Measuring VAT Compliance Gap in Indonesia

Directorat Potential, Compliance and Revenue

Directorate General of Taxes

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Executive Summary

1. This study estimates VAT compliance gap with bottop-up and top-down approach for the last five years.
2. The result of bottom-up approach shows stagnant trend in 25% gap in 2017 to 2021 but increases in nominal from Rp.79 trillion to 92 trilion.
3. The result of top-down approach shows downtrend in percentage gap in from 44% in 2020 to 33% in 2024 but increases in nominal from Rp.336 trillion to 391 trilion.
4. From sectoral view, tax gap shows downtrend in utility, manufacturing and trade sector.
5. From regional view, tax gap shows the highest in region outside java island.

1. Background

Definition of *tax gap*

In general, the tax gap is defined as revenue lost from the tax system as a result of taxpayer non-compliance

Tax gap is the difference between the potential revenue from the underlying economic tax base and the actual revenue collected. This gap consists of compliance gap and policy gap (**IMF**, 2017; 2021)

Tax gap is the difference between the revenue potential (based on legal framework) and the actual revenue collected by the tax authorities (**World Bank**, 2014)

Tax gap is the difference between the amount of tax that should, in theory, be collected and what is actually collected (**OECD**, 2017)

Gross tax gap is the amount of true tax that is not paid on time and net tax gap is the difference between the gross tax gap less enforced and other late payments (**IRS**, 2023)

Tax gap is the difference between the amount of tax that should be paid (theoretical tax liability) and the amount that is actually paid (**HMRC**, 2024)

Tax gap is the difference between the amount of tax it expects to collect and the amount that would have been collected if every taxpayer was fully compliant with the law (**ATO**, 2023)

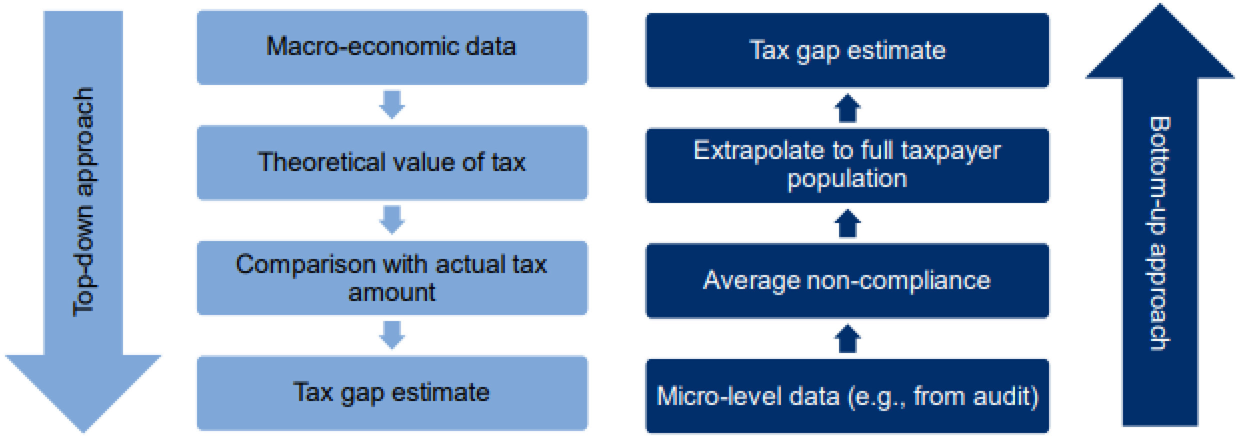
Approaches to *tax gap* analysis

In general, the top-down approach is applied to indirect taxes (VAT) and the bottom-up approach to direct taxes (income tax)

Top-down approach

- This approach uses aggregate macroeconomic data.
- Ideally, these aggregate macroeconomic data are compiled by an independent party, without the involvement of the tax authority, so that the data obtained are free from bias.
- Because the data are aggregated, they offer only limited granularity.
- Macroeconomic data also tend to *underestimate* value added and income at the upper end of the distribution.
- As a result, *tax gap* estimates produced under this approach reveal little about the underlying drivers of the gap.
- This approach cannot identify the tax gap at the individual taxpayer level.

Figure 11.4. Two main approaches to estimate a tax gap



Bottom-up approach

- This approach uses audit data from both *random audits* and *risk-based audits*.
- Under *random audit*, every taxpayer has an equal probability of selection, so the sample is representative and the *tax gap* estimate can be extrapolated to the population.
- Under *risk-based audit*, cases are selected non-randomly according to tax risk priorities, so the sample is not representative and the *tax gap* estimate cannot be extrapolated to the population. The *Heckman correction* is the standard remedy for such samples.
- Estimates produced under this approach can identify the behavioural root causes of non-compliance, informing the design of compliance improvement strategies.
- This approach can compute the *tax gap* at the individual taxpayer level.

Source: OECD (2014), DGT (2023), ATO (2024)

Tax gap analysis is established international practice

Indonesia is among the small group of countries that already produce bottom-up tax gap estimates, although its random audit programme is not yet fully established

Figure 49. Tax Gap Estimates Conducted by Tax Type, 2017
(Percent)

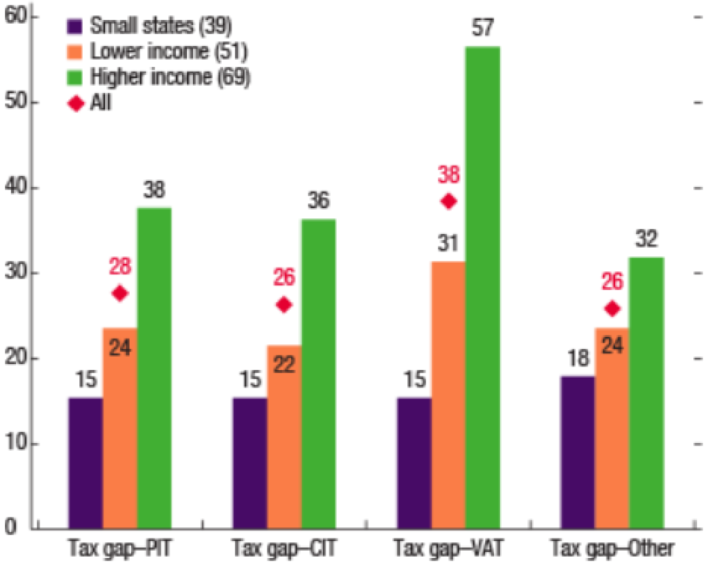
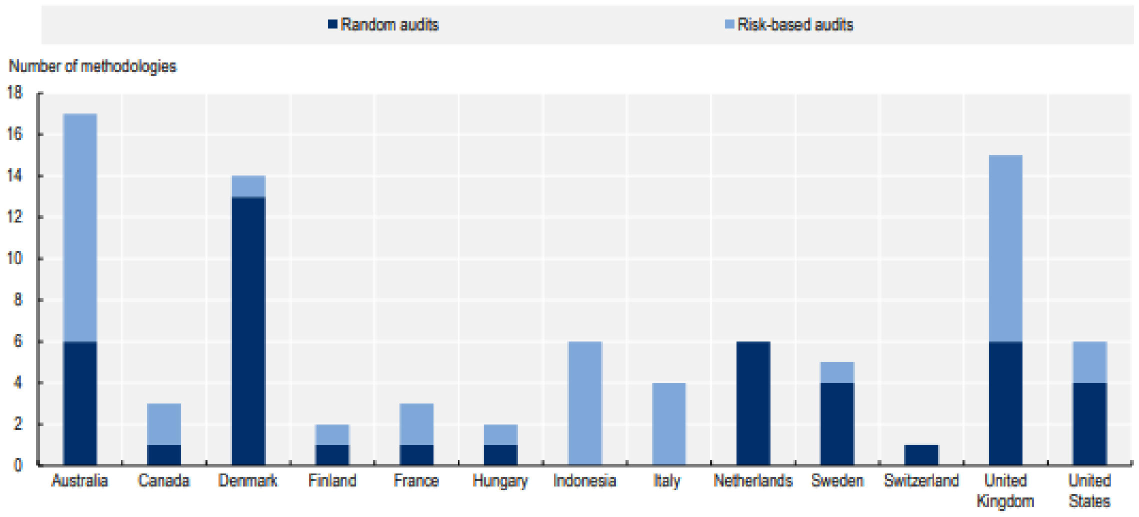


Figure 11.5. Number of bottom-up methodologies by data sources



Source: Annex Table 11.A.4.

