argumentation could also be the other way round: countries that have a high score in the 3P-index, fight more rigorously against human trafficking and thus the prevalence of the crime is less intense within the country. This would imply a negative relationship between the 3P-index and the HT inflow measure. However, policies are usually implemented if the problem reaches public awareness, which is usually the case when the scale increases. Presumably this does not change in the context of human trafficking. We argue that besides the pressure the U.S. puts on countries to comply with Victims of Trafficking and Violence Protection Act (TVPA), countries intensify their fight against HT parallel to the intensity of the problem within their national boundaries. This leads to the second hypothesis:

H2: The more intense the fight against HT in a country the larger the scale of HT, *ceteris paribus*.

The illicit nature of the process has to be addressed by additional aspects that capture the intensity of exploitation indirectly. As argued above, the awareness within countries plays an important role in the identification of HT. Given that human trafficking is a large-scale business infrastructure must be highly developed. This is also supported by findings in the criminology literature, which stresses the link between the transport of illegal migrants, human trafficking and organized crime along the whole process of deceiving people, transporting and exploiting them (Salt and Stein 1997, Salt 2000, Schloenhardt 2001). Additionally, and given the hidden nature of the phenomenon, the institutional resources allocated to fight crime should also influence the presence of criminal groups or specifically HT in the country. Strong institutions and plenty of resources in the country should increase the detection rate of the crime. This suggests that the prevalence of HT is indicated by the occurrence of crime, leading to the third hypothesis⁶:

H3: The higher the crime rate in a country and the more resources are allocated to fight the crime the more exploitation of individuals and thus HT takes place, *ceteris paribus*.

2.2 Causes of human trafficking

Since the application of the common definition of human trafficking in 2000, the number of studies on the causes of human trafficking has increased substantially (e.g., Akee et al. 2010a, Cho 2012, Hernandez and Rudolph 2011).⁷ One of the main drivers of migration as well as human trafficking are differences in economic opportunities driving people to seek profitable benefit either through criminal activity or formal job seeking. This makes prosperous countries one of the main targets. The extent of economic opportunities and thus demand for HT is reflected in the GDP per capita of a country making it ideal destination countries for HT and breeding grounds for this type of activity.

H4: The richer the country, the larger are the HT inflows, *ceteris paribus*.

Most cases of forced labor involve migrant workers in economic sectors such as agriculture and construction (Zhang 2012). They account for 18 percent of identified cases of HT according to the UNODC (2009). The increased chances of employment caused by the increased demand for cheap unskilled labor increases the attractiveness of the countries as destination for migration workers (Hernandez and Rudolph 2011). In addition, high demand in the commercial sex market or other informal markets increases the probability of pushing people to-

⁶ Theoretically it is plausible that the crime rate is causing HT as well as indicating its prevalence. This issue is discussed in the next section.

⁷ All determinants used in the empirical literature so far are tested in the meta-study by Cho (2012) where she identifies robust causes of human trafficking flows.

wards these locations (Cho et al. 2012, Jacobson and Kotsadam 2013 Danailova-Trainor and Belser 2006). The demand structure is mirrored in the size of the market. This suggests hypothesis five:

H5: The larger the demand for low-skilled services where exploitation takes place the, more HT will be allocated in the country, *ceteris paribus*.

Globalization leads to increased cultural, social and economic interrelation between countries, which can also be associated with HT. HT is a negative externality of globalization facilitated, but also hampered, by different aspects of the globalization processes. On the one hand HT is facilitated because the transport of individuals is simplified via the establishment of international trade routes and investment connections. International crime groups are large-scale business operations that are active in both the official and the shadow economies, corrupting officials and legal networks (UNODC 2010). On the other hand trafficking is limited via the technological advancements and more personal contacts which increases available information for migrants on migration opportunities as well as job offers and thus presumably reduces the risk of being trafficked. Therefore foreign direct investment (FDI) as share of GDP should have an enhancing effect on HT whereas international tourists as share of the total population and information flows should have a restricting effect on trafficking.

H6: International trade routes increase HT whereas information exchange via international tourism reduces knowledge and HT, *ceteris paribus*.

For migrants being away from home puts them in a vulnerable position which is increased by language differences and incomplete knowledge of the destination country. These differences are controlled for by including linguistic fractionalization and the share of international migrants in the local population in the model. Additionally the size of the countries measured by log population size is presumably an important determinant of the demand structure and the size of the market within countries of exploitation. Therefore both aspects are tested in the model.

Given that the most vulnerable part of the migrant population is the most prone to traffickers, e.g., refugees fleeing situations in which they face political harassment and life-threatening persecution, it seems reasonable that this part of the population is also largely affected. Additionally, recruitment often takes place through deceptive job offers and family members in migrants' countries of origin. This suggests that networks of ethnic groups in destination countries are optimal locations to place victims and exploit them (UNODC 2012). This hypothetical relationship is accounted for by the number of refugees in destination countries. To capture ethnic (dis-) similarities and also address the role of cultural effects in the trafficking

process the share of Catholics is included. This variable should give an indication for the role religion in the trafficking process.

H7: HT is increased by factors enforcing migration and attracting people to a specific (rich) country, *ceteris paribus*.

Trafficking in people is associated with mafia-like structures of criminal activity including not only the exploitation of individuals but also other international organized crime such as drug smuggling (Europol 2011). Criminal businesses are diversified including for instance people and drug trafficking as well as other forms of criminal activities. This drives the extent of activities and reinforces its intensity (Aronowitz 2001, Salt 2000, Schloenhardt 2001). In this context it is reasonable to imagine that the trafficking routes established by criminal networks reinforce further trafficking. This hypothesized relationship is analyzed by testing how both the amount of heroin seized in countries and the number of drug trafficking offences creates human trafficking.

H8: Crime activities also have causal effects on HT, *ceteris paribus*.

2.3 Estimation strategy

To test these eight hypotheses we employ the structural equation approach of unobserved variables where multiple indicators and multiple causes are tested at once. We are thus able to control for the determinants as well as for the effects of human trafficking in the destination countries by employing the Multiple Indicators Multiple Causes (MIMIC) model for the empirical analysis. The main idea behind the model is to use covariance information of observed factors influencing the latent variable, i.e. human trafficking. The two groups of observed variables, i.e. indicators and causes are then modeled according to hypothesized relationships. The indicators are related to the unobserved variable in a measurement model showing the effect of the latent variable. The relation of the causes with the unobservable variable are simultaneously modeled in a structural model. The MIMIC model specifically compares the covariance matrix of the imposed relationships with the sample covariance and allows estimating a measure of the extent of the latent construct. This leads to the following two equations:

$$\mathbf{y} = \beta\eta + \varepsilon \quad (1)$$

$$\eta = \alpha'\mathbf{x} + \omega, \quad (2)$$

In the measurement model (1) the vector $\mathbf{y} = (y_1, y_2, \dots, y_m)'$ is the vector of indicators solely determined by the latent factor η , $\beta = (\beta_1, \beta_2, \dots, \beta_m)'$ is the corresponding coefficient vector and $\varepsilon = (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_m)'$ is the disturbance vector. In equation (2) the structural model shows that the latent variable η is determined by exogenous causes with error ω . The vector

$\mathbf{x} = (x_1, x_2, \dots, x_s)'$ is the vector of all potential causes and $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_s)'$ is the coefficient vector that describes the relationship between the causes and the latent variable.⁸ This estimation strategy has not only the advantage to test the theorized relationships between the causes and indicators and the latent variable human trafficking by estimating the parameters of the model, but it also provides us with the tools to test the fit of the theorized relationships with the underlying data.

3. A MIMIC model of human trafficking

The MIMIC method is introduced in economics by Jöreskog and Goldberger (1975). Subsequently, it has been used in numerous studies to measure unobservable variables such as the underground economy (e.g., Frey and Weck-Hanneman 1984, Loayza 1996, Schneider, Buehn and Montenegro 2010, and Buehn and Schneider 2012), corruption (Dreher et al. 2007), and international goods smuggling (Buehn and Farzanegan 2012).⁹ Multitudinous studies explored further determining aspects and the development of underground activity across and within countries including studies by Loayza (1996) for Latin-American countries and Giles (1999) for New Zealand. Chaudhuri et al. (2005) conduct a detailed analysis of the development of the black market across Indian states over 20 years. Dell'Anno and Schneider (2003) look at the underground activity in Italy, and recently Buehn et al. (2009) and Buehn (2012) conduct an analysis of German regions. Farzanegan (2011) studies underground activity in the Iranian economy.¹⁰ The large amount of studies shows, on the one hand, the importance of structural equation modeling in economics and on the other hand, the value of this approach to address illicit phenomena that are difficult to capture due to their very nature. Given the characteristics and clandestine nature of the trafficking process, this estimation strategy offers a valuable method to address HT in a holistic way by covering indicators and determinants together.

⁸ The formal application of the model can be found in appendix A.

⁹ Additionally, Di Tommaso et al. (2007) and Kuklys (2004) employ the structural equation approach to analyze institutional change in Eastern Europe and to measure welfare, respectively. Buehn (2012) analyzes the underground activity in German regions. In order to estimate cross-country variation in governance Kaufmann, Kraay and Zoido-Lobaton (1999) implement a similar approach. Buehn and Eichler (2009) explore the connection of smuggling illegal and legal goods across the border between Mexico and the USA and Buehn and Farzanegan (2013) develop an index of global air pollution both using SEM with one latent variable.

¹⁰ Further studies on the informal or parallel economy are: Schneider (1994a, 1994b, 1997) provide some early insights; Johnson et al. (1997) and Johnson et al. (1998) and Gerxhani (2003) also use structural equation modelling. Schneider and Enste (2000, 2002) contribute an overall survey of estimates on the size of underground activity around the world. Recently, Schneider and Buehn (2012) look in more detail at the drivers of the shadow market in OECD countries.

HT is an economically significant criminal activity where huge profits are generated on tax evasion. Given the increased attention for international HT on the global policy agenda and a willingness to fight it,¹¹ data collection efforts have been increased and studies to understand the underlying process have proliferated in law, political science and economics. However, research on HT is confronted with the hidden nature of the population active in practice, i.e., victims and traffickers (Tyldum and Brunovskis 2005). This makes it difficult to draw a representative sample or get firsthand information on the circumstances involved. Additionally, the mere focus on either supply side or demand side aspects does not give credit to the complexity, motivations and interaction of agents in the trafficking process (Laczko and Gozdziak 2005). An integral approach is needed. In order to capture HT as precisely as possible both aspects' indicators and causes must be included; this has been neglected in earlier studies. The main idea behind the MIMIC model is to examine the relationship between an unobservable variable, e.g., the shadow economy, corruption, human trafficking, and a set of observable variables using covariance information (Buehn and Schneider 2012). The flexibility in estimating the correlations of observable factors is one of the main advantages of the MIMIC approach.

International trafficking in human beings is a multidimensional unobserved phenomenon, where the whole process happens in the underground economy and neither traffickers nor victims are easy to identify. Through key determinants and indicators being considered at once, light is shed on the presence and magnitude of HT in a country. The method offers the possibility to estimate parameters of a single structural equation, rather than estimating numerous regressions. The MIMIC approach is based on the assumption that the causal factors of the latent phenomena are not considered independently. HT is a process with many facets where several factors shape the incentive structure of all the actors involved, i.e., traffickers, victims and governments. This becomes clear in the discussion of the causes of HT. The assumptions made about the effects of the latent variable have to be considered carefully. Cliff (1983, 120) argues that there might be relevant divergence between the observed indicators and the latent phenomenon.¹² This is especially important when interpreting correlations and model estimates established from the latent variable specifications and relating them directly to the unobserved phenomenon. However, this is no major problem here, because the model is tested on several different specifications and model applications which show that the underlying assumptions seem to be valid and applicable. Nevertheless, estimation models are no

¹¹ Since the adoption of the *Palermo Protocol* global focus on international human trafficking has increased. The protocol forces its progressive representation on the policy agendas of many countries.

¹² Cliff (1983) calls this issue *nominalistic fallacy*.

more than approximations of the unknown true social phenomenon and have to be interpreted cautiously especially when the endogenous component estimated (HT) is not observable.

