RIMCO2

Analysing Criminal Policies

Policy Making in Human Trafficking:

A Critical Examination of a Quantitative Dataset and EU Measures

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1. ***Introduction***

The fight against human trafficking demands both rigorous scientific investigation and practical policy solutions. Human trafficking represents one of the most serious human rights violations in modern society, and this research addresses crucial societal and scientific imperatives in understanding and combating human trafficking, focusing on forced and child labour within the European Union Context.

Quantitative research is essential for evidence-based policy making in this field for several key reasons. As Bryant & Landman (2020) emphasise, systematic data collection and analysis helps policy makers make well-informed decisions rather than relying on assumptions or emotions. Additionally, reliable quantitative data enables governments to identify priorities, evaluate past initiatives' effectiveness, and make informed resource allocation decisions.

However, several critical challenges exist in current trafficking datasets. As Cockbain & Kleemans (2019) note, research has focused predominantly on sex trafficking, with Forced Labour (FL) and Child Labour (CL) receiving less scholarly attention (Andrees, 2008). The transnational nature of trafficking also complicates data collection, as traffickers often recruit victims in their home countries before exploiting them at their destination (UNODC, 2017). Thus, failure on the part of the destination country to identify, protect and support victims and victim witnesses through an effective criminal justice system will result in a greater negative impact. Furthermore, while countries employ various policy approaches –from strict enforcement and prosecution to victim-centred services– their relative effectiveness in addressing different forms of trafficking remains unclear.

This research aims to address these gaps by examining two interconnected questions.

1. To what extent do different policy measures (enforcement, conviction and victims services) predict a country's likelihood of being identified as a destination for FL and CL trafficking in EU countries?
    a. How do the factors influencing a country's status as a destination for FL trafficking differ from the factors influencing its status as a destination for CL trafficking?

2. ***Reflection on available datasets***

Choosing the right dataset is a fundamental step in conducting research to inform policy making. The available data and its characteristics will significantly shape the type of questions that can be addressed, the insights that can be generated and the quality of the evidence used to guide policy decisions. There are several key factors to evaluate when assessing the suitability and appropriateness of datasets for policymaking research.

2.1. Datasets Categories and Research Applications

In the field of HT research, there are several key categories of quantitative datasets that can be distinguished. These datasets reflect the complex, multi-layered nature of this criminal phenomenon. From global prevalence estimates to individual case files, trafficking data can be broadly categorised into macro- and micro-level measurements (Goździak & Bump, 2008). At the macro-level, datasets are able to capture national and international patterns through not only government reports but also using global estimates and economic indicators. Micro-level data, on the other side, encompasses individual cases, local law enforcement records, and community-based studies. While macro data typically informs broad policy decisions and resource allocation, micro data provides crucial insights for program implementation and victim services.

Although the amount of empirical research has increased in the previous years, the issue of measurement is still a challenge in accurately representing the scope of the problem (Russell, 2017, p.125). The range of estimates of the scope create uncertainty in the validity of the research as well as the statistics used to create awareness (Zhang, 2009, p.192-193). This is what is known as the blatant use of unstandardised sources and extrapolation methods in macro-level research when creating trafficking estimates.

This dual classification is supported by various research papers that help contextualise macro- and micro-level datasets.

2.2. Research Questions Addressable by each Dataset Type

The selection of the dataset fundamentally shapes what research questions can be investigated in HT research. Understanding which ones can be addressed by different categories of data is essential in building strong research.

Major international datasets like from the Walk Free Foundation in 2013 provide a comprehensive information estimating the prevalence of modern slavery in countries. It encompasses various forms of exploitations, including forced labour and debt bondage, while also ranking countries based on prevalence and assessing government responses to combat trafficking (Russell, 2017).

Two other prominent international datasets that scholars use are the UNODC[1] and ILO[2]. On one hand, the UNODC reports the use of official data reported by national authorities, which provides a degree of consistency and comparability across countries, as well not only showing various forms of exploitation but also the profiles of traffickers and trafficking victims. However, Russell (2018) notes important limitations, including varying capacities between countries to detect and report cases, along with a lack of standardised definitions and data collection methods.

On the other hand, the ILO has been a key source of FL and trafficking data since its first global estimate in 2005, identifying 12.3 million victims. Academics are now suggesting that there are 40.3 million victims of modern slavery worldwide, after using the ILO macro dataset (Bryant and Landman, 2020). Further, it is important to recognise the strength of the dataset because of the consistent definition of forced labour, which is based on the ILO's Forced Labour Convention of 1930[3]. Additionally, Sweileh (2018) notes that international agencies, like the above mentioned, or health authorities may use bibliometric analysis to these macro datasets to map research gaps and assess national and international contribution to literature.

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[1] UNODC: United Nations Office on Drugs and Crime

[2] ILO: International Labour Organization

[3] According to the ILO Forced Labour Convention, 1930 (No. 29), forced or compulsory labour is defined as "*all work or service which is exacted from any person under the menace of any penalty and for which the said person has not offered himself voluntarily.*" The Convention provides specific exceptions including compulsory military service, normal civic obligations, and certain forms of prison labour.