- According to the *International Survey on Revenue Administration* (ISORA) 2018, published by the IMF in 2021, from 159 tax administrations surveyed, 28% estimate the personal income tax (PIT) gap, 26% the corporate income tax (CIT) gap and 38% the value added tax (VAT) gap.
- Tax gap analysis is concentrated in advanced economies.
- VAT gaps are estimated most often, as the data and methods are more accessible.

- In the OECD 2023 survey, 57% of the tax administrations surveyed conduct tax gap analysis using a bottom-up approach. Within that group, Indonesia and Italy have yet to implement *random audit*.
- Random audit is the highest-quality tax gap estimation method (OECD, 2017), but it is resource-intensive and yields less additional revenue than risk-based audit.

Source: IMF (2021), OECD (2024)

Timeline of *tax gap* analysis at the DGT

Tax gap analysis under the 2025–2029 strategic plan is expected to drive improvements in compliance and organisational effectiveness

2016-2018

- *Tax gap* analysis using the *top-down* approach began in 2016 at the *Center for Tax Analysis* (CTA).
- *Short technical assistance* from the ATO (AIPEG).

2019-2020

- Establishment of the DGT *tax gap* team.
- Income tax and VAT *tax gap* report for 2016–2018, *top-down* approach.

2021

- Development of a *bottom-up* CIT gap estimation model.
- Technical assistance on *top-down* estimation from an AFD expert.
- *Tax gap* analysis in the 2021–2024 directorate strategic plan.

2022

- 2021 *tax gap* estimation report (*top-down* and *bottom-up*)

2023

- Technical assistance on *bottom-up* CIT gap estimation from an AFD expert.
- Refinement of the *bottom-up* CIT gap model.

2024

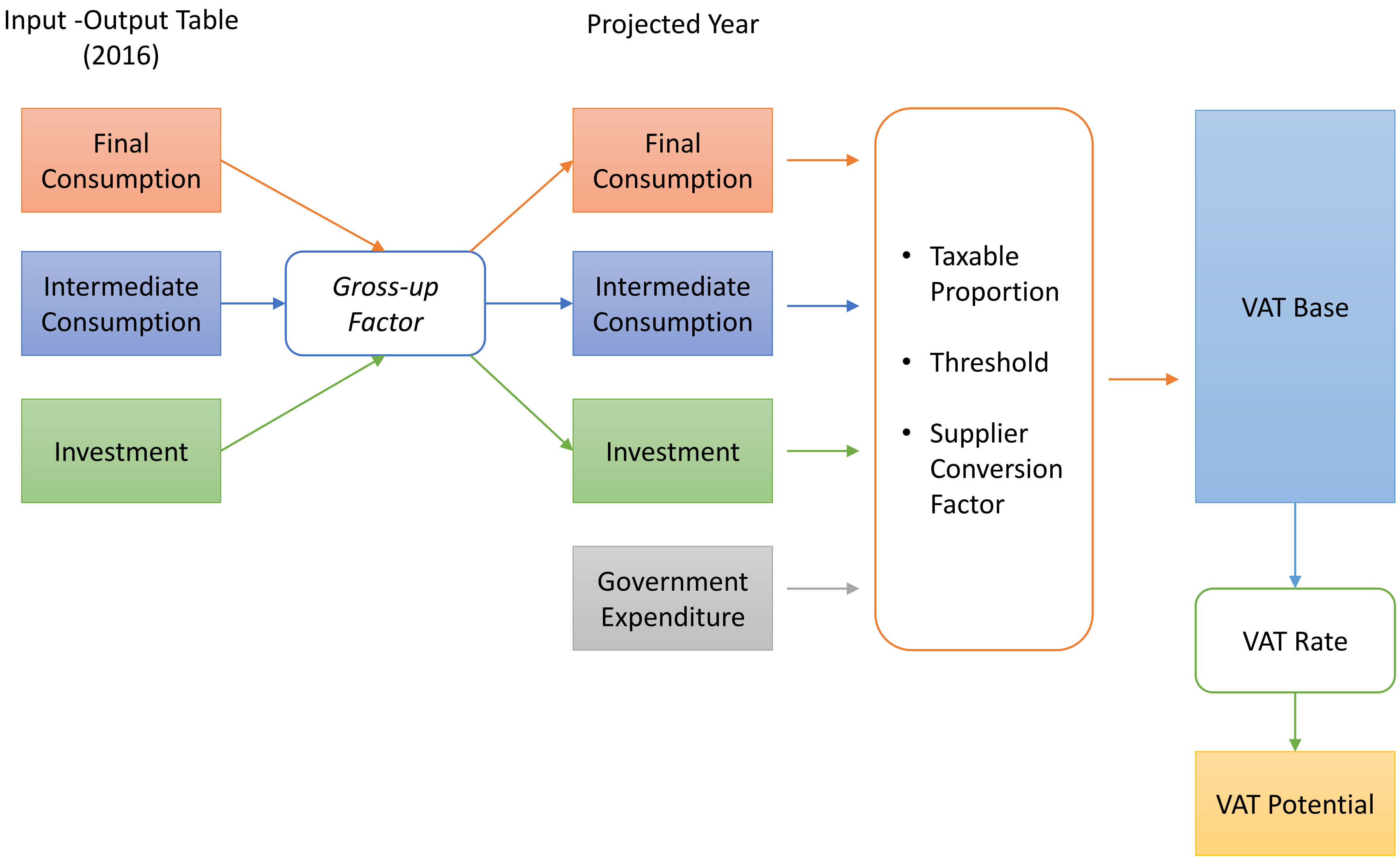
- Taxpayer-level CIT gap predictions used in priority compliance targeting.
- Launch and update of the *tax gap* dashboard.
- Indonesia joined the OECD *Tax Gap* COI.
- *Tax gap* analysis in the DGT 2025–2029 strategic plan.
- *Tax gap* and REP workshop with the ATO.

2025

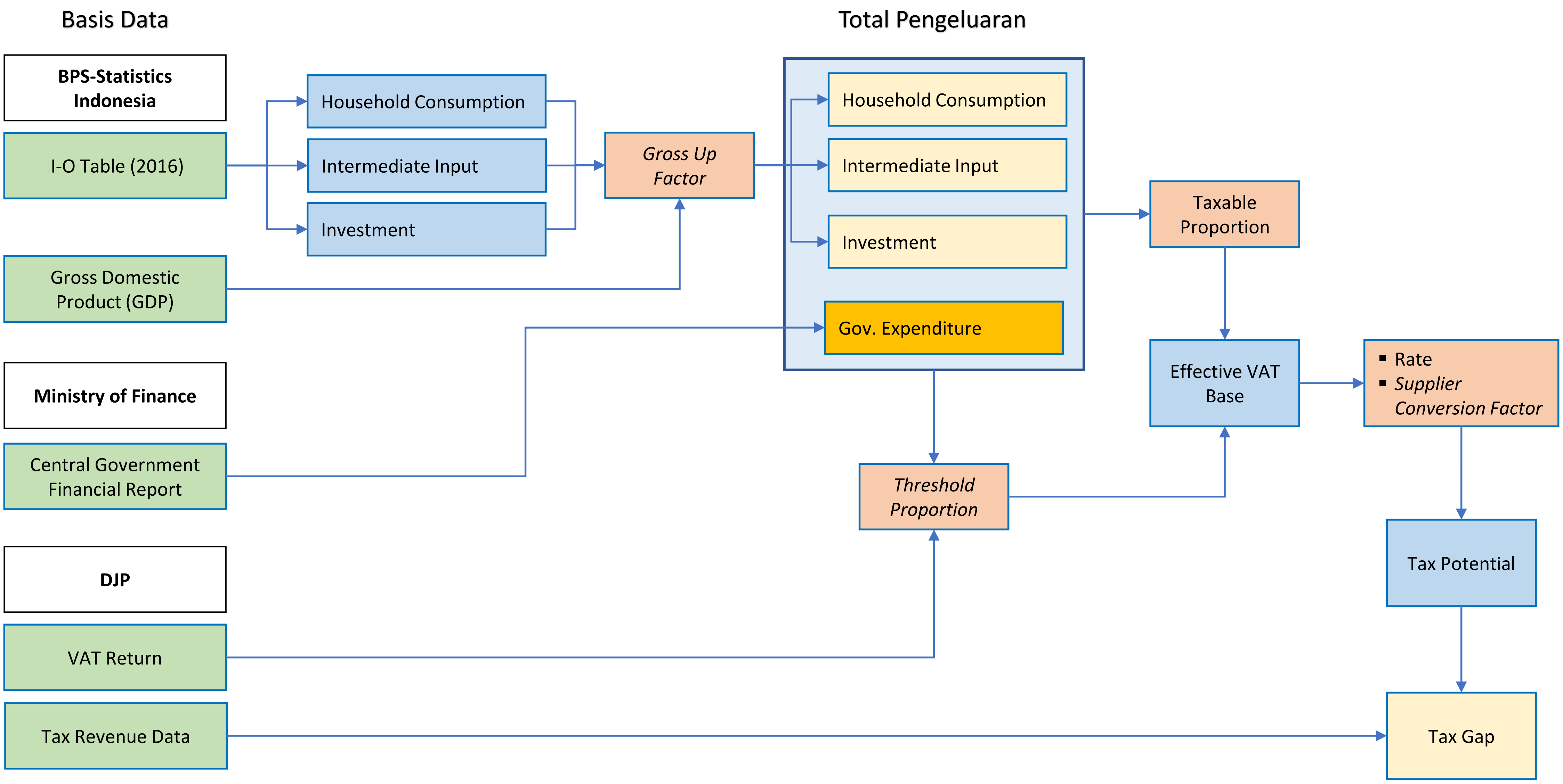
- Rollout of the *random enquiry programme* (REP).
- *Tax gap* estimates for PIT and VAT (*bottom-up*)
- CIT gap analysis report for large taxpayers.