In order to test the hypothesized relationship between the determinants and effects of HT the following (base line) MIMIC model of HT inflows (η) is implemented. The measurement model is specified by the indicators: crime rate per 100,000 people, the 3P-index of anti-trafficking policies and the number of identified victims. In one specification we use the police personnel instead of victims identified in order to test a variation of the institutional infrastructure in the countries employed to identify HT victims.

$$\begin{bmatrix} \text{crime rate}_i \\ 3P - \text{index}_i \\ \text{victims}_i \end{bmatrix} = [\beta_1, \beta_2, \beta_3] \times [\eta] + [\varepsilon_1, \varepsilon_2, \varepsilon_3] \quad (9)$$

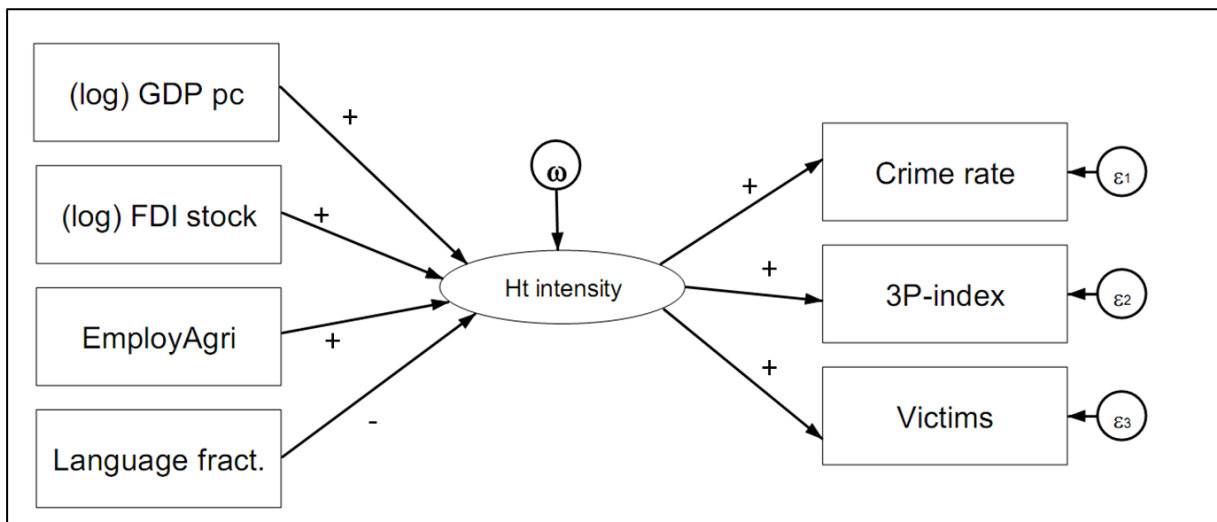
The structural models include all causes of human trafficking that influence the vulnerability of individuals pulling them towards promising destination countries as well as criminal aspects of the phenomenon. The basic causes used in the modeling process of the MIMIC model are income per capita in logs, foreign direct investment flows into destination countries (in logs), employment in agriculture as a percentage of total employment in these countries (employagri) and language fractionalization (language fract.) within the respective countries.

$$[\eta] = [\alpha_1, \alpha_2, \alpha_3, \alpha_4] \times \begin{bmatrix} (\log) \text{GDP pc}_i \\ (\log) \text{FDI stock}_i \\ \text{employ agri}_i \\ \text{language fract.}_i \end{bmatrix} + [\omega] \quad (10)$$

MIMIC models are represented by path diagrams. Figure 1 shows the path diagram for human trafficking intensity in destination countries. The latent variable "HT intensity" is jointly estimated by its causes and indicators. On the left hand side the structural model indicates the relationship between the determinants of human trafficking in destination countries measured with error ω , the disturbance term of the structural estimation. On the right hand side of the path diagram the arrows that point towards crime rate, the 3P-index and identified victims show the measurement model.¹³ The figure displays the specification with the best model fit discussed in section 4.

Figure 1: Path diagram of MIMIC

¹³ In a path diagram the circles indicate unobservable aspects of the model whereas the squares indicate observable variables.



Note: The path diagram is based on specification three, table 2.

The MIMIC model specified uses a maximum likelihood estimation strategy including the information contained in missing values, i.e., no observations are dropped (maximum likelihood with missing values). Studies have shown that using all the information available leads to unbiased and efficient estimates, which is thus preferable to list-wise or case-wise deletion (Collins et al. 2001). Therefore the number of observations does not change across specifications (table 2). After the model is implemented and specified for the 2000-2010 period, the basic specification shown in the path-diagram is used to generate yearly estimates. For the yearly specification multiple imputation is used for the main variables, which is equivalent to the use of maximum likelihood with missing values; both approaches are model based methods of dealing with incomplete data analysis (Little 1992).

The results reported in the next section include several combinations of causes and indicators. This takes stock of the fact that causes and indicators are not clearly separable (Dreher et al. 2007). In some cases it is theoretically plausible to interchange causes and indicators and vice versa, which becomes obvious in the discussion of the influence of trafficking victims. In these cases of uncertainty, the indicators are also implemented as determinants and vice versa. As the MIMIC is a special case of confirmatory structural equation models, a priori decisions on the model composition become necessary. Following standard practice, all variables are included with their contemporaneous values after having been transformed to deviations-from-mean and are scaled to have unit standard deviation. The reason for this transformation is that the different variables are measured on different scales. In order to have the same scale when entering the ranking estimation the variables are standardized (Buehn and Farnazegan 2012). Concerns about endogeneity or reverse causality in these specifications could arise due to the simultaneous implementation of variables. In order to deal with this issue of simultanei-

ty bias the results are re-estimated by including all quantitative causal variables with one period lag as suggested by Dreher et al. (2007). The results do not change qualitatively. They are also fairly robust to different stress tests.

Final judgment is based on the importance of the causes and indicators as well as fit indices common in structural equation modeling (Bollen 1989). Together with theoretical considerations the simplest specification is finally used to compare human trafficking in destination countries. The results do not change qualitatively when additional causes or indicators are included (all 14 specifications are displayed in table 2 and explained below). I constructed indices for all specifications and compared the rank correlation of the different indices (table 1). All combinations are highly significant with a rank correlation close to one. This shows that the simplest base specification suffices to derive conclusions about the position of countries and their intensity of human trafficking.

4. Results

4.1 Data and model fit indicators

The first indicator covering the extent of observed human trafficking is proxied by the number of victims identified. The United Nations Office on Drugs and Crime (UNODC) provides the number of identified victims in their Global reports on Trafficking in Persons (UNODC 2009, 2012) for a large set of countries.¹⁴ Anti-trafficking instruments are provided by the 3P-index of anti-trafficking policies provided by Cho et al. (forthcoming). The measure is available for the 2001 to 2012 period for over 180 countries. It covers the prosecution of traffickers, the protection of the victims and the extent of prevention in the countries. The higher the score a country receives in the 3P-index (on a score of 3-15), the more rigorous are the anti-trafficking measures. The third indicator used in the analysis of the MIMIC model is the level of crime in the country measured by the crime rate per 100,000 people taken from United Nations Surveys on Crime Trends and the Operations of Criminal Justice System (CTS) (UNCTS 2008), which is the most complete cross country crime data available. Other indicators test are also taken from that database namely drug trafficking offences per 100,000 persons as well as police personnel per 100,000 people. Given that heroin seized in kg is suggested to have a causal influence on human trafficking we test the hypothesized causal relationship in the structural model.

¹⁴ An overview of all variables used can be found in appendix B.

Coming to the causal variables we use income measured by GDP per capita (in logs) and taken from the World Bank's (2012) Development Indicators. In order to govern exploitation in low skilled jobs we use the employment in agriculture as a percentage of total employment variable provided by the World Bank (2012).¹⁵ Linguistic fractionalization is measured by the language component of the distance-adjusted ethno-linguistic fractionalization index (DELFI) developed by Kollo (2012). This index accounts for (dis-) similarities between languages, which is crucial in human trafficking because potential victims are more vulnerable if the destination country's language is different from their own. These new data are an improvement compared to Cho (2012) and Akee et al. (2010b) who use the ethnic fractionalization index (ELF) of Alesina et al. (2003). The ELF only considers the number of different languages in a country thereby disregarding crucial aspects of distance between languages accounted for in the DELFI, which are relevant in the context of the trafficking process.¹⁶

Foreign investment connections and trade relations are captured by the stock of foreign direct investment (FDI) as percentage of GDP (UNCTAD 2012). Covering the information dissimilarities the information flow variable is implemented which is a sub-component of the KOF globalization index of Dreher et al. (2008). The variable considers telecommunication as well as access to internet and newspaper proliferation. Increased personal contacts are captured by tourism arrivals as an additional channel of information transmission using the variable provided by the World Development Indicators (World Bank 2012). The size of the population in logs, which reflects the size of the countries, as well as the number of international migrants and the number of refugees by country of origin, are all drawn from the same database (World Bank 2012). The share of Catholics as a share of the whole population captures ethnic diversity of a country and is taken from the Encyclopedia Britannica (2001).

Given that structural equation modeling is confirmative in nature the significance of the variables is one indication of model quality, together with the overall fit of the model that should be acceptable in order to confirm the hypothesized relationships (Bollen 1989). The judgment of the quality of the model is based on whether the estimated covariance is equal or close to the real sample covariance. To decide which model fits the data best and thus approximates the extent of HT in destination countries most precisely, Barrett (2007, 815) argues that the chi-square hypothesis test is "the only substantive test of fit for SEM" because it is based on

¹⁵ Although an important exploitation market is the commercial sex market, there is almost no reliable information on the country level on the size of this market. Therefore, we refrain from using unreliable estimations and decided to use as proxy for all low-skilled exploitation markets the size of the agricultural sector.

¹⁶ The results are not qualitatively different when the ELF index is employed.

conventional hypothesis testing and compares the estimated covariance with the covariance structure of the data rather than using approximations. Nevertheless other fit indices suggested in the literature are reported and evaluated as well in the tables below. The chi-square statistic compares the empirical model against the alternative that the covariance matrix of the observable variables is unconstrained. The null hypothesis is that the model reproduces the covariance matrix of causes and indicators. Smaller test statistic values indicate that the model is a better fit, which implies that the null hypothesis is not rejected. Looking at the main results in table 2 the null hypothesis of a perfect fit cannot be rejected for specifications (1), (3), (7), (10) and (11). In these estimated specifications the p-values range between 0.13 (specification 10) and 0.32 (specification 7).

The root mean square error of approximation (RMSEA) evaluates the model fit on the basis of the difference between the two co-variances. Better fit is implied with a RMSEA value equal to or below 0.05 and a high p-value, indicating high probability to have a low RMSEA (Browne and Cudeck 1993). This is the case in all three of the five specifications not rejected by the chi-square statistic: (3), (7) and (11). Bentler (1990) suggests that model fit can be judged by using the comparative fit index (CFI) and the Tucker-Lewis index (TLI). A good model fit is indicated by values close to one (Hu and Bentler 1999). This criterion is met by all five specifications with values around 0.93-0.99. The coefficient of determination (CD) is comparable to the R-squared statistic of conventional regression analysis with higher values indicating better fit. The variation explained by the model is around 0.60 in the five models that generally show good model fit in all of the fit indicators considered here.¹⁷ All five models with acceptable model fit are used to generate HT intensity and test whether they generate different rankings. Table 1 shows their rank correlation. The indices are constructed generating a factor score or a linear prediction for all five models with acceptable model fit.¹⁸ The rank correlation is larger than 0.9 and highly significant over all pairs. The results support that the fit indicators give a good indication of which model to choose. Additionally, it is also im-

¹⁷ A detailed description of all goodness of fit indices in structural equation modelling is given by Iacobucci (2010). A critical assessment of the use of goodness of fit indicators is provided by Barrett (2007) who argues that the decision rules based on these indicators are arbitrary. He argues that the chi-square statistic is the “only substantive test of fit for SEM” (p. 815).

¹⁸ The factor score is the preferred method to build the ranking of countries, because it includes more structural information in the final index. It is suggested by Jöreskog (2000) and employed by most of the studies mentioned above. Another approach multiplying the standardized coefficients with the standardized data in order to derive a measure of the latent variable is the linear prediction. It is employed by Frey and Weck-Hannemann (1984), Loyaza (1996) and recently by Buehn and Farnazegan (2013). In order to test whether the country ranking depends on the method of index construction both approaches are implemented. The rank correlation is larger than 0.9 showing that the method is not decisive for ranking.

portant to consider the estimation results and underlying theory when deciding which model to choose.

4.2 MIMIC estimation results

The principal MIMIC specification considers only cross-country variation. After testing for the robustness of the different specifications and evaluating the model fit the specification with the best fit is used for the final index. In this way country rankings for every single country-year combination are generated which makes it possible to assess the development of the problem HT inflow prevalence over time. As discussed above the decade of 2000-2010 saw a rise in quantitative research on HT, which was at least partially spurred by the UN officially defining HT in 2000. Additionally due to the availability of data the years between 2000 and 2010 appear to be the most useful in exploring the major causes and indicators of modern day slavery empirically. All variables discussed above are tested in a number of specifications. Subsequently the general to specific approach is applied in order to exclude the variables that are insignificant at least at the 10 percent level or above.

The results of the MIMIC estimations are displayed in table 2. The top panels show the structural model and the relationship of causes. The middle panels show the measurement model with the indicators and the lower panels display the fit indices. Column one presents the base line specification of principal causes and indicators and all additional causes of human trafficking are included in the subsequent specifications 2-12. The focus is on the causes and indicators of HT in countries where exploitation takes place, i.e., destination countries. Table 2 shows the estimated MIMIC results in point estimates.¹⁹ Specification 1 includes only significant causes with an acceptable overall model fit. Looking at the intensity of human trafficking in these countries (log) income per capita, the share of employment in agriculture and (log) foreign direct investment, form the simplest and most basic combination of determinants. The observed correlation of GDP per capita is positive and significant at the one percent level in all specifications supporting the hypothesized relationship that richer countries experience more HT. Investment flows into the countries are also positively associated with HT. This is in line with the hypothesis that more international business and investment relations increase the intensity of illicit human movement. The effect is robustly significant over all specifications. The observed robust positive influence of the share of employment in agriculture can be understood as it is used as a proxy for cheap working opportunities in these countries leading to more potential placements for traffickers to exploit people. Our results support this indicat-

¹⁹ All estimations have been performed using STATA 12.1.

ing that labor exploitation is a major precondition for trafficking to occur. All three effects are according to expectation and economic intuition.