While these macro-level datasets are valuable, they face limitations due to the hidden nature of the forced labour and challenges in collecting reliable data on sensitive topics, meaning that these estimates are necessarily imprecise and should be interpreted with caution (DoCarmo, 2020, p.186). As a result, Wietzer (2015) encourages increased research at the micro-level or with special populations to produce more reliable estimates as trafficking can vary by context and location. Here, scholars often decide for surveys and interviews as their primary data collection directly from trafficking survivors about their experiences. For instance, a study in Mexico City interviewed trafficked women about experiences of sexual violence and associated risk factors (Acharya, 2011) or other interviews with hundreds of sex workers and trafficking victims have been conducted in studies in Ukraine or the Netherlands to understand their experiences (Hughes & Denisova, 2001; Vocks & Nijboer, 2000). However, these studies typically rely on non-random sampling with sample sizes ranging from just a few individuals to hundreds of respondents, demonstrating that accessing representative samples is challenging.

Further, some other studies have analysed police records, court documents and service provider case files to collect data on trafficking incidents, victim experiences and criminal justice outcomes. For example, scholars have looked at hundreds (Scott & Harper, 2006) or even thousands of court cases (Curtol et al., 2004) to extract data. Often micro-level data used in human trafficking research tends to come from relatively small, and non-representative samples using surveys, interviews, and analysis of official case records. The reason behind it is that the hidden nature of the population makes large-scale representative sampling very difficult. However, it can provide important insights not captured in macro-level datasets to help understand the dynamics and nuances of trafficking.

2.3. Systematic Analysis of Dataset Limitations

Both macro-level and micro-level datasets in human trafficking research have significant limitations that impact their internal and external validity, as well as raise ethical and moral concerns. Sometimes to obtain internal validity, the large global reports (ILO or UNODC) often rely on aggregated data from various sources, often mixing official statistics with estimates derived from predictive models of extrapolation techniques (Guth et al, 2014, p.18). Further, lack of standardised definitions, inconsistent data collection methods, and varying capacity of victim identification across countries can introduce measurement errors and biases that threaten the internal validity of these datasets (Tyldum & Brunovskis, 2005, p.24-25). At the micro level, while studies using interviews, case files and fieldwork can provide detailed context-specific data, they suffer from selection bias due to small, non-representative and skewed samples (Tyldum, 2010, p.6). The reliability of self-reported data is further compromised by recall bias, social desirability bias and the impact of trauma on victims (Cwikel & Hoban, 2005, p.310).

In contrast, external validity can be seen reflected in the hidden and diverse nature of human trafficking making it inherently difficult to obtain representative samples that allow for generalisation to wider populations. This is why macro-level estimates are often presented as definitive global or regional figures, but their external validity is questionable given the numerous assumptions and methodological limitations involved (Guth et al., 2014). Further, in the micro-level studies as they focus on specific subgroups such as specific geographical contexts, or types of trafficking, this limits their generalisability to other settings or populations. This will then show a lack of replication and comparative studies which also makes it difficult to assess the external validity of micro-level findings across contexts (Zhang, 2012, p.479).

Beyond methodological limitations, collecting data on human trafficking raises significant ethical and moral concerns, particularly when it involves direct contact with trauma and exploitation survivors. Policy makers must carefully navigate issues of confidentiality and potential re-traumatisation, while also ensuring that their work does not inadvertently cause harm or stigmatise already marginalised populations.

The use of macro-level estimates to influence global policy and funding allocations has been critiqued as potentially distorting priorities and resources away. Further, over-reliance on sensationalised statistics and narratives can fuel moral panics and lead to poorly designed policies that may actually harm the populations that seek for protection. As Cockbain and Kleemans (2019, p.2) emphasise, “it is not enough just to do *more* research on trafficking: but the research needs to consistently meet high standards”. Moving forward requires transparency about limitations, triangulation of data sources, and strict adherence to ethical principles.

3. ***Empirical analyses***

3.1. Data description

This paper will use the Human Trafficking Indicators (HTI) dataset that includes a country-year level information on 46 variables for up to 186 countries from 2000 to 2017. It uses country-year as its unit of analysis and most measurements are categorical rather than numerical. The main measurements are by tracking four main flows: sources, transit, destination and internal, covering 7 types of human trafficking.

This dataset also includes 18 measures of a government's prosecutions, protection and prevention efforts. Rather than attempting to estimate the precise number of trafficking victims, which can be unreliable, the dataset focuses on documenting the presence and patterns of trafficking flows and policy measures. Further, the analysis employs exploratory and descriptive methods including visualization of trends in trafficking types and flows over time through line graphs, cross-tabulations examining relationships between trafficking measures and policy responses, correlation analysis to assess associations between variables. The methods focus on identifying patterns and trends rather than testing causal hypotheses.