2. *Top Down Approach*

VAT Compliance Gap Scheme



Skema *tax gap* PPN



VAT Compliance Gap Method

VAT Potential Model

The calculation of the VAT base uses the consumption method, which encompasses final consumption values of households and non-profit institutions (C) and government (G) on taxable commodities, as reflected in the Input-Output table. However, policy exemptions and VAT relief mean that a portion of input VAT cannot be credited. Consequently, a portion of intermediate inputs (N) and investment/gross fixed capital formation (I) also contributes to forming the VAT base. The VAT potential model is formulated as follows:

$$VAT_i = (\Sigma C_i . \partial_i + G.\partial + \Sigma N_i . \delta_i + \Sigma I_i . \delta_i) \times r$$

Dimana :

VAT_i	= VAT Potential
C_i	= Household Consumption for Commodity (sector) i
N_i	= Intermediate input of commodity i
I_i	= Gross investment from commodity (sector) i
G	= Government Expenditure
∂_i	= Effective taxable proportion for final consumption of commodity (sector) i, which consists of the taxable proportion and the proportion of supplies made by Taxable Entrepreneur (PKP).
δ_i	= Effective taxable proportion for intermediate input and investment) of commodity (sector) i, which consists of the taxable proportion, the proportion of supplies made by Taxable Persons, dan *supplier conversion factor*.
r	= VAT rate

Gross-up Factor

The 2016 Input-Output table (I-O table) needs to be projected forward to values in the analysis year. This projection is carried out by multiplying values in the I-O table by a multiplier factor (gross-up factor) for each analysis year. To calculate the multiplier factor (gross-up factor), the following formula is used::

$$G_i = \frac{GDP_{i,t}}{GDP_{i,o}}$$

Dimana :

G_i	= Gross-up Factor
$PDB_{i,t}$	= GDP sector i year 2016-2024
$PDB_{i,o}$	= GDP sector i year 2016 (I-O table)

VAT Compliance Gap Estimation Result

A decrease in the VAT tax gap percentage indicates an improvement in compliance and tax administration effectiveness, while an increase in nominal value reflects economic growth and a larger potential revenue base.

Chart 1: *VAT Compliance Ratio Gap* (%)

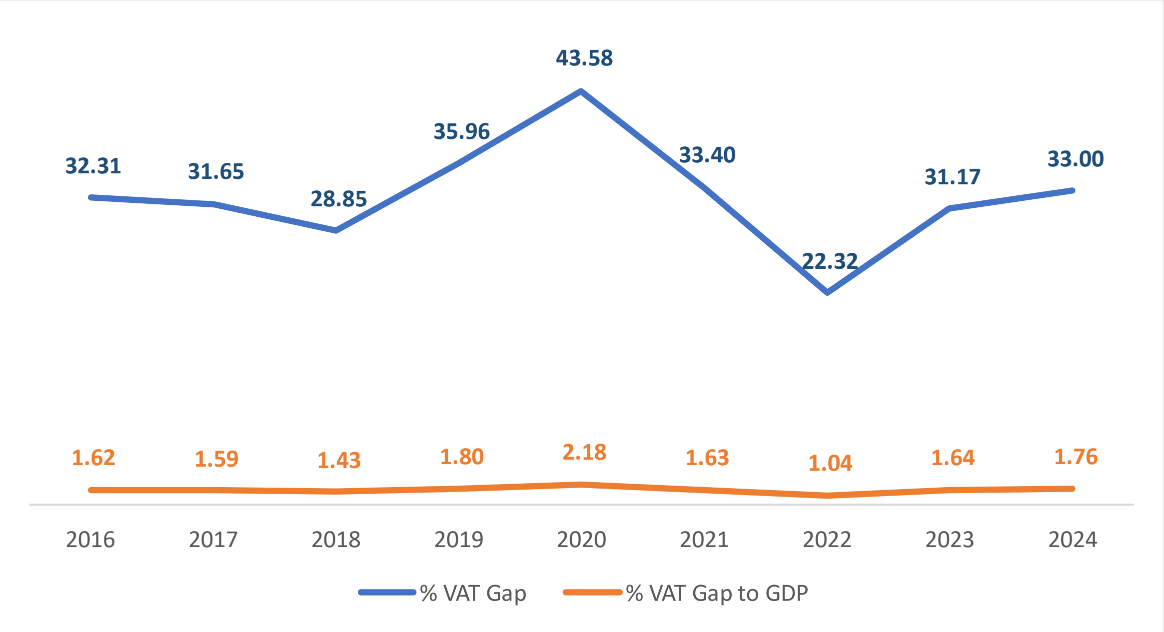
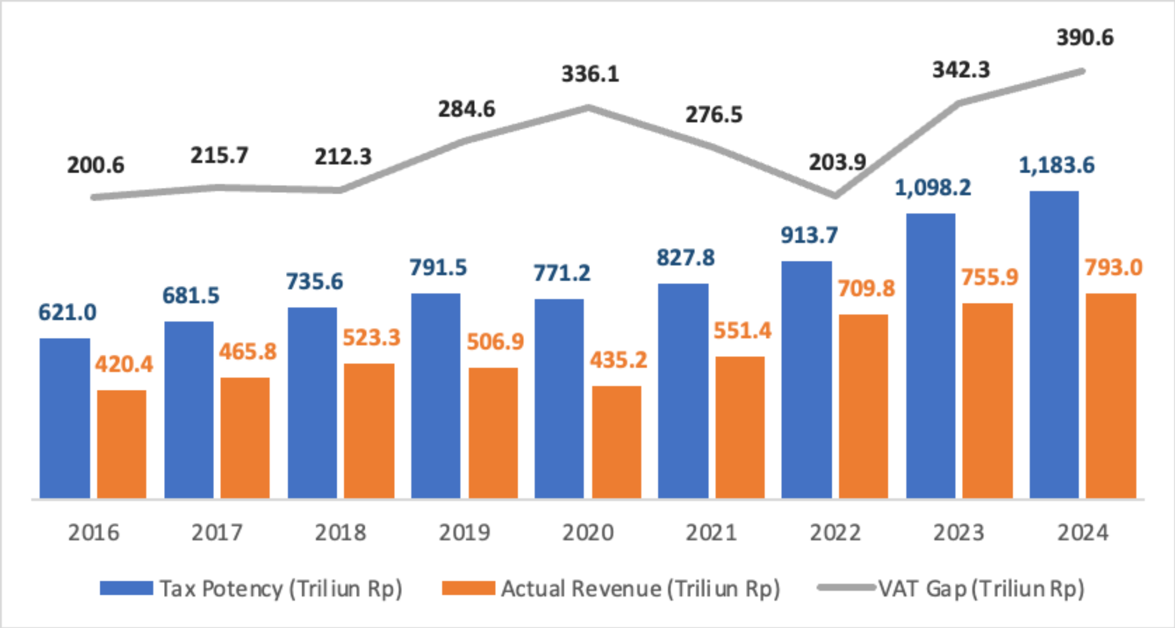


Chart 2: *VAT Compliance Nominal Gap (Trillion Rupiah)*



- Chart 1 shows that the VAT tax gap fluctuated, starting from 32.31% in 2016, dropping to 28.85% in 2018, then surging sharply in 2020 to 43.58% during the pandemic, and improving back to 22.32% in 2022 alongside the economic recovery. Following that, it widened again to 31.17% in 2023 and 33.00% in 2024.