The availability of information measured by the information component of the KOF globalization index never becomes significant at conventional levels. Linguistic fractionalization within countries has a negative and significant influence on the trafficking process (column 3). This suggests that less diverse countries observe more human trafficking. Presumably these countries are in the same geographical region which reduces costs for traffickers and for migrants, increasing the amount of people trafficked. This seems plausible, because larger criminal networks might evolve in less diverse countries thereby increasing exploitation opportunities. While column 2 has no acceptable model fit with a low p-value and a large chi-square statistic, column 3 shows acceptable values in all fit indicators according to the cut off thresholds of the indices, even better than in column one.

The size of the market for victim exploitation is measured by (log) population which shows the expected sign and is highly significant. However, the model fit is unsatisfactory with a low p-value and incongruous fit indicators. Columns 5 and 6 test how the share of international migrants in a country and the arrival of international tourists affect the intensity of human trafficking. Both show negative correlations and are significant on the one and five percent level, respectively. These results are in contrast to general expectations and difficult to explain. We refrain from a detailed explanation because the fit indices show poor model fit which indicates that the results are not reliable. The test of the correlation between refugees, share of HT victims and the share of Catholics in the country do not turn out to have significant correlation.²⁰ The results do not support the hypothesized relationship between refugees and HT intensity. The model fit, however, suggests that the estimated covariance resembles the actual covariance of the data quite well. Therefore, specification 7 is also tested for the prediction of the index.

The hypothesized relationship between criminal activities such as drug trafficking and HT is supported by the findings. The coefficient is positive and highly significant when the other influencing factors are controlled for. The larger the share of drug trafficking offences detected in a country the larger HT (column 10). The fit indicators show a good model fit. The resources allocated to fight crime within countries are captured by the number of police person-

²⁰ The test of identified victims as a causal variable for trafficking intensity is based on the argument of Dreher et al. (2007) and Buehn and Schneider (2012) who write that it is difficult to clearly differentiate between causes and indicators in the MIMIC approach. This is applicable here as well: identified victims could theoretically also induce trafficking inflows. Established placements of victims and former victims turning into traffickers would suggest a determining nature. However, this is not supported by the data.

nel, which turns negative but not significant at conventional levels (column 11). The model fits the data acceptably well and both models are used for index construction, in order to test whether the different specifications and respective indices are similar. Finally, in column 12, the police personnel variable is also tested as an indicator in the measurement model that reduces model fit drastically.

In the measurement model the indicators of trafficking in destination countries are tested. One of the indicators of the latent variable has to be normalized and used as an anchor variable for the scale and identification.²¹ The anchor used here, consistently over all models in the analysis, is the crime rate. The coefficient is normalized to one, resulting in a standardized coefficient of around 0.88 on average across all specifications. We follow the literature using the indicator with the largest standardized coefficient as the anchor variable (e.g., Schneider et al. 2010, Buehn and Schneider 2012, Dreher et al. 2007). All four indicators are positively related to the latent variable human trafficking, which is in line with theoretical considerations and economic intuition. The number of identified victims as a share of the population turns significant in only some of the yearly applications (table 6). Arguably this indicator is very important but identification capacity depends on many aspects of countries' legislative infrastructures (Laczko and Gozdziaik 2005). The findings show that important aspects of the trafficking process are identifiable by employing victim numbers as in Hernandez and Rudolph (2012). The 3P-index of anti-trafficking policies reflecting the instruments employed by countries in order to fight human trafficking is the third indicator. It turns positive and significant at the one percent level in all specifications showing the importance of anti-trafficking policies that protect victims, prosecute traffickers and prevent HT in reflecting the intensity of HT in the country. These results support the hypothesized relationship between efforts to curb HT and the extent of HT: countries with more HT and more exploitation of its people are more proactive in their fight against HT.

The response of HT into the country is expressed in units of standard deviation for a one standard deviation change in an explanatory causal variable holding all other variables constant (Bollen 1989).²² The effects of the main causal variables of the full model in column 3 of table 2 (not reported in the table) indicate that a one standard deviation increase in GDP per capita leads to an increase in the magnitude of human trafficking by 1.08 standard deviations. A one standard deviation increase of the FDI share and the share of employment in agricul-

²¹ The choice of the anchor does not change estimation results (Bollen 1989).

²² The standardized coefficients are calculated by using $\tilde{\beta}_{ij} = \hat{\beta}_{ij} \sqrt{\hat{\sigma}_{ii} / \hat{\sigma}_{jj}}$ where i stands for the causal variables and j for the unobservable variable. The predicted variances under the squared root are the variances of the i th and j th variables, respectively.

ture increases human trafficking by 0.2 and 0.48 standard deviations respectively. A decrease in the standard deviation of language diversity increases human trafficking by more than 0.15 standard deviations. In a globalized world, countries are becoming more rather than less alike, with languages being a factor in this. Turning to the other effects that support our hypotheses we see that human trafficking responds to an increase of one standard deviation of the exploitation market (measured by population) by 0.28 standard deviations (specification table 2 column 4). The magnitude of the effect for drug trafficking detected shows an increase of HT of 0.31 standard deviations if the share in detected offences increases by one standard deviation. Turning to the indicator variables the standardized coefficient of the crime rate indicates that an increase in human trafficking by one standard deviation increases the crime rate by around 0.88 standard deviations on average over all specifications. The 3P-anti-trafficking policy measure increases by 0.62 standard deviations and the number of victims by 0.04 standard deviations given an increase in human trafficking by one standard deviation on average. The results are fairly robust over all specifications.

The described results do neither depend on the method used nor are they driven by specific countries. The first test of the robustness of the results to different method applications is displayed in table 3 where the models are estimated using maximum likelihood and case-wise deletion. The number of observations drops to around 80 countries and varies across specifications due to availability of data on causes and indicators. The results do not change qualitatively and stay largely the same quantitatively. The significance of the factors decreases, which does not affect the model fit. The goodness of fit indicators still show good results for the five specifications highlighted above, showing large p-values and a large proportion of explained variability in the values of the coefficient of determination (CD). As has been shown by several studies (see, e.g., Little and Rubin 1987, and their references) the deletion of observational units due to missing values is rather ad hoc and comes with several well-documented problems. Case-wise deletion, common in social science, might remove a high proportion of observations and make the estimates inefficient because only few observational units have complete data. This comes together with a possible selection bias if the complete cases are not representative of the entire sample (Schafer and Olsen 1998).

A second stress test suggested by the literature on MIMIC is to exclude the three highest and lowest ranking countries of the resulting measure (e.g., Buehn and Farzanegan 2012). The exclusion tests whether outliers at the top and bottom of the ranking drive the results. The results are displayed in table 4. Generally the fit of the specifications decreases, but qualitatively the results are not affected. The p-values show a good model fit for the same specifica-

tions. Also the other fit measures are in line with expectations of the previous findings. To rule out endogeneity concerns the results are also estimated following Dreher et al. (2007) and lagging all quantitative causal variables by one period and then estimating the model again. The analysis survives is robust to this sensitivity analysis and the results are not changed dramatically.²³ Based on the results, the final specification is chosen. Model three (column 3) includes the main causes of HT inflows together with the main indicators making HT visible in countries. In table 5 we show the empirical confirmation or rejection of our eight hypotheses. Table 5 clearly confirms that we got the theoretically expected signs of our eight hypotheses and all independent variables, which stand for these hypotheses are statistically significant.²⁴ For example, a high crime rate in a country is the results of high human trafficking in these countries, *ceteris paribus*. Or, traditional crime activities have a positive effect on HT, *ceteris paribus*, with the expected positive sign and the independent variable “drug trafficking offences share is highly statistically significant.

4.3 Human trafficking index

An objective ranking of countries is constructed that allows one to compare the scale of HT inflows into destination countries. The main criticism of existing rankings, such as the tier score of the U.S. Department of State (United States 2001-2012) which addresses compliance with U.S. policies only, is the one-sided nature of this approach reflecting political interest rather than a transparent independent score of the variety of international policy approaches (Simmons and Lloyd 2010).²⁵ The underlying measures implemented in the construction of the intensity index are based on publicly available data that influence human trafficking through different channels. The index based on the MIMIC approach, in contrast, is based on structural relationships between observable causes and indicators of human trafficking common to all countries.

By using the parameters of the MIMIC approach which are directly related to the determinants and consequences of human trafficking, we derive the HT measure.²⁶ The MIMIC estimates (table 5) are robust over time and point in the same direction as in the baseline specifi-

²³ These findings are available from the authors upon request.

²⁴ Full models with all significant variables together shown in tables 2, table 3 and table 4 can be found in appendix A, table 1.

²⁵ Simmons and Lloyd (2010) criticise that the ranking of countries by the Department of State is influenced by political interest of the US and eventually serves to get other countries to apply the norms set out by the world's referee.

²⁶ The main variables (table 2, column 3) are imputed using multiple imputation (MI), i.e., the standardized continuous variables are imputed using chained regression with 20 imputations. Application of Rubin's (1987) rules of adjustment leads to efficient estimates of the coefficients and standard errors.

cation described above. The chi-square test and the respective p-values of the models show a good fit in almost all years.²⁷ Based on these estimates the HT intensity index is constructed. The next step is to generate the country ranks according to their expected rate of HT inflow. The results for the intensity index and the ranking of all 142 countries for the year 2000 to 2010 are presented in table 6. The rank indicates the relative position of each country according to the prevalence of human trafficking into its borders. The measure is scaled between 0 and 100 with lower values for countries having lower HT prevalence. Unsurprisingly industrialized countries are on top of the ranking. In 2000 only four non-OECD countries are located in the top 30. These are the Bahamas, Malta, Gabon and Trinidad and Tobago. This is in line with observations in the U.S. TIP report (United States 2001), where Malta is reported as being a destination for women and girls exploited in prostitution. Furthermore, men are known to be exploited in restaurants. Malta still ranks in the top 30 in 2005, but in 2010 its rank is 39. Malta is also a destination country for many African migrants aiming to enter Europe who are vulnerable to human trafficking in informal sectors of the Maltese economy (United States 2010). The Bahamas rank very high in the trafficking index throughout the ten years (among the top 30 countries in all years apart from 2004 when it ranks 37). A likely reason is the Bahamas' status as a destination country for many migrants of other Caribbean countries who seek better economic conditions and who are consequently vulnerable to exploitation. With the lowest unemployment statistics in the region these seem to be promising conditions for many migrants (IOM 2010). The country is also known to be a destination and transit country for victims trafficked to Europe and Northern America (United States 2010). Additionally, the government of the Bahamas only ratified the Palermo Protocol in 2008 (United Nations 2013), which indicates potentially lower efforts to fight human trafficking in the beginning of the research period. All of these aspects together might explain the high ranking of the country, and thus the high magnitude of HT into the country. Since 2009 Trinidad and Tobago has been evaluated by the U.S. Department of State in its TIP report. According to the investigation the country is known to be a destination and transit country where female victims are exploited in the commercial sex industry and forced labor and men are exploited on construction sites and other low skilled activities such as fishing. The country lacks rigorous HT legislation and the prosecution of traffickers is limited (United States 2012). This suggests that trafficking is a lucrative business in the country, which makes it an attractive destination country for traffickers. According to the intensity measure the problem

²⁷ It is only for 2003 and 2005 that the models show no good fit. However, this might be due to data quality issues that are not eliminated by imputation, because MI uses the information available and fills in the missing values.

within the country increased and in 2010 Trinidad and Tobago ranks among the top 20 destination countries. In the case of Gabon, the only African country ranking among the top 30 countries in 2005, the trafficking problem is large in magnitude because of many children being trafficked into the country. They are bought by traffickers from their parents promising better living conditions. However, they are trafficked and exploited at destination (United States 2009). The country is seen as one of the most prosperous in the region, with more opportunities for work (United Nations 2012). This might explain the high position of the country in the index.

The United States - as the state pushing initiatives against human trafficking such as the implementation of anti-trafficking instruments - ranges between position eight (2004) and 17 (2000). In the last two years they rank 15th which suggests that they are a destination country for victims of exploitation. This relatively constant position might suggest that despite its intense anti-trafficking efforts and awareness campaigns run locally and internationally, the magnitude of the problem seems to be quite stable within the United States. Human trafficking seems to be most prevalent in the United Kingdom (UK). The country is the top rank for five of the ten years and except for 2000 to 2002 it holds the second position. Taking into account that the UK is traditionally an immigration country, where many international migrants seek better living conditions, all forms of exploitation are identified in the country. Illegal drug cultivation and smuggling as well as exploitation in low skilled jobs together with lax law enforcement in parts of the country seem to support the high prevalence of HT (United States 2010). Germany and the Netherlands rank among the top ten countries throughout the years supporting reports of a high magnitude of HT in these countries. On the lower end of the list are mainly Sub-Saharan African countries. These are mainly low-income countries that act as a source rather than a destination for victims of human trafficking.