For this research paper, I conducted analyses of all types of human trafficking. After reviewing the data, I decided to focus on Forced Labour and Child Labour, as these two forms of trafficking appear to have significant crossover.

3.2. Trafficking types by flows

Figure 1. Forced Labour trafficking by flow types.

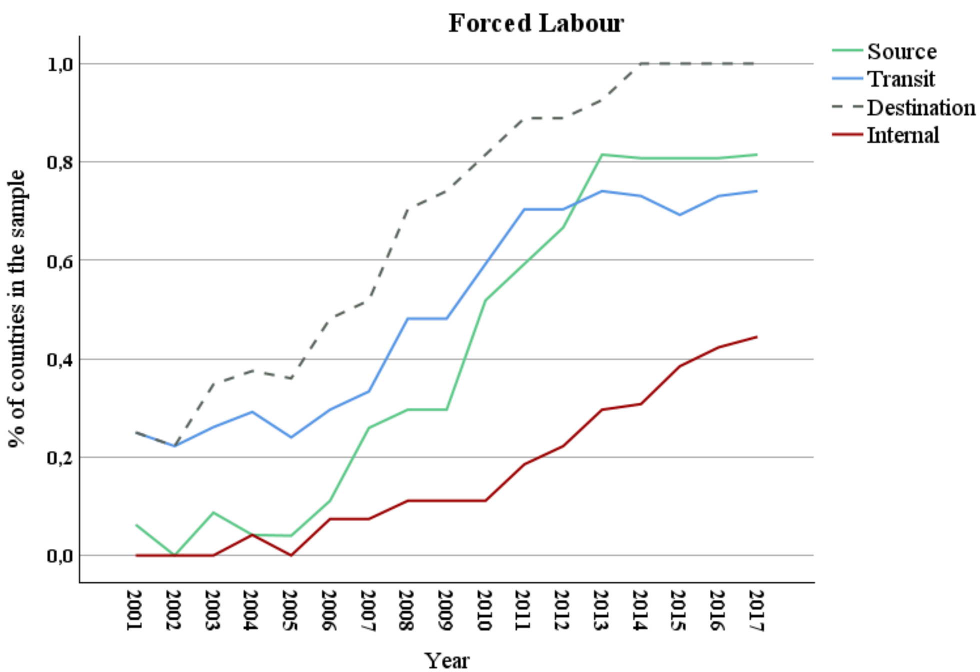


Figure 2. Child Labour trafficking by flow types.

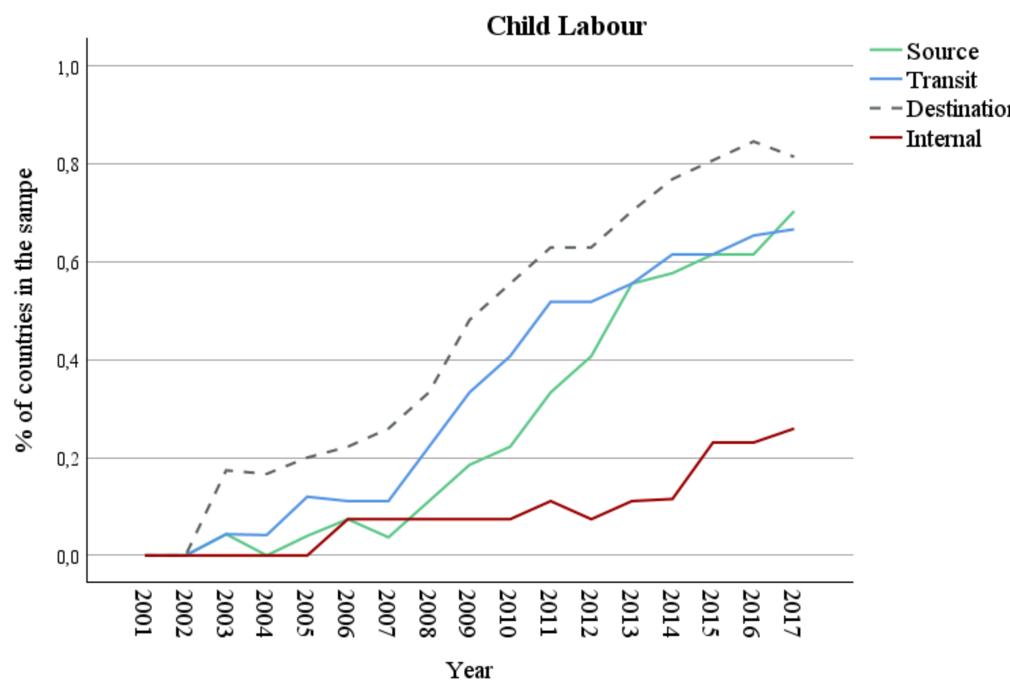


Figure 1 and 2 illustrate notable trends in the growth in countries reporting for trafficking in Forced Labour and Child Labour. A few stand out.