- Chart 2 indicates that the nominal value of the VAT tax gap increased from around Rp201 trillion in 2016 to Rp391 trillion in 2024. In percentage terms, the VAT tax gap in 2024 is lower compared to 2020 (which recorded the highest level due to the pandemic), but its nominal value is higher. This condition reflects that VAT collection performance has improved in percentage terms, accompanied by an expansion of the total VAT base alongside economic growth.

VAT Gap influenced by VAT Revenue Sensitivity and Energy Price Index

Chart 1: GDP Growth and VAT Revenue

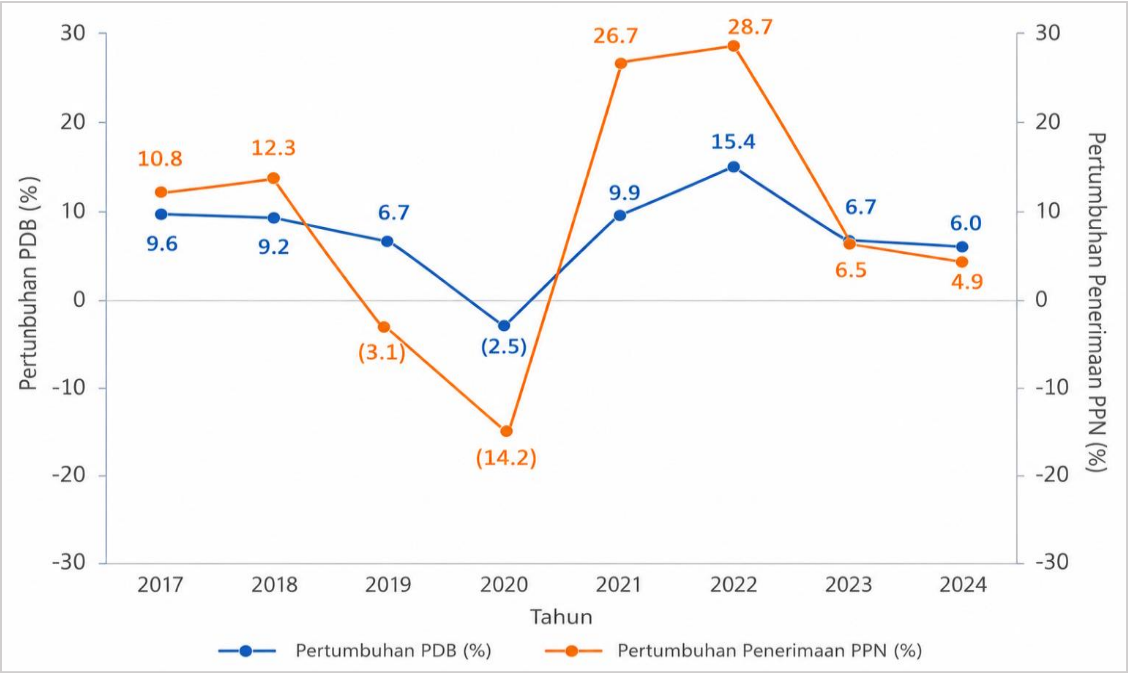
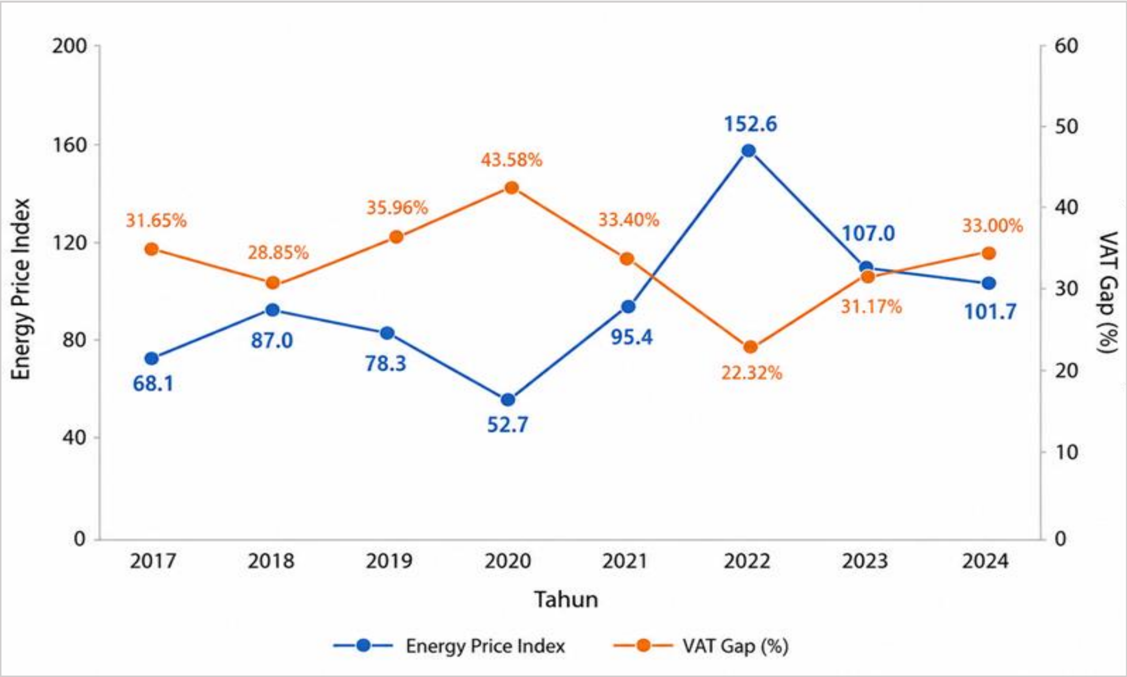


Chart 2: VAT Compliance Gap Estimation



- VAT revenue growth is more volatile than GDP growth, indicating that revenue responds to price changes and economic activity more rapidly than the macro base used in tax gap estimations.
- This dynamics differences affects the tax gap estimation, as revenue volatility directly alters the spread relative to the potential tax base.

- The VAT tax gap estimation also relies on a transaction base derived from the Input-Output Table, which is relatively static, whereas actual VAT revenue fluctuates according to dynamic changes in prices and economic activity.
- The link between revenue and the Energy Price Index causes shifts in energy prices to directly reflect in year-over-year VAT tax gap movements.

VAT Compliance Gap Estimation Result - Sectoral

Manufacturing recorded the largest nominal VAT tax gap, followed by construction. The highest ratios were found in other services, healthcare, and mining due to VAT facilities and the dominance of taxable goods exports.