The graphic representation of the trends in human trafficking (figure 1) reflects the general findings described above. The darker a country is the more intense the magnitude of human trafficking into its national borders. Western Europe and Northern America together with Australia are the main destinations where victims are exploited. This is the only constant visible trend. Asian countries are located rather in the middle range of the index with a lighter shade. The same holds true for South America. Africa in contrast is very lightly shaded. The countries that are lower on the ranking are generally more prone for trafficking outflows, with the exception of Gabon.

Overall, the index shows a correlation of coefficients with other relevant measures of HT of around 0.5 (table 9). The intensity index (HT inflow) is positively correlated with the tier rank

of the U.S. State Department with a Spearman rank correlation of 0.47. This is expected given that high values of the tier rank indicate compliance with the Victims of Trafficking and Violence Protection Act, presumably because the problem in the country is more intense. In the 2006 Global Report on Trafficking, a measure of human trafficking in destination, transit and countries of origin is constructed - called citation index (UNODC 2006). This country classification is based on open source information and is only available in 2006 based on information of the 1995-2003 period. Looking at the UNODC citation indices, again a positive correlation exists with the constructed HT index. Countries with a high citation index value (destination countries) also have a larger value on the inflow index. Likewise, the negative and significant correlation with citation as origin countries points in the right direction. One could argue that the correlation between the indices is only modest (0.35 to 0.49) but this can be attributed to the different aspects of HT that they measure. The tier rank addresses compliance with the Victims of Trafficking and Violence Protection Act and thus political decisions on fighting HT. This is only one aspect of the process of trafficking in human beings, which is included in the intensity index. The latter, however, also captures country characteristics as well as the criminal dimension and vulnerability of victims. The same holds true for the citation indicators. Both measures are based on and capture human trafficking visible to society that receives public awareness. By including identified victims as well as the other indicators in the measure this aspect of the trafficking process is included in the inflow index together with the causes. Although these correlations only provide descriptive evidence, it is a reassuring signal for the adequacy of the measurement.

5. Conclusion

This paper is the first study that uses a structural equation model in a holistic approach to measure human trafficking. Both causes and indicators of human trafficking intensity in destination countries are included and thus the clandestine nature of the phenomenon is addressed. MIMIC models are special cases of structural equation models combining a structural model and a measurement model. This empirical instrument provides both estimates of the correlation between determinants of HT as well as estimates on the relationship between HT and its consequences in destination countries. From these results, a yearly index on the intensity of HT in destination countries is constructed for the 2000-2010 period considering 142 countries around the world.

This approach goes beyond existing studies, which consider only partial aspects of HT. It also provides a holistic approach including causal factors and indicators together acknowledging

the illicit nature of the phenomenon. The causes mirror the incentive structure for traffickers by taking into account their chances of making high profits while having low probability of detection. Furthermore, the causes also capture the vulnerability of trafficking victims by addressing their incentives to move in the first place from which point they are vulnerable to false promises of better opportunities. By travelling from a poorer country to a wealthier one individuals are inherently vulnerable- this is the case especially as they are not moving to linguistically fractionalized countries. The indicators on the other hand show the outcome of illegal trafficking of human beings in countries. Human trafficking induces a higher crime level in destination countries with, e.g., a larger underground economy. Identified victims, that only provide a fraction of victims in trafficking, provide a bottom measure of the phenomenon, and although this number is related to the ability of countries to identify victims, it is an indicator of the extent of the problem. The dimensions of the fight against HT are captured by the 3P-index. The measure quantifies the application of anti-trafficking policies within countries, which arguably is a consequence of the intensity of the phenomenon.

The developed measure of the extent of HT in destination countries identifies the development of HT over time and across a large set of countries. It is the first measure to quantify illegal trafficking of humans in these countries. The pattern of the development of HT over the observed period is in line with expectations. Developed countries are highly ranked and observe a large amount of trafficking within their borders. These countries are the primary targets of traffickers, supposedly because the potential for large profits is greatest in wealthier countries. The lowest ranking countries are the countries in Sub-Sahara Africa which is not surprising as it was expected that they would be source rather than destination countries for HT. Asian countries are in the middle range.

Researchers and policy makers alike are interested in a numerical evaluation of human trafficking to respond more adequately to the issue of trafficking in persons. To date, this information was lacking. The information provided by this paper's new human trafficking measure fills this knowledge gap by providing researchers with a measure of the intensity of HT over time that allows for an in depth analysis of related aspects. This will add to further research on the consequences of HT and increase the toolbox of policy makers to understand and combat HT. In particular, the relationship between human trafficking inflows and its auxiliary aspects could be analyzed in more detail, giving a better understanding of the intensity of victim exploitation and inflows. Studies that leveraged situations in countries with the existence of human trafficking such as ethnic fractionalization, conflict or displaced populations could further profit from an analysis of the intensity of HT rather than only looking at the existence

measured by binary variables. Using the MIMIC approach also provides the possibility to assess human trafficking in a social context and investigate its relationship with labor market reforms in destination countries. Similarly, the effect of migration legislation on human trafficking inflows is an important part in the fight against HT. Investigating these interrelations will enhance the knowledge of the crime and help fighting to control HT in developed as well as developing countries alike.

Policy makers could use this numerical assessment of human trafficking to see their position relative to other countries and further understand the problem within their national area. Although we estimate a country specific measure one should keep in mind that HT is a transnational problem and that the fight against this crime can only be fought simultaneously across national borders. The resources allocated to the fight should especially be allocated to supranational institutions with different foci, i.e. Interpol or international organizations, in order to address all aspects of the multidimensional problem.

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Table 1: Pairwise rank correlation of different specifications and index construction methods

	(1) Factor score	(3) Factor score	(7) Factor score	(10) Factor score	(11) Factor score	(1) Linear prediction	(3) Linear prediction	(7) Linear prediction	(10) Linear prediction	(11) Linear prediction
(1) FS	1									
(3) FS	0.994 ^{***}	1								
(7) FS	0.998 ^{***}	0.992 ^{***}	1							
(10) FS	0.998 ^{***}	0.991 ^{***}	0.996 ^{***}	1						
(11) FS	1.000 ^{***}	0.993 ^{***}	0.998 ^{***}	0.997 ^{***}	1					
(1) LP	0.905 ^{***}	0.902 ^{***}	0.897 ^{***}	0.906 ^{***}	0.905 ^{***}	1				
(3) LP	0.906 ^{***}	0.916 ^{***}	0.898 ^{***}	0.906 ^{***}	0.906 ^{***}	0.984 ^{***}	1			
(7) LP	0.903 ^{***}	0.901 ^{***}	0.900 ^{***}	0.903 ^{***}	0.903 ^{***}	0.994 ^{***}	0.979 ^{***}	1		
(10) LP	0.928 ^{***}	0.924 ^{***}	0.921 ^{***}	0.936 ^{***}	0.927 ^{***}	0.986 ^{***}	0.972 ^{***}	0.981 ^{***}	1	
(11) LP	0.905 ^{***}	0.902 ^{***}	0.896 ^{***}	0.904 ^{***}	0.905 ^{***}	0.999 ^{***}	0.984 ^{***}	0.993 ^{***}	0.983 ^{***}	1
<i>N</i>	142									

Note: Factor score and linear prediction are index construction method. Construction is based on specifications (1), (3), (7), (10) and (11), because all five
Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2: MIMIC HT-inflow determinants and indicators

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Structural model (causes)	(log) GDP per capita	0.949***	0.828***	0.979***	0.948***	1.131***	1.037***	0.926***	0.966***	0.959***	0.810***	0.943***	0.948***
		(6.436)	(4.945)	(6.685)	(6.716)	(8.150)	(6.890)	(6.182)	(6.485)	(6.549)	(5.515)	(6.277)	(6.481)
	(log) FDI stock	0.168**	0.104	0.179**	0.242***	0.131*	0.210***	0.176**	0.175**	0.153***	0.148*	0.168**	0.169**
		(2.202)	(1.253)	(2.370)	(3.227)	(1.922)	(2.705)	(2.269)	(2.279)	(1.975)	(1.943)	(2.199)	(2.229)
	Employment in agriculture	0.383**	0.477***	0.438***	0.405***	0.412***	0.415***	0.367**	0.398**	0.415***	0.309**	0.375**	0.378**
		(2.455)	(2.991)	(2.796)	(2.848)	(2.966)	(2.729)	(2.344)	(2.535)	(2.604)	(1.981)	(2.349)	(2.458)
	Info flow		0.234										
			(1.509)										
	Language fractionalization			-0.132*									
				(1.882)									
	(log) Population				0.230***								
					(3.237)								
	Migrants					-0.300***							
						(4.837)							
Tourism arrivals						-0.159**							
						(1.966)							
Refugees							-0.087						
							(0.858)						
Victims								-0.060					
								(0.812)					
Catholics									0.057				
									(0.778)				
Drug trafficking offences										0.277***			
										(3.506)			
Heroin seizures											-0.019		
											(0.209)		
Measurement model (indicators)	Crime rate	1	1	1	1	1	1	1	1	1	1	1	1
	Overall 3P-index	0.690***	0.773***	0.684***	0.828***	0.751***	0.742***	0.671***	0.687***	0.724***	0.705***	0.689***	0.691***
		(5.973)	(5.672)	(6.065)	(6.115)	(6.612)	(6.086)	(5.920)	(5.963)	(5.618)	(6.266)	(5.975)	(6.085)
	Victims	0.040	0.063	0.038	-0.006	0.018	0.036	0.040		0.040	0.067	0.040	
		(0.333)	(0.490)	(0.319)	(0.044)	(0.145)	(0.292)	(0.340)		(0.323)	(0.543)	(0.337)	
	Police personnel												0.081
													(0.611)
	Number of countries	142	142	142	142	142	142	142	142	142	142	142	142
	Chi-square	9.39	31.03	9.40	36.07	16.16	16.54	9.26	6.34	26.26	12.52	9.90	29.94
	(P-value)	0.15	0.00	0.31	0.00	0.04	0.04	0.32	0.10	0.00	0.13	0.27	0.00
	RMSEA	0.06	0.14	0.04	0.16	0.08	0.09	0.03	0.09	0.13	0.06	0.04	0.17
	Probability RMSEA<0.05	0.33	0.00	0.55	0.00	0.15	0.14	0.56	0.20	0.01	0.32	0.51	0.00
	CFI	0.97	0.83	0.99	0.81	0.94	0.93	0.99	0.97	0.86	0.96	0.98	0.83
	TLI	0.94	0.69	0.98	0.65	0.89	0.87	0.98	0.92	0.74	0.93	0.97	0.65
	CD	0.59	0.63	0.62	0.68	0.75	0.63	0.59	0.59	0.61	0.68	0.59	0.60

Note: Absolute z-statistics in parenthesis; *** p<0.01, ** p<0.05, * p<0.1; 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. Model fit increases with larger p-values. The root mean squared error of approximation (RMSEA) evaluates the fit of the model on the basis of the deviance between the estimated and the real covariance. Brown and Cudeck (1993) assume that RMSEA values smaller than 0.05 imply a good model fit which corresponds to a probability close to 1. The two fit indices suggested by Bentler (1990) are the comparative fit index (CFI) and the Tucker-Lewis index (TLI). They indicate a good model fit with values close to 1 (Hu and Bentler 1999). The coefficient of determination (CD) is similar to the R-squared with higher values showing better fit.

Table 3: MIMIC estimates (ML)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	
Structural model (causes)	(log) GDP per capita	0.989*** (5.109)	0.910*** (4.336)	1.037*** (5.488)	0.994*** (5.388)	1.296*** (7.493)	1.118*** (5.967)	0.988*** (5.107)	1.010*** (5.222)	0.989*** (4.823)	1.002*** (4.179)	0.849*** (3.972)	1.012*** (5.881)	
	(log) FDI stock	0.118 (1.087)	0.046 (0.346)	0.127 (1.189)	0.205* (1.805)	0.066 (0.720)	0.180* (1.690)	0.126 (1.151)	0.134 (1.224)	0.118 (1.071)	0.030 (0.247)	0.134 (1.224)	0.125 (1.278)	
	Employment in agriculture	0.294 (1.370)	0.384* (1.662)	0.373* (1.756)	0.298 (1.454)	0.465*** (2.647)	0.322 (1.597)	0.305 (1.417)	0.316 (1.474)	0.294 (1.242)	0.322 (1.184)	0.204 (0.890)	0.330* (1.817)	
	Info flow		0.212 (0.906)											
	Language fractionalization			-0.165* (1.692)										
	(log) Population				0.194** (2.076)									
	Migrants					-0.417*** (5.237)								
	Tourism arrivals						-0.251*** (2.632)							
	Refugees							-0.103 (0.526)						
	Victims								-0.078 (0.946)					
	Catholics									0.000 (0.004)				
	Drug trafficking offences										0.258*** (2.777)			
	Heroin seizures											-0.046 (0.618)		
	Measurement model (indicators)	Crime rate	1	1	1	1	1	1	1	1	1	1	1	1
	Overall 3P-index	0.601*** (6.612)	0.639*** (6.310)	0.632*** (6.839)	0.644*** (6.914)	0.736*** (7.863)	0.648*** (7.097)	0.598*** (6.586)	0.605*** (6.646)	0.601*** (6.268)	0.617*** (6.989)	0.761*** (6.312)	0.666*** (5.758)	
	Victims	0.042 (0.358)	0.051 (0.415)	0.045 (0.377)	0.033 (0.269)	0.021 (0.162)	0.042 (0.342)	0.041 (0.355)		0.042 (0.358)	-0.024 (0.160)	0.090 (0.539)		
	Police personnel												0.070 (0.527)	
	Number of countries	84	84	84	84	84	84	84	84	84	60	53	88	
	Chi-square	9.66	23.06	12.82	21.40	20.36	13.82	9.94	5.04	20.82	9.12	8.58	21.30	
	(P-value)	0.14	0.00	0.12	0.01	0.01	0.09	0.27	0.17	0.01	0.33	0.38	0.00	
	RMSEA	0.09	0.15	0.08	0.14	0.14	0.09	0.05	0.09	0.14	0.05	0.04	0.17	
	Probability RMSEA<0.05	0.24	0.01	0.22	0.02	0.03	0.18	0.41	0.25	0.03	0.44	0.48	0.01	
	CFI	0.97	0.88	0.96	0.89	0.91	0.95	0.98	0.98	0.89	0.99	0.99	0.85	
	TLI	0.93	0.77	0.92	0.79	0.83	0.91	0.97	0.94	0.80	0.98	0.98	0.71	
	CD	0.54	0.57	0.58	0.60	0.74	0.62	0.54	0.55	0.54	0.68	0.65	0.60	

Note: Absolute z-statistics in parenthesis; *** p<0.01, ** p<0.05, * p<0.1; 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. Model fit increases with larger p-values. The root mean squared error of approximation (RMSEA) evaluates the fit of the model on the basis of the deviance between the estimated and the real covariance. Brown and Cudeck (1993) assume that RMSEA values smaller than 0.05 imply a good model fit which corresponds to a probability close to 1. The two fit indices suggested by Bentler (1990) are the comparative fit index (CFI) and the Tucker-Lewis index (TLI). They indicate a good model fit with values close to 1 (Hu and Bentler 1999). The coefficient of determination (CD) is similar to the R-squared with higher values showing better fit.