First, destination countries have outnumbered source states since 2005 for FL, while compared to CL it's been a slow but progressive increase since 2004. Second, internal trafficking appears to be more stable during the span of the 16 years. Compared to international flows and destination as the outcome, it might be that it is because it has received less attention in relevant literature. Further, there was no data of internal forced and child labour until 2003 and 2005 respectively. Also, there is a stability of internal child labour trafficking indicating that this form of exploitation might remain deeply rooted in local context and economic systems.

In order to explore the trends observed in Figures 1 and 2, the following section will explore how they are linked to key European Union directives.

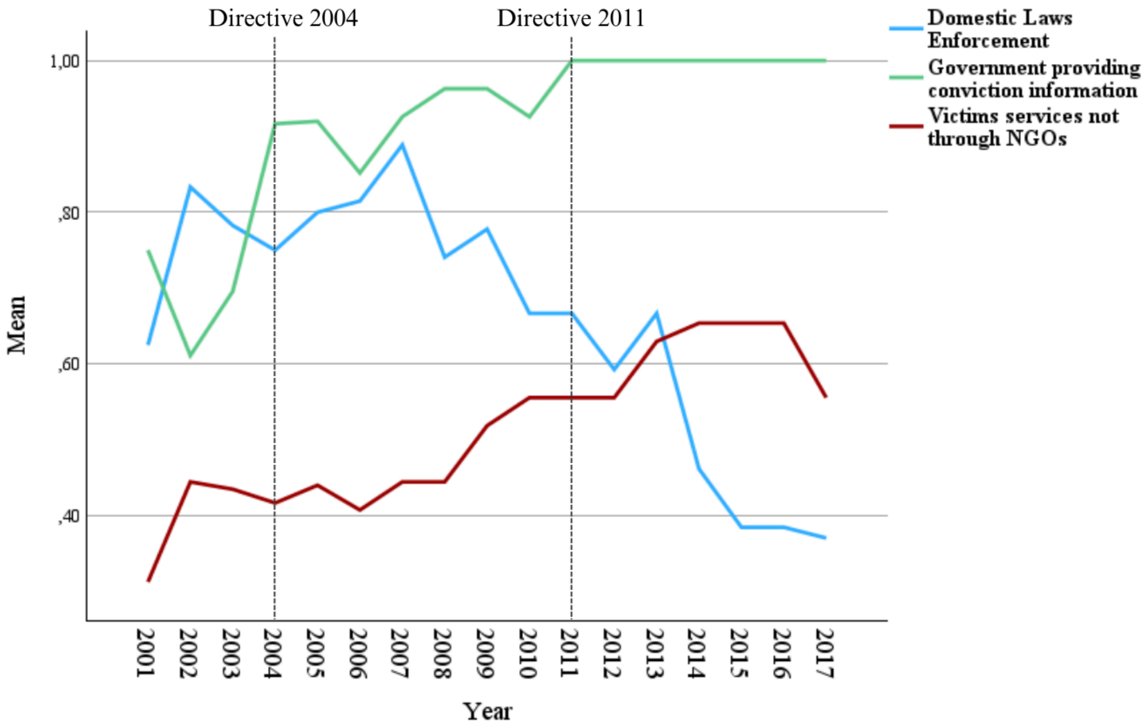
3.3. Resident Permit Directive (2004) and Reflective Period Directive (2011)

The implementation of the 2004 Directive on Residence Permits and the 2011 Directive on Prevention and Protection marked significant turning points in EU anti-trafficking policy, each introducing distinct changes in Member States' approaches to trafficking identification and victim support.

To assess their impact, this paper examines trends in three key policy measures: **enforcement of domestic laws, government provision of conviction information, and victims provided with services (not through NGOs).** It will do so by relating the most pertinent articles from the directives to *Figure 3*, and making connections with their increasing and decreasing values.

To make the trends more visible, I decided to include a dotted line indicating when both directives came into place, allowing an easier observation of the differences before and after the directives were implemented.

Figure 3. Trends after the effect of the EU Directive 2004 and the Directive 2011.



After the implementation of the 2004 Directive (Residence Permit), we can observe a slight increase, representing the key provisions about enforcing domestic laws *in Article 8(1)(b) and (c)* stating that Member States must consider whether the victim has shown a clear intention to cooperate when deciding whether to issue the residence permit.

However, the directive does not specifically address **enforcement of domestic laws in prosecution or investigation**, as it focuses primarily on the conditions and procedures for issuing residence permit to trafficking victims who cooperate with authorities rather than on law enforcement aspects. Further on that, the directive does require **Member States and governments to report statistics** on residence permit issued and resulting trafficking convictions, observed in Article 10 (4)(c). This is why we see a small increase on both policy measures. However, the directive does not create a comprehensive framework on **providing conviction information**, as we can see in *Figure 3*, which remains stable and has dropped between 2005 and 2006, this framework would be later developed more fully in the 2011 Directive. Additionally, the directive also specifically mandates that "*Member States shall ensure that victims who do not have sufficient resources are granted standard of living (...)*" in Article

7(1), placing this responsibility directly on state authorities rather than NGOs, where I indeed see a slow but progressive increase in the graph.