Chart 3: *VAT Gap Compliance* 2024 (%)

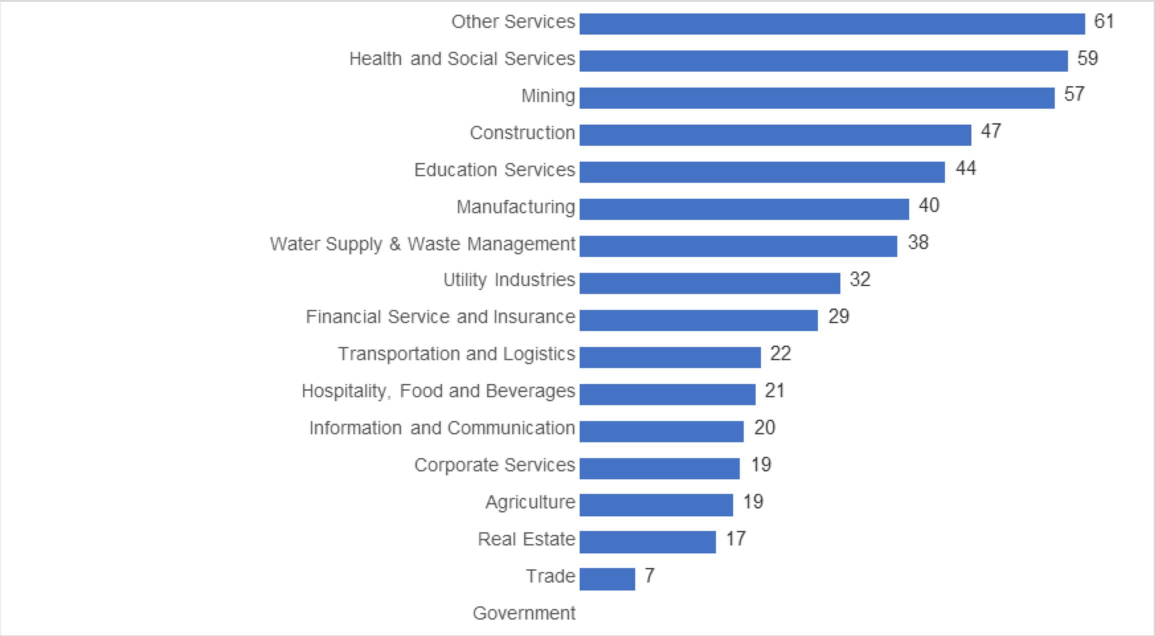
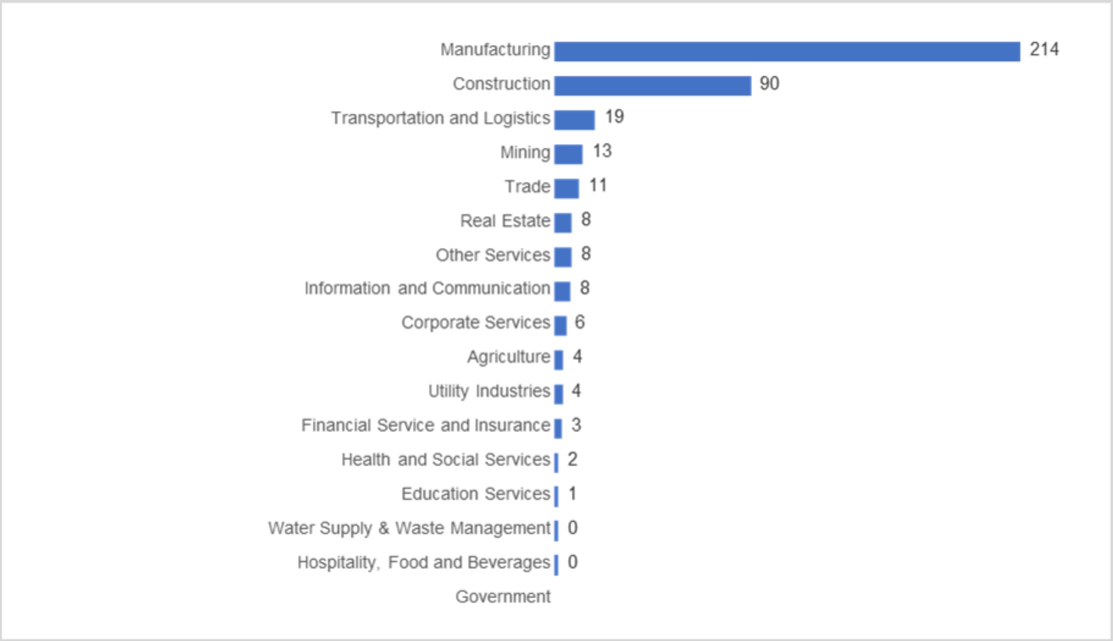


Chart 4: *VAT Gap Compliance* 2024 (Trilion Rupiah)



- Chart 3 indicates that three sectors have a VAT tax gap ratio above 50%: other services, human health and social work activities, and mining and quarrying.

- Chart 4 indicates that although those three sectors have a VAT tax gap ratio above 50%, in nominal terms the manufacturing sector dominates the VAT tax gap at Rp214 trillion, followed by the construction sector at Rp90 trillion..

VAT Compliance Gap Estimation Result - Sectoral

VAT Gap between 2020-2024 fluctuates in all economic sectors

Chart 1: VAT Compliance Gap Estimation Result 2020–2024

No	Sektor	2020				2021				2022				2023				2024			
		VAT Potential	VAT Revenue	VAT Nominal Gap	VAT % Gap	VAT Potential	VAT Revenue	VAT Nominal Gap	VAT % Gap	VAT Potential	VAT Revenue	VAT Nominal Gap	VAT % Gap	VAT Potential	VAT Revenue	VAT Nominal Gap	VAT % Gap	VAT Potential	VAT Revenue	VAT Nominal Gap	VAT % Gap
1	Agriculture	14.93	7.25	7.68	51.42%	15.83	5.93	9.90	62.55%	17.15	12.16	4.99	29.10%	20.17	14.14	6.03	29.90%	21.25	17.30	3.95	18.57%
2	Mining	7.26	4.36	2.90	39.91%	15.16	2.99	12.17	80.29%	17.41	10.08	7.32	42.06%	21.27	10.73	10.55	49.59%	22.58	9.61	12.97	57.44%
3	Manufacturing	350.21	195.00	155.21	44.32%	392.13	212.87	179.26	45.71%	405.91	311.49	94.42	23.26%	500.03	321.96	178.07	35.61%	537.38	323.29	214.09	39.84%
4	Utility Industries	5.56	2.89	2.68	48.13%	6.08	0.72	5.36	88.18%	6.98	5.29	1.68	24.12%	10.24	7.22	3.02	29.52%	11.85	8.11	3.73	31.51%
5	Water Supply & Waste Management	4.31	2.98	1.33	30.93%	0.65	0.69	(0.04)	-6.08%	0.69	0.48	0.21	30.58%	0.82	0.51	0.31	38.08%	0.88	0.54	0.34	38.47%
6	Construction	113.93	48.97	64.96	57.02%	139.73	39.67	100.06	71.61%	154.61	102.26	52.35	33.86%	176.70	91.35	85.35	48.30%	190.54	100.24	90.30	47.39%
7	Trade	87.60	64.28	23.32	26.62%	104.91	202.57	(97.66)	-93.09%	137.59	126.10	11.49	8.35%	159.37	148.40	10.98	6.89%	168.26	156.93	11.33	6.73%
8	Transportation and Logistics	46.83	30.65	16.18	34.56%	46.67	24.24	22.43	48.06%	61.10	51.62	9.49	15.52%	74.44	62.53	11.90	15.99%	84.65	66.05	18.61	21.98%
9	Hospitality, Food and Beverages	1.05	0.74	0.32	30.16%	1.08	0.74	0.34	31.84%	1.16	0.94	0.21	18.55%	1.44	1.27	0.17	11.51%	1.56	1.23	0.33	21.31%
10	Information and Communication	36.01	21.88	14.13	39.25%	27.39	18.60	8.79	32.09%	28.14	25.36	2.78	9.88%	34.07	27.40	6.68	19.60%	37.72	30.19	7.53	19.97%
11	Financial Service and Insurance	38.74	23.07	15.67	40.45%	8.51	5.73	2.78	32.68%	9.05	7.38	1.68	18.50%	11.20	7.62	3.58	31.98%	11.93	8.48	3.45	28.92%
12	Real Estate	37.83	19.72	18.11	47.86%	38.82	11.71	27.11	69.83%	41.69	34.67	7.02	16.83%	47.30	36.73	10.56	22.33%	49.25	41.11	8.14	16.52%
13	Corporate Services	15.62	10.69	4.93	31.56%	19.19	22.21	(3.01)	-15.71%	18.92	16.07	2.85	15.06%	25.49	19.79	5.70	22.35%	28.45	22.90	5.54	19.48%
14	Government	-	-	-		-	-	-		-	-	-		-	-	-		-	-	-	-
15	Education Services	0.94	0.48	0.46	49.07%	0.93	0.49	0.44	47.60%	0.99	0.51	0.49	49.01%	1.06	0.55	0.51	47.78%	1.13	0.63	0.50	44.22%
16	Health and Social Services	2.14	0.84	1.30	60.89%	2.36	1.08	1.28	54.33%	2.59	1.16	1.42	54.97%	2.85	1.25	1.61	56.34%	3.14	1.28	1.85	59.06%
17	Other Services	8.27	1.38	6.89	83.33%	8.40	1.14	7.27	86.47%	9.75	4.23	5.52	56.58%	11.71	4.47	7.25	61.86%	13.01	5.06	7.95	61.09%
	Total	**771.24**	**435.17**	**336.07**	**43.58%**	**827.84**	**551.35**	**276.49**	**33.40%**	**913.72**	**709.81**	**203.91**	**22.32%**	**1,098.17**	**755.91**	**342.26**	**31.17%**	**1,183.57**	**792.96**	**390.60**	**33.00%**

- In ratio terms, over the past 5 years, the mining, sector, educational services, human health and social work activities, and other services sector represent the sectors with the largest VAT tax gap, averaging over 40%.
- Meanwhile, in nominal terms, the manufacturing sector has the largest VAT gap, averaging more than Rp160 trillion and reaching a peak value of Rp214 trillion in 2024.