Table 4: MIMIC estimates (exclusion of highest and lowest ranking countries)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Structural model (causes)	(log) GDP per capita	0.694*** (5.468)	0.634*** (4.616)	0.721*** (5.697)	0.721*** (6.036)	0.874*** (7.421)	0.734*** (5.440)	0.682*** (5.348)	0.727*** (5.792)	0.720*** (5.869)	0.632*** (5.105)	0.689*** (5.343)	0.704*** (5.591)
	(log) FDI stock	0.179*** (2.771)	0.131* (1.752)	0.184*** (2.895)	0.228*** (3.542)	0.140** (2.440)	0.192*** (2.889)	0.187*** (2.879)	0.187*** (2.929)	0.151** (2.331)	0.138** (2.097)	0.178*** (2.768)	0.175*** (2.747)
	Employment in agriculture	0.207 (1.569)	0.281** (1.983)	0.250* (1.870)	0.246** (1.990)	0.254** (2.173)	0.226* (1.699)	0.205 (1.556)	0.239* (1.834)	0.267** (2.021)	0.191 (1.473)	0.202 (1.491)	0.218* (1.672)
	Info flow		0.153 (1.104)										
	Language fractionalization			-0.094 (1.612)									
	(log) Population				0.165** (2.526)								
	Migrants					-0.242*** (4.738)							
	Tourism arrivals						-0.054 (0.751)						
	Refugees							-0.079 (0.892)					
	Victims								-0.107* (1.685)				
	Catholics									0.090 (1.534)			
	Drug trafficking offences										0.292*** (2.780)		
	Heroin seizures											-0.013 (0.187)	
	Measurement model (indicators)	Crime rate	1	1	1	1	1	1	1	1	1	1	1
	Overall 3P-index	0.703*** (4.946)	0.792*** (4.774)	0.705*** (5.068)	0.889*** (5.207)	0.809*** (5.922)	0.741*** (4.885)	0.693*** (4.931)	0.707*** (5.128)	0.788*** (5.084)	0.750*** (5.277)	0.703*** (4.943)	0.722*** (5.077)
	Victims	-0.085 (0.582)	-0.053 (0.332)	-0.082 (0.564)	-0.115 (0.694)	-0.090 (0.582)	-0.081 (0.544)	-0.084 (0.584)		-0.076 (0.493)	-0.074 (0.490)	-0.084 (0.580)	
	Police personnel												0.028 (0.168)
	Number of countries	136	136	136	136	136	136	136	136	136	136	136	136
	Chi-square	10.56	31.99	10.83	41.56	18.28	20.91	10.93	6.50	24.02	12.38	11.07	34.59
	(P-value)	0.10	0.00	0.21	0.00	0.02	0.01	0.21	0.09	0.00	0.13	0.20	0.00
	RMSEA	0.07	0.15	0.05	0.18	0.10	0.11	0.05	0.09	0.12	0.06	0.05	0.19
	Probability RMSEA<0.05	0.25	0.00	0.43	0.00	0.09	0.04	0.42	0.18	0.02	0.32	0.41	0.00
	CFI	0.96	0.81	0.97	0.77	0.92	0.89	0.97	0.97	0.87	0.96	0.97	0.79
	TLI	0.92	0.65	0.95	0.56	0.86	0.79	0.95	0.91	0.75	0.93	0.95	0.57
	CD	0.55	0.60	0.58	0.66	0.74	0.57	0.54	0.58	0.61	0.63	0.55	0.56

Note: Absolute z-statistics in parenthesis; *** p<0.01, ** p<0.05, * p<0.1; 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. Model fit increases with larger p-values. The root mean squared error of approximation (RMSEA) evaluates the fit of the model on the basis of the deviance between the estimated and the real covariance. Brown and Cudeck (1993) assume that RMSEA values smaller than 0.05 imply a good model fit which corresponds to a probability close to 1. The two fit indices suggested by Bentler (1990) are the comparative fit index (CFI) and the Tucker-Lewis index (TLI). They indicate a good model fit with values close to 1 (Hu and Bentler 1999). The coefficient of determination (CD) is similar to the R-squared with higher values showing better fit.

Table 5: Empirical confirmation/rejection of the eight hypotheses

Hypotheses	Independent Variables	Theoretical expected signs	Hypotheses confirmed	Statistical significance
H1: A high number of identified victims in a country increases the extent of human trafficking, ceteris paribus.	Number of victims (per 100,000 people)	+		
H2: The more intense the fight against HT in a country the larger the scale of HT, ceteris paribus.	3P-anti trafficking index	+	√	***
H3: The higher the crime rate in a country and the more resources are allocated to fight the crime the more exploitation of individuals and thus HT takes place, ceteris paribus.	Crime rate (per 100,000 people)	+	√	***
	Police personnel (per 100,000 people)	+		
H4: The richer the country, the larger are the HT inflows, ceteris paribus.	GDP per capita	+	√	***
H5: The larger the demand for low-skilled services where exploitation takes place the, more HT will be allocated in the country, ceteris paribus.	Employment in agriculture as share of total employment	+	√	**
	FDI stock as share of GDP	+	√	**
H6: International trade routes increase HT whereas information exchange via international tourism reduces knowledge and HT, ceteris paribus.	Information flow	+		
	Tourism arrivals (per 100,000 people)	+		
	Linguistic fractionalization (DELFI)	-	√	*
H7: HT is increased by factors enforcing migration and attracting people to a specific (rich) country, ceteris paribus.	Migrants (share in population)	+		
	Size of population	+	√	***
	Refugees (per 100,000 people)	+		
	Catholics (share on population)	-		
	Heroin seized (kg)	+		
H8: Crime activities also have causal effects on HT, ceteris paribus.	Drug trafficking offences (per 100,000 people)	+	√	***

Note: Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 6: MIMIC estimates (yearly)

		(2000)	(2001)	(2002)	(2003)	(2004)	(2005)	(2006)	(2007)	(2008)	(2009)	(2010)
Structural model (causes)	(log) GDP pc const	0.839*** (6.467)	0.925*** (7.390)	0.955*** (7.521)	0.847*** (6.403)	0.728*** (5.219)	0.834*** (6.051)	0.808*** (5.886)	0.818*** (6.235)	0.820*** (6.071)	0.857*** (6.120)	0.827*** (5.809)
	(log) FDI stock	0.085 (1.349)	0.066 (1.122)	0.046 (0.802)	0.029 (0.473)	-0.007 (0.110)	0.073 (1.124)	0.088 (1.355)	0.098 (1.555)	0.071 (1.107)	0.042 (0.640)	0.061 (0.896)
	Employment in agriculture	0.258* (1.950)	0.378*** (3.060)	0.424*** (3.411)	0.342** (2.560)	0.379*** (2.951)	0.310** (2.184)	0.296** (2.172)	0.276** (2.090)	0.267** (1.976)	0.330** (2.365)	0.299** (2.094)
	Language fractionalization	-0.073 (1.158)	-0.066 (1.123)	-0.050 (0.867)	-0.067 (1.083)	-0.045 (0.737)	-0.065 (1.001)	-0.061 (0.964)	-0.089 (1.441)	-0.089 (1.404)	-0.097 (1.502)	-0.101 (1.508)
	Crime rate	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Measurement model (indicators)	Overall 3P-Index	0.588*** (4.999)	0.735*** (5.719)	0.720*** (5.103)	0.796*** (5.315)	0.990*** (4.392)	0.678*** (5.014)	0.722*** (5.224)	0.666*** (5.089)	0.621*** (4.890)	0.638*** (4.867)	0.501*** (3.792)
	Victims	0.196 (1.562)	0.272** (2.085)	0.283** (2.046)	0.129 (0.814)	0.280 (1.635)	-0.001 (0.011)	-0.008 (0.059)	-0.038 (0.297)	-0.012 (0.099)	0.030 (0.244)	0.146 (1.307)
	Number of countries	142	142	142	142	142	142	142	142	142	142	142
	Chi-square	12.49	8.47	11.09	20.61	15.55	15.86	8.37	6.84	5.54	4.13	3.16
	(P-value)	0.13	0.39	0.20	0.01	0.05	0.04	0.40	0.55	0.70	0.84	0.92

Note: Absolute z-statistics in parenthesis. Estimation with MLMV; *** p<0.01, ** p<0.05, * p<0.1. 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: larger p-values indicate better model fit.

Table 7: Country ranking and index (2000-2010)