On the other side, with the 2011 Directive we observed several key developments. First, there were **strengthened victim protection measures.** This is specifically outlined in Article 13(1) ("General provisions on assistance, support and protection measures for child victims of trafficking in human beings"). Second, in regard to the government providing conviction information we can observe a sharp constant value in Figure 3.

Finally, it is also important to mention that the EU directives established clear governmental responsibilities for **victim service provision independently from NGO involvement**. The 2004 Directive first established this through Article 7(1), requiring Member States to ensure subsistence standards and emergency medical treatment for victims without sufficient resources. While NGOs can still supplement these services, the directives place primary responsibility for victim support directly on state authorities.

3.3.1. Broader factors

There are some other possible explanations for the trends, not only examining the policy details but also the broader global events and societal changes.

For example, the 2015-2016 migration crisis highlighted migrant vulnerabilities, driving a need for stronger victim identification and support systems. Also, enforcement measures showed notable growth between 2012 - 2017 probably due to the creation of the EU Anti-Trafficking Coordinator position that enhanced policy coherence across Member States, while EUROPOL’s EMPACT[4] priority on trafficking strengthened operational cooperation.

The notable increase in victim services post-2011 coincided with multiple reinforcing factors. The EU’s Stockholm Programme (2009-2014) elevated trafficking to a key priority, while increased funding through the Internal Security Fund provided resources for implementation. Additionally, a monitoring report from GRETA highlighted critical service gaps, creating pressure for improvement.

[4] EMPACT: European Multidisciplinary Platform Against Criminal Threats.

3.4. Does the presence of policy measures relate to the EU directives?

Beyond question, the presence and implementation of policy measures can certainly be influenced by EU directives in a number of ways. But Member states have a significant degree of autonomy in how they implement these directives through following domestic policies. For example, while the directives mandate that victims be provided assistance and protection, support services or counselling programs, etc. Implementing these can vary across countries based on resources and existing social welfare systems. Additionally, prevention efforts can take different forms, with some countries focusing more on awareness campaigns or border control, depending on the national context. These variations in implementation raise an important question about the relationship between national policy measures and EU directives.

3.5. Associations between Trafficking Flows and Policy Measures

Table 1. Bivariate relations of three types of policy measures on being a destination country of forced labour

		No Forced Labour Flow	Forced Labour Flow	Chi 2 Test	Cramérs V	Phi	N
Government enforcing domestic laws	**No/No mention/ Some**	38 (8.9%)	87 (20.37%)	1.269	.055	-.055	125 (29.27%)
	Yes	109 (25.53%)	193 (45.20%)				302 (70.72%)
Government providing conviction information	**No/No mention/ Some**	19 (4.45%)	106 (24.82%)	15.138**	.188	.188	125 (29.27%)
	Yes	13 (3.04%)	289 (67.67%)				302 (70.72%)
Providing victim services not through NGOs	**No/No mention/ Some**	78 (18.27%)	47 (11.01%)	14.185**	.182	.182	125 (29.27%)
	Yes	128 (29.68%)	174 (40.75%)				302 (70.72%)
N							427

Note: ** p<.01, *p<.05. Percentages are calculated from total N=427.

Table 2. Bivariate relations of three types of policy measures on being a destination country of child labour

		No Child Labour Flow	Child Labour Flow	Chi 2 Test	Cramérs V	Phi	N
Government enforcing domestic laws	**No/No mention/ Some**	67 (15.69%)	159 (37.24%)	4.860*	-.107	.107	226 (52.93%)
	Yes	80 (18.74%)	121 (28.34%)				201 (47.07%)
Government providing conviction information	**No/No mention/ Some**	23 (5.39%)	203 (47.54%)	4.985*	.108	.108	226 (52.93%)
	Yes	9 (2.11%)	192 (44.96%)				201 (47.07%)
Providing victim services not through NGOs	**No/No mention/ Some**	132 (30.91%)	94 (22.01%)	19.862**	.216	.216	226 (52.93%)
	Yes	74 (17.33%)	127 (29.74%)				201 (47.07%)
N							427

Note: ** p<.01, *p<.05. Percentages are calculated from total N=427.

After conducting a bivariate analysis, I observed notable patterns regarding the relationship between policy measures and the likelihood of a country being a destination for forced labour and child labour. Due to the limited number of cases falling into the "no" and "no mention" categories for the two selected trafficking types and their flows, these categories were recorded as dichotomous and combined into one category.

For forced labour, significant associations were observed for two policy measures: providing conviction information ($\chi2=15.138$, $p<0.01$, Cramér's V=0.188) and providing victim services not through NGOs ($\chi2=14.185$, $p<0.01$, Cramér's V=0.182). Countries offering victim services directly without relying on NGOs were more likely to experience forced labour flows (40.75%) compared to those not providing such services (11.01%). Similarly, countries that provided conviction information had a higher proportion of forced labour flows (67.67%) compared to those that did not (24.82%). Conversely, enforcing domestic laws did not exhibit a statistically significant relationship ($\chi2=1.269$).