3. Bottom-up Approach

Why we needed a model

VAT audit results reveal non-compliance, but risk-based audits do not represent the whole taxpayer population.

Why this matters

VAT gaps are observed only when an audit produces a complete outcome.

Direct PPN audits are targeted rather than randomly assigned.

Audited and non-audited NPWP-months differ systematically.

Non-filing months require a separate information set because no current VAT return exists.

Research question

Can two-step gradient boosting estimate the national VAT gap while accounting for audit selection, signed adjustments, and non-filing months?

Methodological basis

Stage 1 models audit selection and produces cross-fitted stabilized IPW. Stage 2 predicts signed audit adjustments, while complete audited outcomes remain observed in national accounting.

Methodological inspiration: Di Loro et al. (2023), adapted to Indonesian VAT data and DGT audit structure.

Data and estimation scope

The core filed modeling unit is NPWP-month (Taxpayer ID-month); repeated taxpayer identifiers are intentionally retained.

43,646,072
Filed NPWP-months (Taxpayer ID-months)
2016–2024

778,168
Unique taxpayers
Repeated NPWP retained (Taxpayer IDs across months)

427,896
Audited NPWP-months (Audited Taxpayer ID-months)
Direct PPN audit flag (Direct VAT audit indicator)

70 / 30
Stage-1 split
Train / validation

60/20/20
Stage-2 split
Train / calib. / val.

Stage 1

All filed PPN (VAT) NPWP-months (Taxpayer ID-month records) with a direct-audit indicator. Target: audited versus non-audited.

Stage 2

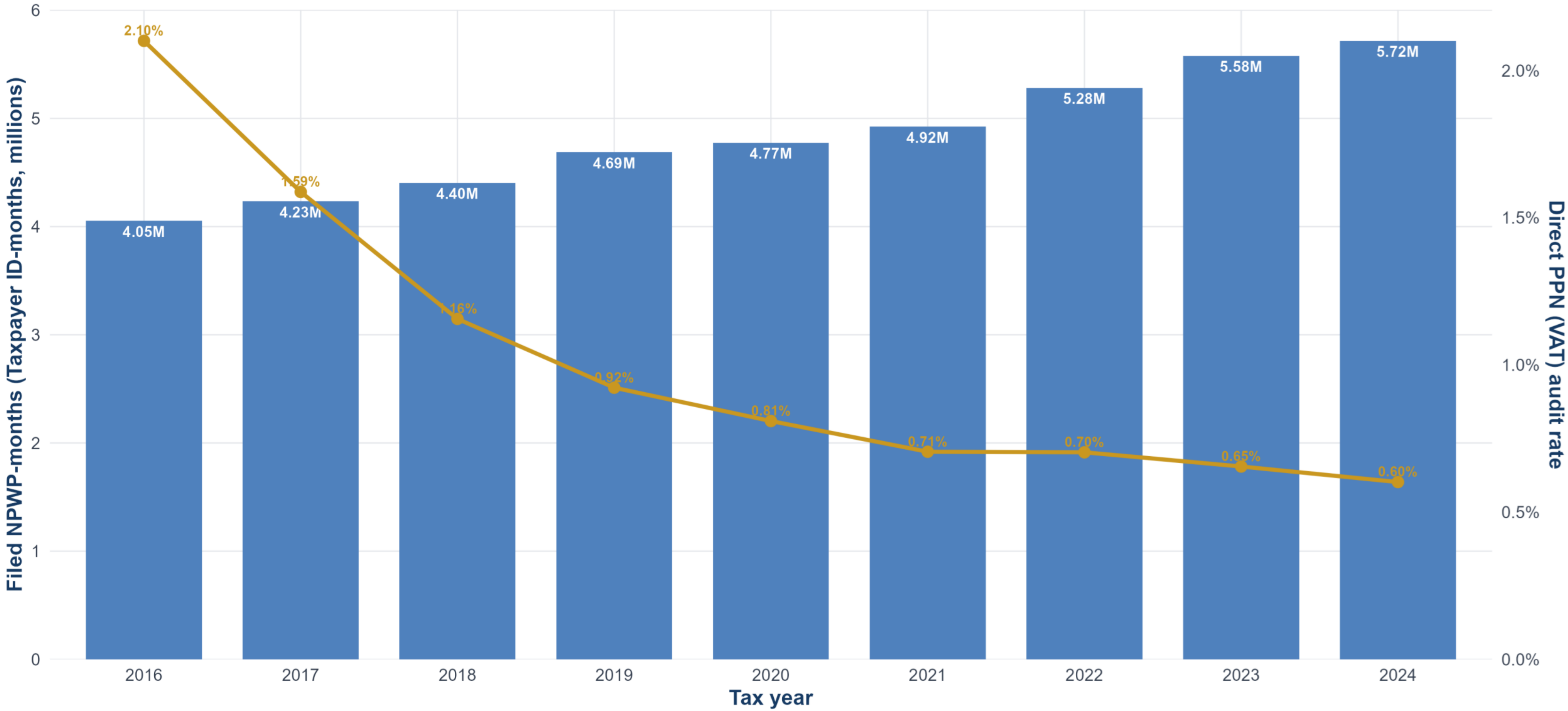
Complete audited filed NPWP-months (Taxpayer ID-month records). Signed outcome architecture retains negative, zero, and positive audit adjustments.

National accounting

Complete audited outcomes use observed audit results. Other rows use final model predictions, while the four accounting components remain separate.

- **The estimation framework separates audit selection, audit-gap prediction, and national accounting so each step can be interpreted clearly.**

The filing population grew as direct-audit coverage declined



Because audit prevalence changes over time, the model first estimates the probability that an observation is audited.

- **The audited sample changes over time and is not a random representation of all filed taxpayers.**

The estimation journey

One reproducible workflow connects the VAT population, audit selection, outcome prediction, and national accounting.

1 Population & features

Filed PPN NPWP-months and pre-audit predictors.

2016–2024

2 Stage 1

Estimate P(audit | X) and validate probability quality.

70 / 30 split

3 Selection weights

Three-fold OOF propensity and stabilized bounded IPW.

Cross-fitted

4 Filed Stage 2

Signed multipart outcome model for complete audited filed months.

60 / 20 / 20

5 Non-filing Stage 2

Separate model for approved non-filing universe.

Separate feature set

6 Calibration & scoring

Lock calibration, validate, then score filed and non-filing populations.