Country	Rank 2000	Rank 2001	Rank 2002	Rank 2003	Rank 2004	Rank 2005	Rank 2006	Rank 2007	Rank 2008	Rank 2009	Rank 2010
United Kingdom	6 (68)	7 (58)	10 (53)	1 (74)	2 (57)	1 (96)	1 (84)	1 (70)	1 (76)	2 (79)	2 (92)
Sweden	2 (76)	3 (65)	5 (54)	2 (60)	3 (49)	2 (74)	2 (69)	2 (69)	2 (76)	3 (72)	3 (87)
Belgium	9 (63)	4 (61)	9 (53)	5 (58)	6 (49)	3 (66)	3 (62)	3 (64)	4 (68)	7 (60)	7 (64)
Norway	8 (66)	2 (71)	2 (61)	3 (60)	1 (90)	4 (64)	4 (61)	6 (61)	6 (62)	1 (85)	1 (100)
Denmark	4 (70)	6 (60)	4 (55)	4 (59)	7 (49)	5 (63)	5 (61)	4 (63)	3 (69)	6 (61)	6 (65)
Netherlands	7 (67)	5 (60)	8 (54)	6 (57)	4 (49)	6 (62)	6 (59)	5 (62)	5 (65)	4 (66)	5 (72)
New Zealand	3 (71)	18 (50)	20 (49)	24 (43)	21 (41)	7 (60)	7 (56)	8 (57)	8 (58)	13 (53)	12 (53)
Australia	16 (53)	15 (51)	19 (50)	7 (56)	10 (48)	8 (57)	21 (46)	14 (54)	13 (56)	14 (52)	14 (51)
Germany	10 (62)	10 (57)	15 (51)	11 (54)	9 (48)	9 (57)	11 (55)	15 (53)	12 (56)	11 (54)	9 (57)
Austria	14 (56)	12 (55)	11 (52)	12 (54)	11 (47)	10 (56)	8 (55)	10 (56)	7 (60)	12 (53)	10 (55)
United States	17 (52)	16 (51)	14 (51)	10 (54)	8 (48)	11 (56)	12 (55)	13 (54)	14 (55)	15 (51)	15 (50)
Switzerland	19 (51)	13 (54)	6 (54)	9 (55)	13 (46)	12 (55)	13 (54)	12 (55)	15 (54)	17 (47)	18 (47)
Iceland	1 (80)	1 (73)	1 (62)	13 (53)	17 (44)	13 (54)	9 (55)	9 (57)	9 (57)	5 (65)	4 (74)
Luxembourg	13 (56)	9 (58)	3 (60)	8 (55)	5 (49)	14 (54)	10 (55)	7 (58)	10 (57)	10 (55)	13 (51)
Finland	5 (68)	8 (58)	12 (52)	18 (49)	19 (43)	15 (54)	14 (54)	11 (55)	11 (57)	8 (58)	8 (60)
France	15 (55)	17 (51)	17 (50)	14 (52)	12 (46)	16 (53)	16 (52)	16 (52)	17 (52)	16 (50)	16 (50)
Canada	11 (61)	11 (56)	16 (50)	15 (52)	16 (45)	17 (52)	15 (53)	17 (51)	16 (53)	9 (56)	11 (54)
Israel	23 (46)	23 (44)	31 (42)	23 (43)	28 (38)	18 (51)	18 (49)	20 (47)	20 (46)	18 (47)	17 (48)
Ireland	22 (46)	14 (52)	7 (54)	16 (50)	18 (43)	19 (48)	19 (47)	18 (50)	22 (46)	19 (47)	23 (43)
Italy	21 (47)	20 (48)	21 (48)	17 (50)	14 (46)	20 (48)	17 (49)	21 (46)	25 (44)	20 (47)	22 (43)
Spain	24 (45)	19 (49)	22 (47)	19 (46)	15 (46)	21 (47)	20 (46)	23 (45)	23 (45)	25 (41)	20 (44)
Bahamas,The	18 (52)	21 (46)	23 (46)	21 (44)	37 (35)	22 (46)	22 (46)	19 (48)	18 (48)	26 (41)	24 (43)
Portugal	25 (44)	24 (44)	26 (45)	20 (44)	20 (41)	23 (45)	24 (43)	25 (43)	24 (44)	29 (39)	34 (36)
Slovenia	34 (38)	27 (42)	30 (42)	26 (43)	23 (40)	24 (44)	23 (45)	22 (46)	21 (46)	22 (42)	25 (41)
Malta	28 (41)	33 (39)	35 (39)	29 (40)	34 (35)	25 (43)	27 (41)	26 (42)	27 (42)	31 (39)	39 (34)
Czech Republic	26 (41)	32 (39)	37 (37)	28 (40)	32 (36)	26 (43)	26 (42)	28 (42)	28 (41)	28 (39)	28 (39)
Japan	40 (35)	28 (41)	24 (46)	22 (44)	24 (39)	27 (42)	29 (40)	30 (41)	29 (40)	37 (36)	49 (30)
Gabon	33 (38)	37 (37)	43 (35)	37 (36)	27 (38)	28 (41)	35 (38)	32 (40)	32 (39)	30 (39)	27 (40)
Trinidad and Tobago	37 (36)	40 (36)	41 (36)	41 (35)	57 (29)	29 (40)	25 (43)	27 (42)	26 (43)	21 (43)	19 (46)
Chile	12 (57)	42 (35)	49 (34)	46 (33)	45 (32)	30 (38)	34 (38)	40 (37)	31 (39)	24 (42)	26 (40)
Estonia	32 (39)	41 (36)	51 (34)	44 (34)	49 (31)	31 (38)	40 (36)	38 (38)	35 (38)	35 (37)	33 (37)
Singapore	42 (35)	30 (41)	28 (44)	35 (37)	35 (35)	32 (38)	28 (40)	29 (42)	40 (36)	41 (34)	40 (33)
Croatia	44 (33)	43 (35)	40 (36)	42 (34)	31 (36)	33 (38)	36 (37)	34 (39)	34 (38)	34 (37)	43 (33)
Poland	35 (38)	35 (38)	39 (37)	34 (37)	29 (37)	34 (37)	38 (37)	24 (45)	19 (48)	27 (40)	30 (39)
Bahrain	41 (35)	38 (37)	34 (39)	47 (33)	61 (28)	35 (37)	45 (35)	45 (35)	39 (36)	44 (33)	46 (31)
Greece	46 (32)	29 (41)	27 (45)	30 (39)	30 (36)	36 (37)	30 (39)	31 (40)	30 (39)	23 (42)	35 (36)
Hungary	29 (41)	36 (38)	42 (36)	39 (36)	47 (32)	37 (36)	33 (38)	33 (39)	36 (37)	33 (38)	31 (38)

Table 7: (continued)

Country	Rank 2000	Rank 2001	Rank 2002	Rank 2003	Rank 2004	Rank 2005	Rank 2006	Rank 2007	Rank 2008	Rank 2009	Rank 2010
Brazil	36 (36)	52 (31)	54 (31)	45 (33)	44 (32)	38 (36)	42 (35)	44 (35)	33 (38)	38 (36)	32 (37)
Korea, Rep.	27 (41)	34 (39)	33 (41)	32 (38)	22 (40)	39 (35)	31 (38)	36 (38)	37 (37)	32 (38)	36 (35)
Cyprus	31 (39)	26 (43)	29 (44)	31 (39)	26 (39)	40 (35)	32 (38)	37 (38)	38 (37)	36 (36)	38 (34)
Lithuania	47 (32)	45 (33)	52 (33)	36 (37)	36 (35)	41 (34)	39 (36)	43 (35)	47 (33)	54 (30)	66 (27)
United Arab Emirates	30 (39)	25 (43)	18 (50)	25 (43)	33 (36)	42 (34)	41 (36)	35 (39)	41 (35)	39 (35)	52 (29)
Swaziland	43 (34)	54 (31)	63 (29)	48 (33)	67 (27)	43 (33)	60 (29)	49 (32)	42 (35)	43 (33)	21 (44)
Turkey	74 (24)	46 (33)	36 (38)	43 (34)	40 (34)	44 (33)	46 (34)	47 (33)	56 (30)	48 (32)	59 (28)
Latvia	56 (29)	55 (30)	56 (31)	51 (32)	46 (32)	45 (32)	43 (35)	46 (33)	49 (32)	53 (31)	50 (30)
Slovak Republic	50 (30)	48 (32)	46 (35)	49 (32)	56 (29)	46 (32)	47 (33)	42 (35)	44 (34)	42 (34)	45 (33)
Mauritius	45 (32)	57 (29)	67 (28)	64 (28)	59 (28)	47 (31)	57 (30)	51 (31)	48 (33)	45 (33)	41 (33)
Qatar	38 (36)	22 (44)	13 (51)	27 (42)	39 (34)	48 (31)	37 (37)	39 (38)	46 (33)	40 (35)	48 (30)
Belize	49 (31)	58 (29)	65 (28)	62 (29)	55 (30)	49 (31)	48 (33)	50 (31)	54 (31)	64 (28)	47 (31)
Brunei Darussalam	39 (35)	31 (40)	25 (45)	38 (36)	50 (31)	50 (31)	44 (35)	41 (37)	50 (32)	49 (32)	51 (29)
Argentina	51 (30)	69 (26)	91 (22)	85 (23)	96 (24)	51 (30)	51 (30)	69 (28)	57 (30)	60 (29)	44 (33)
Belarus	73 (24)	75 (25)	70 (27)	59 (30)	43 (33)	52 (29)	61 (29)	62 (29)	60 (29)	55 (30)	56 (29)
Russian Federation	67 (26)	73 (25)	77 (26)	71 (27)	78 (26)	53 (29)	49 (32)	54 (30)	62 (29)	69 (28)	65 (27)
Namibia	54 (29)	64 (27)	62 (29)	66 (28)	65 (28)	54 (29)	59 (29)	56 (30)	68 (27)	68 (28)	55 (29)
Bosnia and Herzegovina	75 (24)	65 (27)	57 (30)	58 (30)	48 (31)	55 (29)	53 (30)	53 (31)	55 (30)	46 (32)	63 (27)
Cuba	52 (30)	81 (24)	84 (23)	72 (27)	88 (25)	56 (29)	64 (28)	68 (28)	43 (34)	51 (31)	37 (35)
Bulgaria	72 (25)	83 (24)	85 (23)	69 (27)	54 (30)	57 (28)	62 (29)	63 (29)	67 (28)	63 (29)	54 (29)
Romania	48 (31)	39 (37)	44 (35)	40 (35)	25 (39)	58 (28)	55 (30)	55 (30)	61 (29)	58 (29)	67 (27)
Kuwait	55 (29)	44 (35)	32 (42)	33 (37)	42 (33)	59 (28)	54 (30)	52 (31)	52 (31)	62 (29)	82 (23)
Albania	60 (27)	47 (33)	48 (34)	55 (31)	38 (35)	60 (28)	63 (28)	73 (27)	73 (26)	52 (31)	53 (29)
Mexico	53 (29)	49 (32)	50 (34)	63 (28)	64 (28)	61 (28)	56 (30)	61 (29)	74 (26)	67 (28)	77 (24)
Panama	66 (26)	61 (28)	61 (29)	67 (27)	68 (27)	62 (27)	52 (30)	60 (29)	64 (28)	59 (29)	70 (26)
Thailand	69 (25)	56 (30)	53 (32)	50 (32)	41 (33)	63 (27)	58 (29)	58 (30)	63 (28)	73 (27)	76 (25)
Ecuador	64 (26)	67 (27)	99 (21)	87 (23)	105 (22)	64 (27)	67 (28)	71 (27)	70 (27)	71 (28)	75 (25)
Morocco	98 (20)	124 (15)	68 (27)	73 (27)	58 (29)	65 (27)	72 (26)	81 (24)	87 (22)	86 (22)	97 (20)
Kazakhstan	85 (21)	62 (28)	55 (31)	61 (29)	52 (31)	66 (26)	66 (28)	65 (29)	65 (28)	57 (29)	64 (27)
Colombia	76 (24)	70 (26)	73 (26)	70 (27)	66 (27)	67 (26)	68 (27)	76 (26)	80 (24)	79 (25)	87 (22)
Costa Rica	61 (27)	66 (27)	71 (27)	68 (27)	76 (26)	68 (26)	65 (28)	75 (27)	69 (27)	65 (28)	72 (25)
Lebanon	59 (27)	51 (31)	38 (37)	52 (32)	53 (30)	69 (26)	73 (26)	59 (29)	72 (26)	70 (28)	78 (24)
Dominican Republic	57 (28)	79 (25)	78 (25)	78 (25)	95 (24)	70 (26)	74 (26)	72 (27)	66 (28)	76 (26)	60 (28)
Saudi Arabia	62 (26)	60 (29)	47 (35)	53 (32)	60 (28)	71 (25)	70 (26)	74 (27)	75 (25)	72 (27)	90 (22)
Macedonia, FYR	83 (22)	78 (25)	76 (26)	60 (29)	79 (26)	72 (24)	71 (26)	78 (26)	79 (25)	80 (24)	93 (21)
Tunisia	80 (23)	68 (26)	64 (29)	77 (25)	81 (26)	73 (24)	86 (23)	82 (24)	82 (23)	83 (23)	94 (21)
Oman	63 (26)	53 (31)	45 (35)	57 (30)	75 (27)	74 (24)	69 (27)	66 (28)	58 (30)	56 (30)	80 (24)

Table 7: (continued)