Regarding child labour, significant relationships were identified with all three policy measures, although the strength of association varied. Providing victim services had the strongest relationship ($\chi2=19.862$, $p<0.01$, Cramér's V=0.216), with countries implementing this measure being more likely to experience child labour flows (29.74%) than those that did not (22.01%). Providing conviction information ($\chi2=4.985$, $p<0.05$, Cramér's V=0.108) and enforcing domestic laws ($\chi2=4.860$, $p<0.05$, Cramér's V=0.107) were also significantly related to child labour flows, though with weaker associations.

All the interpretations in this section are informed by established theoretical frameworks discussed in previous research (Meyers et al., 2017; Weisburd et al., 2022).

Additionally, I decided to conduct a multivariate analysis because I was interested in examining the relationships between multiple variables simultaneously, which can reveal more complex patterns and account for interrelationships between my variables. I also wanted to see how multiple policies work together in influencing trafficking outcomes.

3.6. Multivariate Model of Trafficking and Policy

Table 3. Logistic regression of three types of policy measures on being a destination country of forced labour.

	B	Wald	Exp (B)
Government enforcing domestic laws	-.323	2.466	.724
Government providing conviction information	1.472**	14.424	4.357
Providing victim services not through NGOs	.830**	13.808	2.294
Intercept β_0	-.638	2.466	.528
Nagelkerke R^2	.91		
CHI^2 (df)	29.966 (3)		
N	427		

** p<.01

Table 4. Logistic regression of three types of policy measures on being a destination country of child labour.

	B	Wald	Exp (B)
Government enforcing domestic laws	-.476	5.19	.621
Government providing conviction information	.966	.415	2.628
Providing victim services not through NGOs	.876**	.201	2.402
Intercept β_0	-1.163	7.286	.313
Nagelkerke R^2	.91		
CHI^2 (df)	30.306 (3)		
N	427		

** p<.01

I employed two parallel multivariate logistic regression analyses examining the factors influencing countries' status as destinations for FL and CL. Both models demonstrated excellent fit (Nagelkerke $R^2 = .91$) and statistical significance (χ^2 (CHI^2)=29.966, $p<.01$ for forced labour; χ^2= 30.306, $p<.01$ for child labour).

The analyses revealed both similarities and distinct patterns between destination determinants. Government provision of victim services through non-NGO channels showed consistently positive and significant associations with destination status for both forced labour (B = .830, $p<.01$, Exp[B] = 2.294) and child labour (B = .876, $p<.01$, Exp[B] = 2.402). This suggests that countries providing direct governmental victim services are approximately 2.3-2.4 times more likely to be destination countries for both types of trafficking.

However, notable differences emerged in the influence of other factors. Government provision of conviction information demonstrated a strong, significant positive association with FL destination status (B = 1.472, $p<.01$, Exp[B] = 4.357), indicating that countries sharing conviction information are more than 4 times likely to be FL destinations. This relationship was markedly weaker and non-significant for CL (B = .966, non-significant, Exp[B] = 2.628).

Conversely, domestic law enforcement showed different patterns of influence. While negative associations were observed in both models, the effect was stronger and achieved statistical significance for child labour (B = -.476, $p<.05$, Exp[B] = .621) compared to forced labour (B = -.323, non-significant, Exp[B] = .724). This suggests that robust domestic law enforcement may be particularly effective in deterring child labour trafficking. The lower intercept value for CL (β_0 = -1.163) compared to FL (β_0 = -.638) indicates that, all else being equal, countries are generally less likely to be destinations for child labour than forced labour. These findings show the dynamics of human trafficking and policy responses may need to be tailored accordingly.

Similar to the bivariate analysis, the interpretation of these results is supported by insights drawn from empirical studies and academic literature (Nathans et al., 2012; Share, 1984).

4. Conclusion and discussion

This research has revealed important insights about both the capabilities and limitations of quantitative HT data. By connecting our theoretical analysis of available datasets with empirical findings, several key conclusions emerge.

My empirical analysis both validated and complicated the limitations of macro-level trafficking data identified in the literature review. The HTI dataset's reliance on categorical rather than numerical measurements reflects a practical response to the challenges of quantifying illicit activities. While this approach enables consistent cross-country comparisons, it also means we cannot measure the true scale of trafficking –only its documented presence or absence. This limitation became particularly apparent when examining the relationship between policy measures and trafficking patterns. Our finding that countries with stronger victim services and conviction reporting were more likely to be identified as trafficking destinations illustrates a crucial paradox: better anti-trafficking measures may lead to increased identification and reporting rather than necessarily indicating higher trafficking levels. This validates earlier scholarly concerns about interpretation challenges with macro-level trafficking data.