No post-validation retuning

Hybrid national accounting

Filed

Observed complete outcomes + predictions for other filed rows

Primary non-filing

Observed complete outcomes + predictions within approved universe

Observed-only non-filing

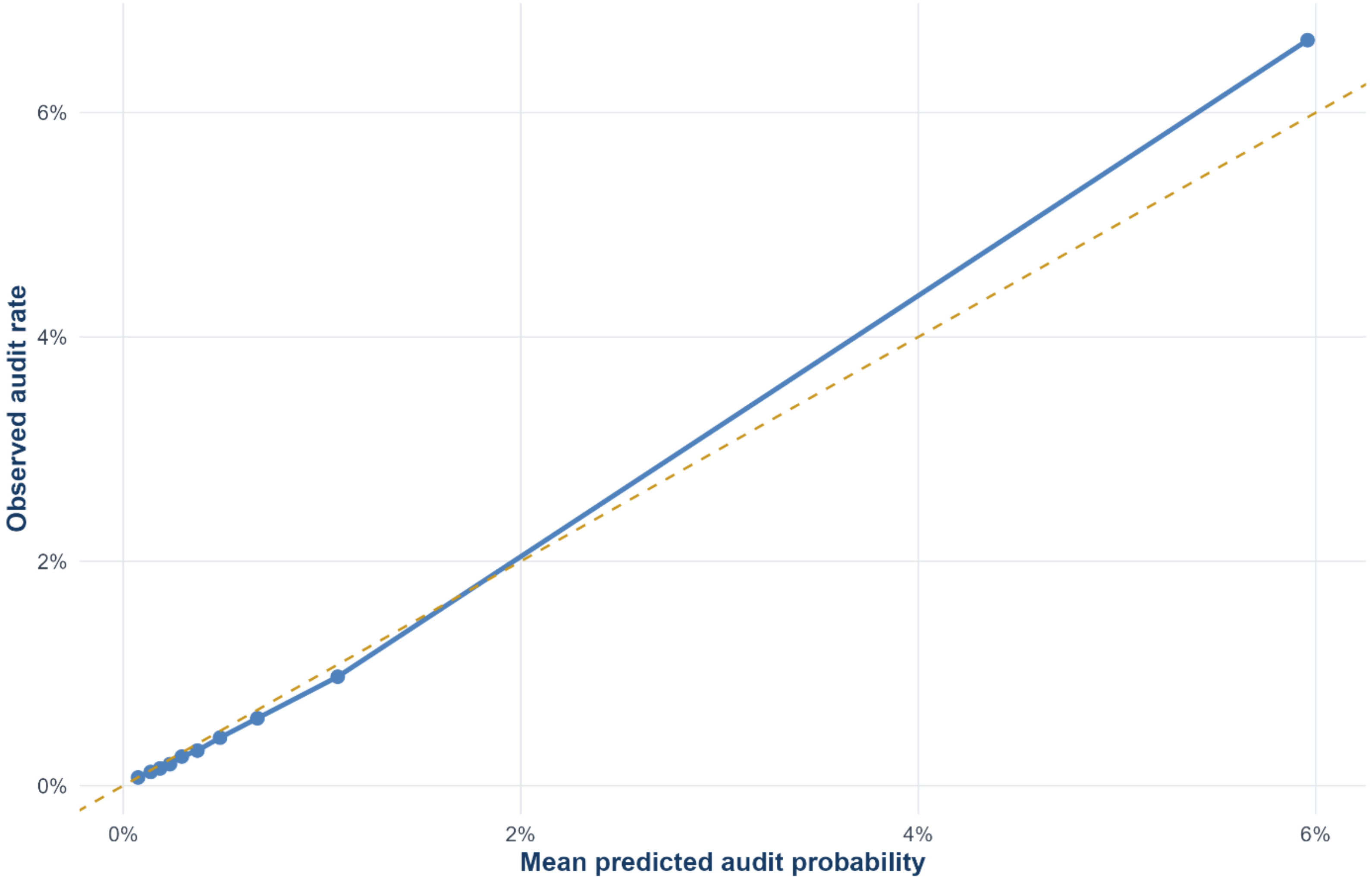
Observed outcomes retained; excluded from Stage 1

Zero / missing NPWP

Observed aggregate component only

= National VAT gap

Stage 1 produced reliable audit probabilities



Dashed line = exact probability calibration.

0.874

ROC-AUC

Held-out Stage 1

Can Stage 1 distinguish audited from non-audited?
0.874 indicates strong discrimination between audited and non-audited observations.

0.0080

Brier score

Probability accuracy

Calibration: Are the probabilities themselves credible?
0.0080 indicates a low average probability-prediction error.

0.0385

Log loss

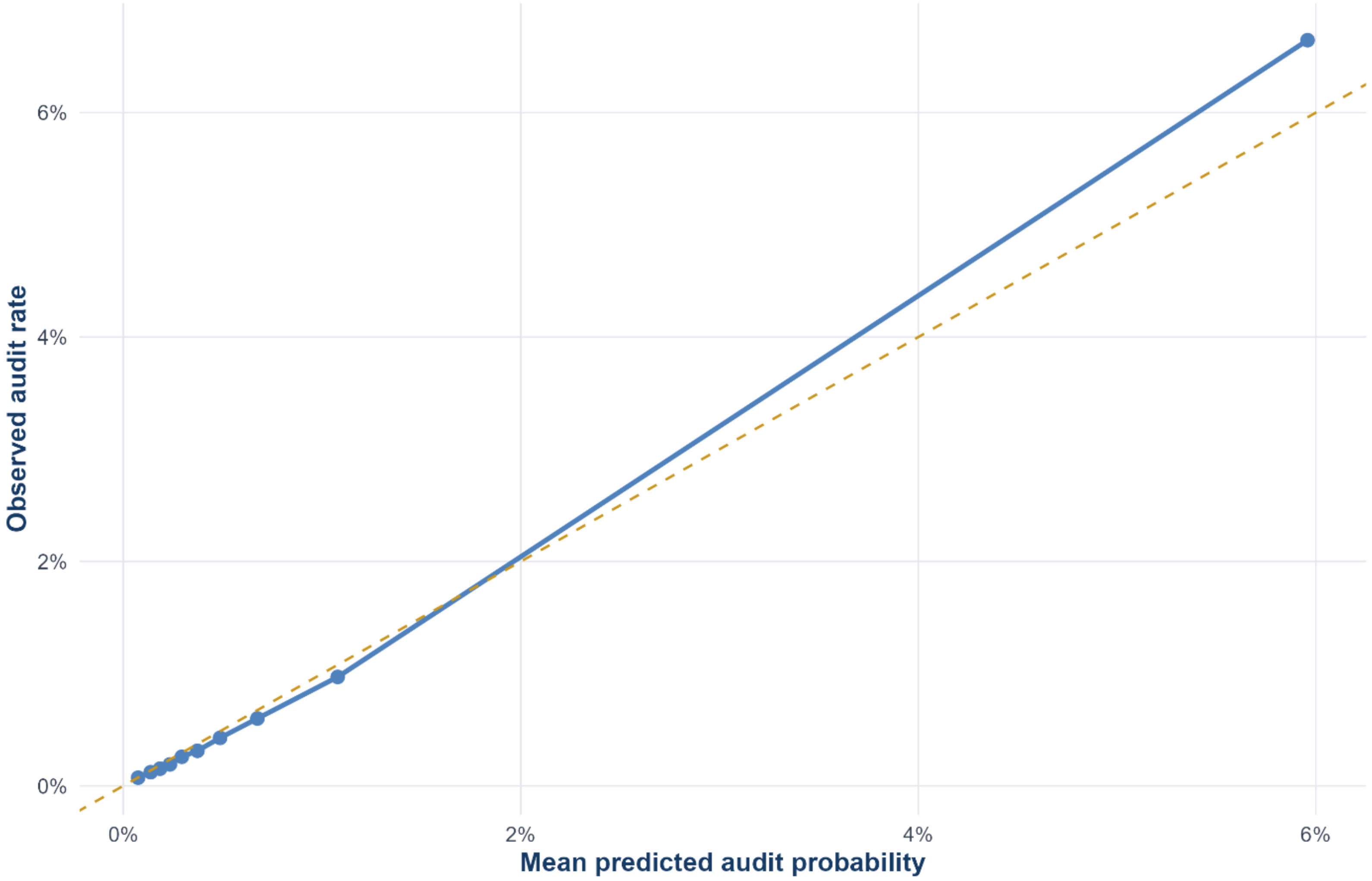
Probability quality

Can those probabilities actually be used safely for IPW?
0.0385 indicates a low penalty from inaccurate probability predictions.

Stage-1 discrimination is useful, but selection correction also depends on support and weight stability.

- discrimination — can the model distinguish observations that are more likely to be audited?
- calibration — when the model says the probability is, say, 2%, is the actual audit rate around 2%?