Country	Rank 2000	Rank 2001	Rank 2002	Rank 2003	Rank 2004	Rank 2005	Rank 2006	Rank 2007	Rank 2008	Rank 2009	Rank 2010
Malaysia	68 (25)	59 (29)	60 (30)	65 (28)	72 (27)	75 (24)	77 (25)	70 (28)	71 (26)	78 (25)	71 (26)
Georgia	107 (18)	87 (22)	80 (25)	82 (24)	69 (27)	76 (24)	50 (30)	64 (29)	59 (29)	66 (28)	62 (27)
Venezuela, RB	78 (24)	71 (26)	72 (26)	92 (22)	116 (20)	77 (24)	83 (24)	77 (26)	77 (25)	75 (26)	81 (24)
El Salvador	97 (20)	84 (23)	87 (23)	81 (24)	98 (24)	78 (24)	75 (25)	85 (23)	83 (23)	90 (22)	99 (20)
Zambia	100 (19)	82 (24)	79 (25)	79 (25)	62 (28)	79 (23)	78 (24)	94 (20)	84 (23)	81 (24)	92 (21)
Zimbabwe	71 (25)	76 (25)	83 (23)	86 (23)	100 (24)	80 (23)	87 (23)	102 (19)	107 (18)	114 (17)	100 (20)
China	87 (21)	74 (25)	74 (26)	76 (26)	70 (27)	81 (23)	81 (24)	83 (24)	76 (25)	74 (27)	61 (27)
Honduras	88 (21)	92 (21)	93 (22)	99 (20)	111 (21)	82 (23)	79 (24)	88 (22)	90 (22)	92 (21)	86 (22)
Ukraine	96 (20)	107 (19)	117 (16)	91 (22)	108 (22)	83 (23)	96 (21)	93 (21)	91 (21)	109 (18)	102 (19)
Indonesia	89 (20)	106 (19)	95 (21)	84 (24)	77 (26)	84 (23)	93 (21)	84 (23)	89 (22)	87 (22)	95 (21)
Guatemala	84 (21)	72 (26)	66 (28)	75 (26)	71 (27)	85 (22)	88 (23)	86 (23)	85 (22)	85 (23)	91 (21)
Sri Lanka	70 (25)	93 (21)	108 (19)	97 (21)	97 (24)	86 (22)	92 (21)	92 (21)	94 (21)	88 (22)	57 (29)
Maldives	65 (26)	88 (22)	88 (23)	88 (23)	123 (19)	87 (22)	85 (23)	67 (28)	45 (34)	89 (22)	68 (26)
Armenia	115 (17)	95 (21)	89 (23)	80 (25)	93 (24)	88 (22)	76 (25)	80 (25)	81 (24)	77 (25)	79 (24)
Nigeria	108 (18)	112 (17)	116 (17)	106 (19)	84 (26)	89 (22)	95 (21)	104 (18)	93 (21)	94 (21)	113 (18)
Botswana	77 (24)	80 (24)	58 (30)	74 (27)	74 (27)	90 (21)	84 (23)	79 (25)	78 (25)	82 (24)	73 (25)
Uruguay	58 (28)	63 (28)	81 (25)	56 (31)	89 (25)	91 (21)	82 (24)	57 (30)	53 (31)	50 (31)	42 (33)
South Africa	20 (47)	50 (32)	59 (30)	54 (32)	73 (27)	92 (21)	94 (21)	48 (33)	51 (32)	47 (32)	29 (39)
Nicaragua	79 (23)	86 (23)	102 (19)	104 (19)	109 (22)	93 (21)	90 (22)	91 (21)	98 (19)	98 (20)	88 (22)
Burkina Faso	86 (21)	94 (21)	94 (21)	90 (22)	51 (31)	94 (21)	101 (20)	113 (17)	102 (18)	93 (21)	106 (19)
Azerbaijan	126 (15)	115 (17)	101 (20)	109 (18)	118 (20)	95 (20)	80 (24)	87 (23)	88 (22)	61 (29)	58 (28)
Congo, Rep.	95 (20)	89 (22)	82 (24)	93 (21)	107 (22)	96 (20)	91 (22)	89 (21)	92 (21)	99 (20)	89 (22)
Philippines	118 (16)	118 (16)	107 (19)	96 (21)	82 (26)	97 (20)	89 (22)	95 (20)	105 (18)	97 (21)	104 (19)
Mongolia	92 (20)	103 (19)	109 (19)	100 (20)	125 (19)	98 (20)	99 (20)	99 (19)	101 (19)	96 (21)	83 (23)
Cambodia	105 (18)	109 (18)	106 (19)	101 (20)	91 (24)	99 (19)	98 (20)	96 (20)	100 (19)	103 (19)	101 (19)
Vietnam	90 (20)	90 (21)	98 (21)	103 (19)	85 (25)	100 (19)	104 (19)	98 (20)	99 (19)	84 (23)	96 (20)
Paraguay	113 (17)	97 (20)	96 (21)	98 (21)	106 (22)	101 (19)	112 (18)	97 (20)	95 (20)	104 (19)	85 (22)
Pakistan	137 (11)	123 (15)	129 (14)	124 (16)	80 (26)	102 (19)	115 (17)	114 (16)	122 (14)	128 (14)	127 (15)
Guyana	106 (18)	110 (18)	125 (15)	134 (13)	137 (17)	103 (19)	97 (20)	105 (18)	104 (18)	118 (16)	121 (16)
Moldova	103 (19)	100 (20)	103 (19)	107 (19)	104 (23)	104 (19)	119 (16)	115 (16)	110 (17)	102 (20)	69 (26)
Papua New Guinea	117 (17)	85 (23)	69 (27)	89 (22)	90 (24)	105 (19)	100 (20)	103 (19)	111 (17)	113 (17)	123 (16)
Iran, Islamic Rep.	99 (20)	98 (20)	92 (22)	94 (21)	87 (25)	106 (18)	106 (18)	108 (18)	116 (16)	106 (19)	103 (19)
Cote d'Ivoire	101 (19)	91 (21)	100 (20)	110 (18)	103 (23)	107 (18)	103 (20)	120 (15)	119 (15)	124 (15)	133 (13)
Cameroon	82 (22)	77 (25)	75 (26)	83 (24)	94 (24)	108 (18)	109 (18)	118 (15)	117 (16)	108 (18)	111 (18)
Tanzania	125 (15)	108 (19)	97 (21)	102 (20)	101 (24)	109 (18)	110 (18)	110 (17)	114 (16)	121 (16)	122 (16)
Peru	94 (20)	116 (17)	120 (16)	116 (17)	138 (17)	110 (18)	102 (20)	100 (19)	96 (20)	91 (22)	84 (22)
Senegal	119 (16)	114 (17)	128 (14)	128 (15)	99 (24)	111 (17)	120 (16)	112 (17)	109 (17)	122 (16)	109 (18)

Table 7: (continued)

Country	Rank 2000	Rank 2001	Rank 2002	Rank 2003	Rank 2004	Rank 2005	Rank 2006	Rank 2007	Rank 2008	Rank 2009	Rank 2010
Mozambique	135 (12)	125 (15)	111 (18)	117 (17)	114 (21)	112 (17)	116 (16)	119 (15)	118 (15)	129 (14)	132 (13)
Lesotho	104 (18)	105 (19)	113 (17)	112 (18)	124 (19)	113 (17)	114 (17)	111 (17)	103 (18)	111 (18)	74 (25)
Ghana	122 (15)	120 (16)	118 (16)	108 (19)	115 (20)	114 (17)	105 (18)	117 (15)	115 (16)	120 (16)	124 (16)
Algeria	102 (19)	96 (20)	90 (22)	105 (19)	121 (20)	115 (17)	113 (18)	106 (18)	112 (17)	112 (18)	114 (18)
Chad	140 (9)	137 (9)	138 (10)	138 (12)	127 (18)	116 (17)	137 (13)	137 (11)	132 (12)	139 (9)	138 (10)
Uzbekistan	129 (14)	134 (13)	134 (12)	119 (17)	113 (21)	117 (17)	127 (14)	121 (15)	113 (16)	105 (19)	119 (17)
Jordan	91 (20)	113 (17)	124 (15)	118 (17)	129 (18)	118 (16)	108 (18)	90 (21)	86 (22)	95 (21)	98 (20)
Uganda	123 (15)	133 (14)	126 (14)	129 (15)	117 (20)	119 (16)	123 (15)	130 (12)	128 (13)	110 (18)	117 (17)
Yemen, Rep.	134 (12)	117 (17)	112 (18)	121 (17)	126 (19)	120 (16)	124 (15)	122 (15)	124 (14)	132 (14)	130 (13)
India	93 (20)	101 (20)	105 (19)	95 (21)	63 (28)	121 (16)	107 (18)	109 (17)	108 (17)	101 (20)	116 (17)
Malawi	136 (11)	138 (9)	141 (6)	140 (9)	134 (17)	122 (16)	132 (14)	138 (10)	139 (10)	138 (9)	136 (10)
Madagascar	130 (14)	126 (14)	122 (15)	120 (17)	92 (24)	123 (15)	122 (15)	123 (15)	121 (14)	136 (12)	139 (9)
Benin	109 (17)	121 (16)	130 (13)	123 (16)	110 (22)	124 (15)	131 (14)	126 (13)	123 (14)	125 (15)	118 (17)
Gambia, The	132 (13)	135 (13)	132 (13)	135 (13)	133 (17)	125 (15)	135 (13)	134 (12)	129 (13)	137 (11)	137 (10)
Egypt, Arab Rep.	110 (17)	122 (15)	119 (16)	130 (15)	139 (16)	126 (15)	134 (13)	116 (16)	127 (13)	119 (16)	107 (18)
Bolivia	112 (17)	104 (19)	110 (19)	115 (17)	136 (17)	127 (15)	111 (18)	107 (18)	97 (20)	107 (19)	105 (19)
Mali	131 (13)	128 (14)	127 (14)	113 (18)	128 (18)	128 (15)	121 (16)	133 (12)	126 (13)	135 (12)	134 (11)
Turkmenistan	116 (17)	99 (20)	86 (23)	111 (18)	130 (17)	129 (15)	117 (16)	101 (19)	106 (18)	100 (20)	112 (18)
Bangladesh	120 (16)	127 (14)	135 (12)	126 (16)	102 (24)	130 (14)	128 (14)	127 (13)	120 (15)	117 (16)	125 (15)
Kyrgyz Republic	128 (14)	129 (14)	131 (13)	127 (16)	122 (19)	131 (14)	136 (13)	135 (11)	133 (12)	126 (15)	126 (15)
Tajikistan	133 (12)	140 (9)	137 (10)	133 (14)	120 (20)	132 (14)	130 (14)	131 (12)	134 (12)	127 (15)	108 (18)
Kenya	114 (17)	111 (18)	114 (17)	114 (17)	86 (25)	133 (14)	126 (14)	124 (14)	130 (13)	116 (16)	110 (18)
Sudan	124 (15)	132 (14)	121 (16)	132 (14)	135 (17)	134 (14)	125 (15)	132 (12)	137 (12)	130 (14)	120 (17)
Iraq	81 (23)	102 (19)	115 (17)	136 (13)	141 (14)	135 (14)	118 (16)	128 (13)	131 (12)	123 (15)	128 (15)
Sierra Leone	121 (16)	131 (14)	123 (15)	131 (15)	119 (20)	136 (14)	129 (14)	125 (13)	125 (13)	115 (17)	115 (18)
Ethiopia	141 (9)	136 (11)	136 (12)	137 (12)	112 (21)	137 (14)	133 (14)	136 (11)	136 (12)	133 (13)	131 (13)
Nepal	127 (14)	130 (14)	133 (12)	122 (17)	83 (26)	138 (13)	138 (13)	139 (10)	138 (11)	134 (12)	135 (11)
Syrian Arab Republic	111 (17)	119 (16)	104 (19)	125 (16)	132 (17)	139 (12)	139 (12)	129 (12)	135 (12)	131 (14)	129 (14)
Niger	138 (10)	139 (9)	139 (8)	139 (12)	131 (17)	140 (10)	141 (10)	141 (8)	141 (10)	141 (7)	140 (8)
Burundi	142 (6)	142 (5)	142 (4)	141 (9)	140 (15)	141 (7)	142 (3)	142 (0)	142 (2)	142 (7)	142 (4)
Liberia	139 (9)	141 (8)	140 (7)	142 (7)	142 (5)	142 (7)	140 (11)	140 (9)	140 (10)	140 (8)	141 (8)

Note: Countries are ranked according to the score in 2005.

Figure 1: Development of HT intensity in destination countries

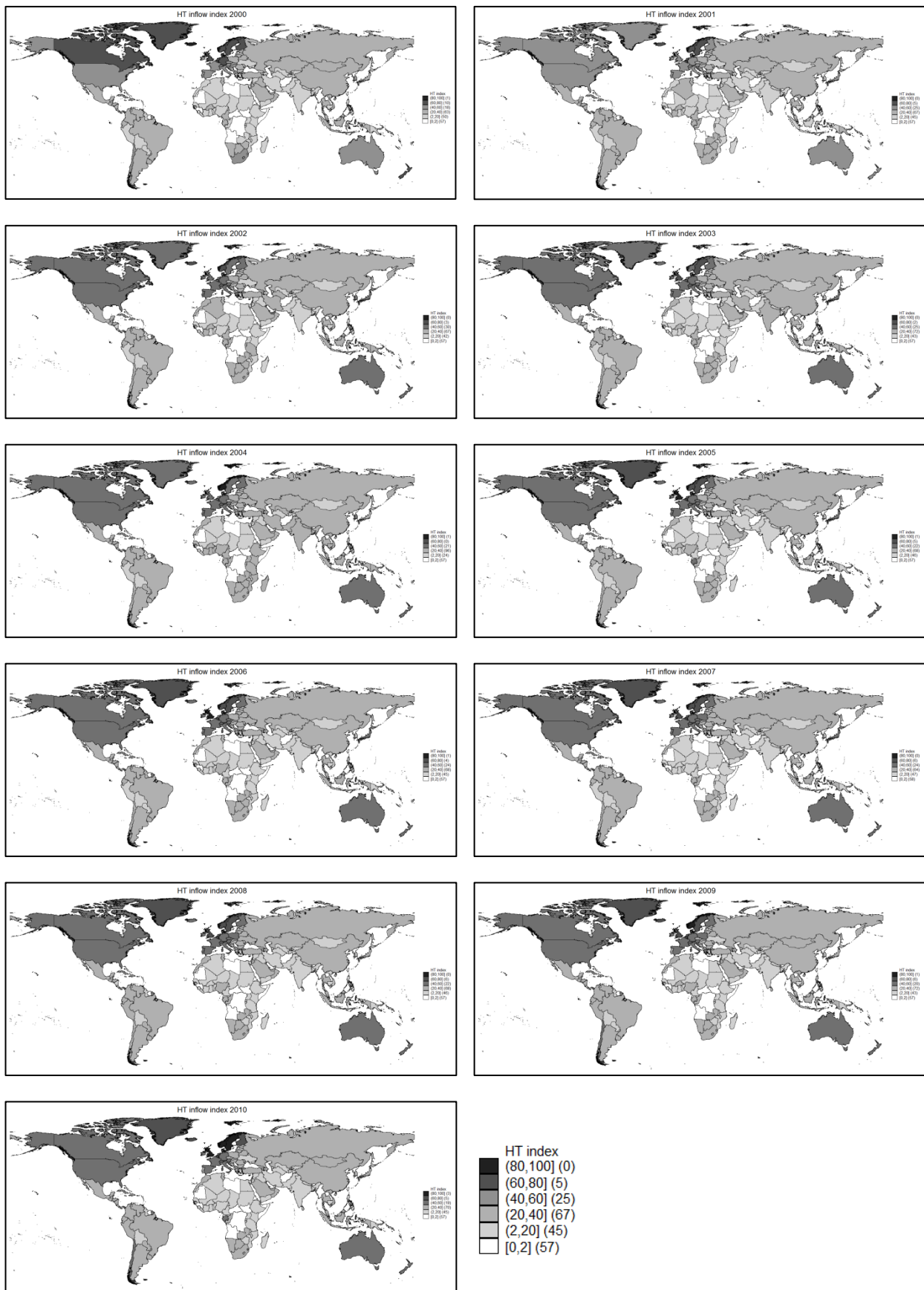


Table 7: Pair wise correlations between indices

	HT inflow	Tier rank	CI: destination	CI: origin
HT inflow	1			
Tier rank	0.473	1		
CI: destination	0.490	0.294	1	
CI: origin	-0.350	-0.166	-0.0743	1

Note: The tier rank is reversed and shows higher values the better countries fulfil the TVPA standards. CI: destination/origin stands for the citation index compiled by the UNODC. The countries are ranked in a five category scale with the highest value indicating that the probability of being a destination/origin country is "very high".