However, in order to conduct truly meaningful cross-border research and provide a solid and empirically sound evidence base for policy making, (Fehér, 2004) argues that data needs to be refined even further. To do so, De Bondt (2014, p.41) explained that a combination of variables such as the country of origin and/or destination is still quite basic. Specifically, there is the need for in-depth phenomenological research that will go beyond these variables and attempt to also look into the context of the offences committed. This could be done by constructing an integrated action plan against human trafficking, requiring data on the associated criminal offenses that are instrumental to trafficking operations. This means that sometimes these related crimes are often critical enablers to trafficking success, making their documentation essential for developing holistic counter-trafficking strategies (De Bondt, 2014, p.41)

Moreover, the empirical analysis of the paper not only helped answer the research questions, but also deepened our understanding of how data limitations affect policy evaluation in various ways. First, the distinct patterns we found between FL and CL suggests that different forms of trafficking may require different measurement approaches. This is reflected in the strong association between conviction information and FL to CL indicating that certain policy measures may be better at detecting some forms of trafficking than others. Second, our finding that enforcement policies showed varying effectiveness between trafficking types highlights how aggregate data can show relevant nuances in policy measures. This reinforces the need for more granular, context-specific data collection alongside macro-level measurements (De Bondt, 2014, p.37).

Based on the insights of the paper, we can also provide some realistic recommendations for future data collection. As Bryand & Landman (2020) argued that because trafficking can vary by context and location, there is an increased importance to strengthen their sense of identity as an integral part of case management. This indicated that the creation of standardised protocols for victim identification could be crucial for accurate data collection. Adding on this, De Bondt (2014) also explored that the current data collection methods are not useful. And that besides the critiques to unreliable and incomplete datasets, the existing data collection is highly criticised for being too focused on regular situation reporting. This creates a little added value for risk-based evaluations and vulnerability studies.

In conclusion, while current macro-level trafficking datasets provide valuable insights, they need to be supplemented with more nuanced measurement approaches. Moving forward, the focus should be on developing data collection methods that can capture both the broad patterns and specific dynamics of different types of HT types while also maintaining consistency across various jurisdictions. This will require international cooperation and investment in data collection, essential elements for developing more effective anti-trafficking policies.

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6. *Appendix*

6.1. SPSS SYNTAX

```
* Encoding: UTF-8.

GET
  FILE='C:\Users\692678az\Desktop\HTI_v1_2021.sav'.
DATASET NAME DataSet1 WINDOW=FRONT.

FREQUENCIES country year.
FREQUENCIES psource to csinternal.

missing values dstransit (-1).

DATASET ACTIVATE DataSet1.
RECODE dstransit (-1=0) INTO dstransit_d.
VARIABLE LABELS  dstransit_d 'domestic servitude transit dichotomous'.
EXECUTE.

RECODE dstransit year (-1=0) (2001 thru 2005=Copy) (2006 thru 2012=Copy) (2013 thru 2017=Copy)
INTO
    dstransit_d year_cat.
VARIABLE LABELS  dstransit_d 'domestic servitude transit dichotomous' /year_cat 'periods'.
EXECUTE.

COMPUTE EUcountry=0.
EXECUTE.

COMPUTE EUcountry=0.
IF(ccode = 211 |ccode = 355 | ccode = 352 | ccode = 205 | ccode = 210 | ccode = 212 | ccode = 220 | ccode
= 230 | ccode = 235 | ccode = 255 | ccode = 290 | ccode = 305 | ccode = 310 | code = 316 | ccode = 317 |
ccode = 325 | ccode = 338 | ccode = 344 | ccode = 349 | ccode = 350 | ccode =355 | ccode = 360 | ccode =
366 | ccode = 367 | ccode = 368 | ccode = 375 | ccode = 380 | ccode = 390) EUcountry=1.

USE ALL.
COMPUTE filter_$=(EUcountry=1).
VARIABLE LABELS filter_$ 'EUcountry=1 (FILTER)'.
VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
FORMATS filter_$ (f1.0).
FILTER BY filter_$.
EXECUTE.
```

```
DATASET ACTIVATE DataSet1.
GRAPH
  /LINE(MULTIPLE)=MEAN(lsource) MEAN(ltransit) MEAN(ldest) MEAN(linternal) BY year
  /MISSING=LISTWISE.

GRAPH
  /LINE(MULTIPLE)=MEAN(dsource) MEAN(dtransit) MEAN(ddest) MEAN(dinternal) BY
domesticlaws
  /MISSING=LISTWISE
  /INTERVAL CI(95.0).

RECODE enforcement (-1=0) (0=0) (1=0) (2=1) INTO enforcement_d.
VARIABLE LABELS  enforcement_d 'does government enforce domestic laws dichotomous'.
EXECUTE.

* Define Variable Properties.
*enforcement_d.
VALUE LABELS enforcement_d
  .00 'No/nomention/some'
  1.00 'Yes'.
EXECUTE.

CROSSTABS
  /TABLES=psource BY enforcement_d
  /FORMAT=AVALUE TABLES
  /STATISTICS=CHISQ PHI
  /CELLS=COUNT ROW
  /COUNT ROUND CELL.

DATASET ACTIVATE DataSet1.
FREQUENCIES VARIABLES=EUcountry enforcement
  /ORDER=ANALYSIS.


FREQUENCIES EUcountry.

GRAPH
  /LINE(MULTIPLE)=MEAN(lsource) MEAN(ltransit) MEAN(ldest) MEAN(linternal) BY year
  /MISSING=LISTWISE.

RECODE enforcement (-1=0) (0=0) (1=0) (2=1) INTO enforcement_d.
VARIABLE LABELS  enforcement_d 'Does government enforce domestic laws dichotomous'.
EXECUTE.
```

```
VALUE LABELS enforcement_d.

RECODE efforts (-1=0) (0=0) (1=0) (2=1) INTO efforts_d.
VARIABLE LABELS  efforts_d "Gov't making significant efforts at combatting trafficking".
EXECUTE.

RECODE convictinfo (-1=0) (0=0) (1=1) INTO conviction_d.
VARIABLE LABELS  conviction_d 'Does government provide conviction information dichotomous'.
EXECUTE.

FREQUENCIES VARIABLES=conviction_d enforcement_d efforts_d
  /ORDER=ANALYSIS.

GRAPH
  /LINE(MULTIPLE)=MEAN(enforcement_d) MEAN(conviction_d) BY year
  /MISSING=LISTWISE.

CROSSTABS
  /TABLES=lsource BY enforcement_d
  /FORMAT=AVALUE TABLES
  /STATISTICS=CHISQ PHI
  /CELLS=COUNT ROW
  /COUNT ROUND CELL.

DATASET ACTIVATE DataSet1.
RECODE victimservices (0=0) (-1=0) (1=1) INTO victimservices_d.
VARIABLE LABELS  victimservices_d 'Provide victim services not though NGOs'.
EXECUTE.

GRAPH
  /LINE(MULTIPLE)=MEAN(efforts_d) MEAN(conviction_d) BY year
  /MISSING=LISTWISE.

GRAPH
  /LINE(MULTIPLE)=MEAN(efforts_d) MEAN(victimservices_d) BY year
  /MISSING=LISTWISE.

DATASET ACTIVATE DataSet1.

RECODE ldest (-1=0) (0=0) (1=1) INTO ldestination_d.
VARIABLE LABELS  ldestination_d 'Forced Labour Destination Dichotomous'.
EXECUTE.
```

```
FREQUENCIES VARIABLES=cldest
  /ORDER=ANALYSIS.

RECODE cldest (-1=0) (0=0) (1=1) INTO cldestination_d.
VARIABLE LABELS  cldestination_d 'Child Labour Destination Dichotomous'.
EXECUTE.

LOGISTIC REGRESSION VARIABLES ldestination_d
  /METHOD=ENTER conviction_d victimservices_d efforts_d
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).

LOGISTIC REGRESSION VARIABLES cldestination_d
  /METHOD=ENTER conviction_d victimservices_d efforts_d
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).

LOGISTIC REGRESSION VARIABLES cldestination_d
  /METHOD=ENTER conviction_d victimservices_d enforcement_d
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).

LOGISTIC REGRESSION VARIABLES ldestination_d
  /METHOD=ENTER conviction_d victimservices_d enforcement_d
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).

DATASET ACTIVATE DataSet1.
CROSSTABS
  /TABLES=ldestination_d BY enforcement_d conviction_d victimservices_d
  /FORMAT=AVALUE TABLES
  /STATISTICS=CHISQ
  /CELLS=COUNT
  /COUNT ROUND CELL.

CROSSTABS
  /TABLES=cldestination_d BY enforcement_d conviction_d victimservices_d
  /FORMAT=AVALUE TABLES
  /STATISTICS=CHISQ
  /CELLS=COUNT
  /COUNT ROUND CELL.

CROSSTABS
  /TABLES=ldestination_d BY enforcement_d conviction_d victimservices_d
  /FORMAT=AVALUE TABLES
  /STATISTICS=CHISQ PHI
  /CELLS=COUNT
  /COUNT ROUND CELL.
```

```
CROSSTABS
  /TABLES=cldestination_d BY enforcement_d conviction_d victimservices_d
  /FORMAT=AVALUE TABLES
  /STATISTICS=CHISQ PHI
  /CELLS=COUNT
  /COUNT ROUND CELL.

DATASET ACTIVATE DataSet1.
RELIABILITY
  /VARIABLES=enforcement_d conviction_d victimservices_d ldestination_d
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=MEANS VARIANCE COV CORR.

GRAPH
  /LINE(MULTIPLE)=MEAN(enforcement_d) MEAN(conviction_d) MEAN(victimservices_d) BY year
  /MISSING=LISTWISE.
```