Appendix A: Formal model

Jöreskog and Goldberger (1975) developed the formal specification of the approach for one latent variable. It encompasses a system of two equations: First, showing how the unobservable variable in the measurement equation model determines the examined endogenous variables; and second how the latent variable and its causes interact. Thus, formally, the model is characterized in the following way. The independent indicators are denoted by y_i ($i = 1, \dots, m$) and η is the latent variable (i.e., human trafficking) such that:

$$y_i = \beta_i \eta + \varepsilon_i \quad (1)$$

The $1 \times m$ parameter vector $\beta_i = \{\beta_1, \beta_2, \dots, \beta_m\}'$ embodies the coefficients which indicate the estimated alteration in the respective indicators after a one unit change in the latent variable. The error terms ε_i , $i = 1, \dots, m$ have mean zero and covariance matrix Θ_ε . The correlation across indicators is exclusively determined by the common factor η . Equation (1) is a confirmatory factor analysis model for the observable indicators $y = (y_1, y_2, \dots, y_m)'$ including the common factor η and the unique factor ε_i . In the covariance matrix Θ_ε , the diagonal elements are represented in the $1 \times m$ vector τ .

Moreover, the latent unobservable variable η can be linearly decomposed in the following way:

$$\eta = \alpha' \mathbf{x} + \omega, \quad (2)$$

where $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_s)'$ are parameters, $\mathbf{x} = (x_1, x_2, \dots, x_s)'$ is the vector of observable exogenous causal variables and a stochastic error term ω . The model described in equation (1) is also called a measurement model of the observed endogenous indicators determined by the latent variable. Any correlation between the elements of y results from the association with η . The indicators are assumed to be partially independent between all indicator pairs i and j setting all diagonal elements of Θ_ε equal to zero. The second component of the model is a structural equation (2) that characterizes the relationship between the latent variable and its causes. The structural parameters α are not directly estimable due to the latent nature of the objective variable. Therefore equation (1) is inserted in equation (2) in order to derive the reduced form which connects the observable variables from (1) and (2) via the equation

$$\mathbf{y} = \mathbf{\Pi}' \mathbf{x} + \boldsymbol{\gamma}. \quad (3)$$

This is a multivariate regression model, which includes the endogenous indicators $\mathbf{y} = (y_1 \dots y_n)'$ and the exogenous causes $\mathbf{x} = (x_1, x_2, \dots, x_s)'$ of the latent factors η . The reduced form coefficient matrix has the rank $(m \times s) = 1$ and is given by $\mathbf{\Pi} = \alpha \beta'$. The $(1 \times m)$ reduced form disturbance vector reads as $\boldsymbol{\gamma} = \beta \omega + \boldsymbol{\varepsilon}$ and has the error covariance matrix

$$\Theta_{\omega} = E[(\beta\omega + \varepsilon)(\beta\omega + \varepsilon)'] = \sigma_{\omega}^2\beta\beta' + \Theta_{\varepsilon}. \quad (4)$$

The variance (σ_{ω}^2) of the stochastic error term ω has the characteristic structure of the covariance matrix of a factor analysis model. This error covariance matrix is constrained similarly to Π , because it is the sum of a one-rank matrix and a diagonal matrix. Therefore one of the elements of the factor loading vector β has to be constrained in order to identify the model (Bollen 1989).²⁸ The choice of which indicator is normalized determines the scale of the latent variable, but it does not affect the results of the measurement. I follow the literature and use the indicator with the largest factor loading (Bollen 1989).

Accordingly, the estimation procedure and the identification of the model are derived by relations of the observable data, $z = (y'x')'$. The $(m + s) \times (m + s)$ covariance of the underlying model defined by equations (1) and (2) shows the relationship in terms of their respective covariance

$$\Sigma(\varphi) = \begin{bmatrix} \beta(a'\phi_x\alpha + \sigma_{\omega}^2)\beta' + \Theta_{\varepsilon} & \beta\alpha'\phi_x \\ \phi_x\alpha'\beta & \phi_x \end{bmatrix}. \quad (5)$$

Where φ is the vector of independent, but correlated parameters β , a , Θ_{ε} and σ_{ω}^2 . The elements on the main-diagonal are $E[yy'] = \beta(a'\phi_x\alpha + \sigma_{\omega}^2)\beta' + \Theta_{\varepsilon}$ and $E[xx'] = \phi_x$ and the off-diagonal components are $E[xy'] = \beta\alpha'E[xx']$. Applying this information for the population, parameters are derived resulting in an estimate of the best approximation of the sample covariance matrix of the observed causes and indicators, $\widehat{\Sigma} = \Sigma(\widehat{\varphi})$. Apparently, this pattern is driven by the unobservable variable.

Given (5), identification depends on the information in the matrix and whether it is sufficient to provide a unique set of values in φ . The set of mean parameters will then be identified if $q - p \geq 0$, with $q = ms$ observable moments in terms of structural parameters and $p = m + s$, which is shaped by the off-diagonal elements. If this condition holds, the remaining parameters on the diagonal will be identified. In combination this implies that the necessary condition for identification of all parameters is given by

$$p \leq \frac{1}{2}(m + s)(m + s + 1). \quad (6)$$

²⁸ Following the literature (e.g., Dreher et al. 2007 and Buehn and Farzanegan 2012) this approach is used here where one of the coefficients of the coefficient vector β is fixed to an a priori value, such that the unit of measurement for the unobserved term is normalized relative to one of the indicator variables. Another possibility is applied mainly in factor analysis where the latent variable is standardized to have unit variance (e.g., Di Tommaso et al. 2009).

Estimation of $\Sigma(\varphi)$, $\widehat{\Sigma} = \Sigma(\widehat{\varphi})$ is obtained if the parameter and covariance values are chosen in such a way that the difference between the estimate and the real sample covariance \mathbf{S} of the causes and indicators is minimized using the following objective function:

$$F = \ln|\Sigma(\varphi)| + tr[S\Sigma^{-1}(\widehat{\varphi})] - \ln|S| - (m + s),^{29} \quad (7)$$

which is a likelihood function assuming a multivariate normal distribution. The sufficient rule for the MIMIC model to be identified is $m \geq 2$ and $s \geq 1$ (Bollen 1989: 331). Perfect fit would be achieved if the real sample covariance is equal to the estimated covariance, $\mathbf{S} = \Sigma(\widehat{\varphi})$. This is evaluated using several indices specified below.

After identification of the relationship between the variables and the estimation of the parameters, the latent scores of η for each country can be specified assigning factor scores using the mean vector and variance matrix of the fitted model. This method was suggested by Jöreskog (2000) and uses more structural information than a simple linear application.³⁰ For this reason the factor score is used for the generation of the final country ranking. The factor score is generated in the following way:

$$\tilde{\eta} = \widehat{\Sigma}'_{z\eta} \widehat{\Sigma}_{zz}^{-1} \hat{\mu}_z + \hat{\mu}_\eta \quad (8)$$

with $z = (y'x)'$ the vector of all observable causes and indicators from equation (3), $Z = (z'\eta)'$ the vector of all variables of the model, $\hat{\mu}_z = \hat{\mu}_z \hat{\mu}_\eta$ is the fitted mean of Z and $\widehat{\Sigma}_Z = \begin{pmatrix} \widehat{\Sigma}_{zz} & \widehat{\Sigma}_{z\eta} \\ \widehat{\Sigma}'_{z\eta} & \widehat{\Sigma}_{\eta\eta} \end{pmatrix}$ is the fitted variance. Thus, the factor score is the fitted mean prediction of the latent variable, similar to prediction of the dependent variable in regression models, weighted by minimizing the objective function (7). The score of the latent variable is subsequently obtained by implementing these weights, the estimated coefficients of the measurement and the structural model in equation (8). This said, the model is applied to measure the extent of human trafficking in destination countries. The application and graphic representation are specified in the following section.

²⁹ The maximum likelihood estimator with missing values (mlmv) is implemented into STATA's sem command in order to account for the missing values in the observable data (Jöreskog 1973). Since the maximization of the log likelihood does not depend on the complete information of individuals the estimator also considers all partially complete data in the estimation process. This procedure is similar to multiple imputation and provides unbiased estimates (Baraldi and Enders 2010).

³⁰ The linear prediction is specified as well and gives similar results with a rank correlation of larger than 85 percent.

Appendix A: Table1: MIMIC with all significant variables

		(Table 2)	(Table 3)	(Table 4)
Structural model	(log) GDP per capita	1.014*** (6.946)	1.334*** (5.755)	0.809*** (6.604)
	(log) FDI stock	0.179** (2.434)	0.071 (0.608)	0.122* (1.857)
	Employment in agriculture	0.387*** (2.788)	0.392 (1.613)	0.263** (2.224)
	Language fractionalization	-0.039 (0.591)	0.048 (0.399)	-0.030 (0.529)
	(log) Population	0.099 (1.339)	-0.034 (0.287)	0.037 (0.555)
	Migrants	-0.219*** (3.142)	-0.372*** (2.767)	-0.194*** (3.371)
	Tourism arrival	-0.068 (0.874)	-0.264* (1.796)	-0.021 (0.323)
	Drug trafficking offences	0.220*** (3.072)	0.192** (2.322)	0.266*** (2.757)
	Measurement model	Crime rate	1	1
Overall 3P-index		0.825*** (6.748)	0.654*** (7.608)	0.920*** (5.810)
Victims per 100,000		0.015 (0.118)	-0.047 (0.307)	-0.125 (0.762)
	Number of countries	142	60	136
	Chi-square	43.72	16.12	47.15
	(P-value)	0.00	0.44	0.00
	RMSEA	0.11	0.01	0.12
	Probability RMSEA<0.05	0.01	0.60	0.00
	CFI	0.84	1.00	0.80
	TLI	0.73	1.00	0.67
	CD	0.86	0.80	0.85

Note: see footnote table 2; absolute z-statistics in parenthesis; *** p<0.01, ** p<0.05, * p<0.1.

Appendix B: Data and Sources

Variables	Description	Sources
(log) GDP per capita	GDP per capita in constant US\$ (2005)	World Bank (2012)
(log) FDI stock share	Inward and outward FDI stock as percentage of GDP	UNCTAD (2012)
(log) Population	Total population per country per year	World Bank (2012)
Employment in agriculture (percent of total)	Share of employment in agriculture as percentage of total employment	World Bank (2012)
International migrants (share)	Number of (officially registered) international migrants in the country as share of total population	World Bank (2012)
Refugees by country of origin	Number of (officially registered) refugees in the country per 100,000 of local population	World Bank (2012)
East Asia and the Pacific (region dummy)	Dummy indicating countries lying in East Asia and the Pacific region according to the World Bank	World Bank (2012)
International tourism arrivals (share)	International tourists arriving in countries per year in 100,000 per local population	World Bank (2012)
Information flow (KOF Social Globalization)	Sub-components of the KOF globalization index including telecommunication as well as access to internet and newspaper proliferation. 0-100, larger values indicating more information availability	Dreher et al. (2008)
Linguistic fractionalization	Linguistic fractionalization in countries as part of the distance adjusted ethnolinguistic fractionalization index (DELFI); 0-1, larger values indicating larger linguistic dissimilarities	Kolo (2012), Alesina et al. (2003)
Heroin seizure	Amount of heroin seized per year in kg	United Nations (2008) CTS Database
Police personnel	Number of police personnel active in the country per 100,000 people	United Nations (2008) CTS Database
Crime rate	Crime rate in the country per 100,000 people	United Nations (2008) CTS Database
Drug trafficking	Drug trafficking offences per 100,000 people	United Nations (2008) CTS Database
OECD membership	Dummy for OECD countries	OECD (2012)
Catholics	Share of Catholics in the overall population	Encyclopedia Britannica Book (2001)
Victims	Number of identified human trafficking victims in destination countries coded by the UNODC in their <i>Global Report on Trafficking in Persons</i>	UNODC (2009, 2012)
CI: destination	Citation index of destination countries coded by the UNODC using open source information. Lower values indicating a larger probability to	UNODC (2006)

	be a destination country	
CI: origin	Citation index of countries of origin coded by the UNODC using open source information. Lower values indicating a larger probability to be a country of origin	UNODC (2006)
3P-anti-trafficking index and sub-components (prosecution, protection, prevention)	Anti-trafficking policy index which shows the application of anti-trafficking instruments in countries; 3-15, larger values indicating more compliance; Sub-components are the policy instruments applicable ranging from 1-5	Cho et al. (forthcoming)