Stage 1 produced reliable audit probabilities



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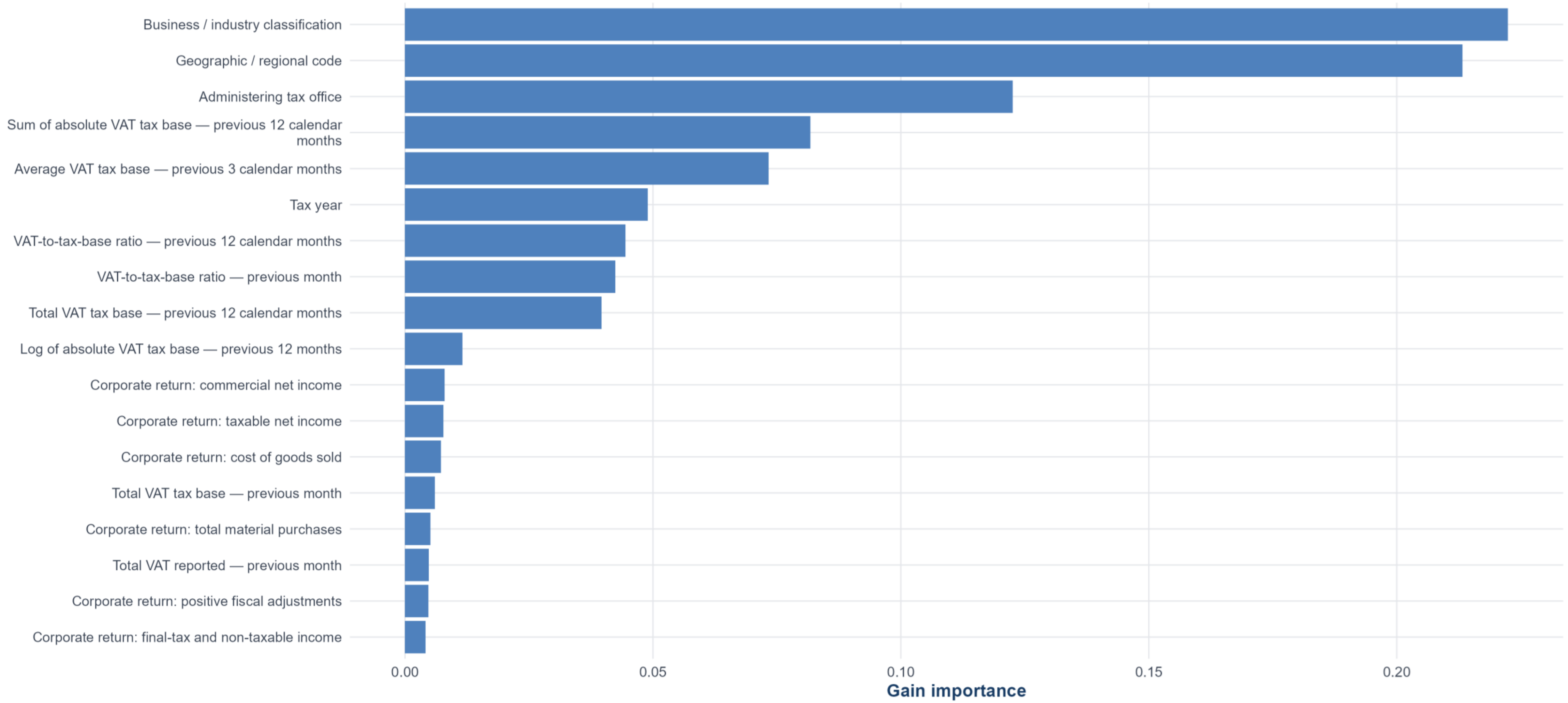
Variables Most Influential in Audit Selection



Feature importance does not identify causal effects.

Feature importance is predictive, not causal.

Stage 2 predicts direction first, then amount

The second stage predicts signed audit adjustments rather than a positive-only VAT gap.

Filed sign model

Three-class LightGBM:

- NEGATIVE → audit reduces the taxpayer's reported liability
- ZERO → no adjustment
- POSITIVE → additional VAT is due

Trained with stabilized IPW from Stage 1 on complete audited filed months.

The sign probabilities determine how expected positive and negative components are combined.

Filed magnitude models

After predicting the sign, separate models estimate how large the adjustment would be.

Positive amount and absolute negative amount are modeled separately.

Expected signed adjustment = P (POS) × E (POS amount) − P(NEG) × E(|NEG amount|).

P= (probability), E= (expected)

This preserves downward audit adjustments instead of discarding them.

Non-filing architecture

Binary LightGBM estimates P(non-positive | X).

A separate positive-magnitude model predicts additional tax due when positive.

Because negative non-filing audits are genuinely rare, the negative magnitude uses a train-only robust fallback with formal sensitivities.

For filled returns, Stage 2 answers two questions:

1. Will the audit adjustment be negative, zero, or positive?
2. 2. If it is positive or negative, how large will it be?

For non-filling returns, Stage 2 answers two questions:

1. . Is there likely to be additional VAT due?
2. 2. If yes, how much?

Calibration and final validation

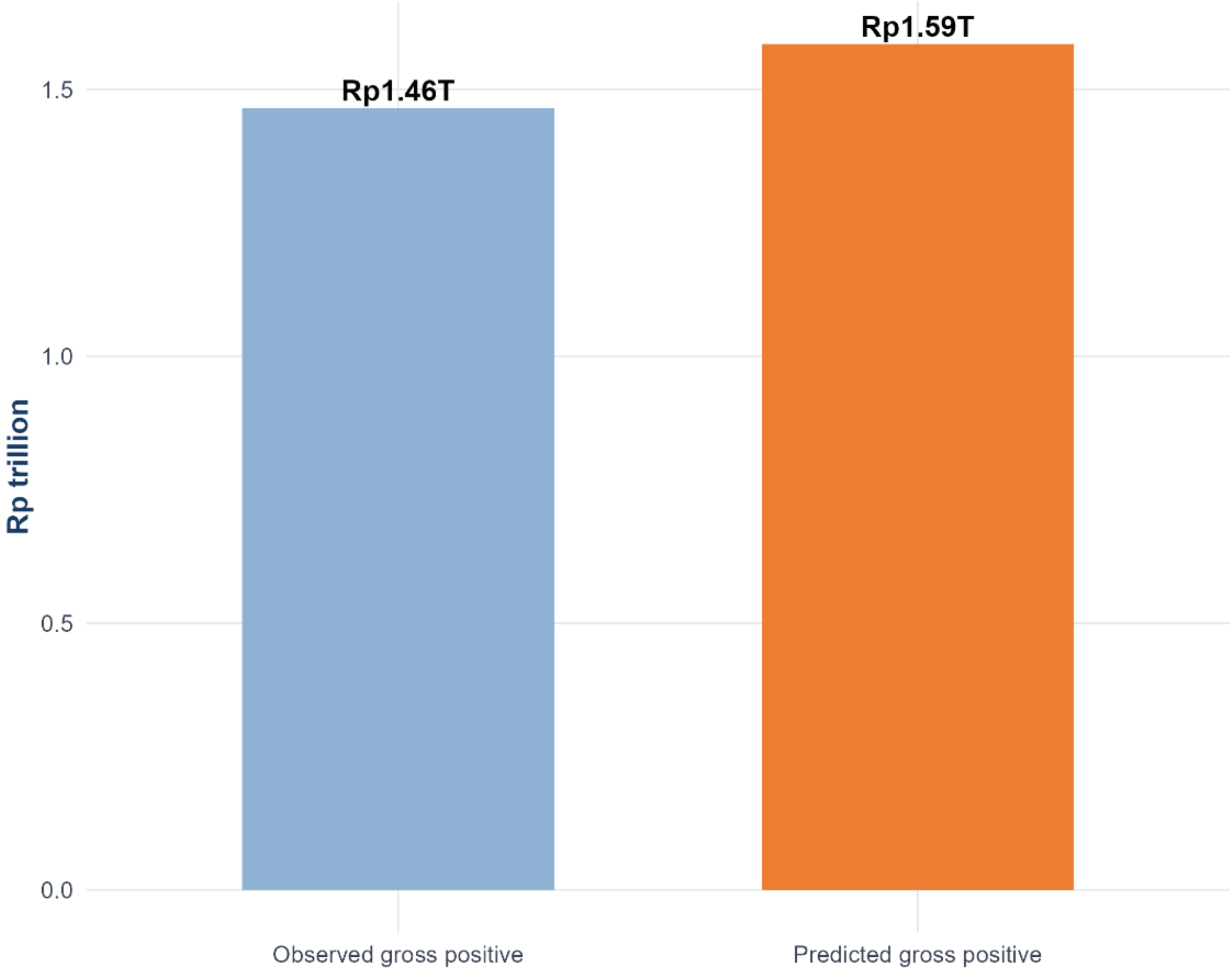
Filed calibration compares no calibration with signed-safe component-power rules. Non-filing calibration adjusts the positive component only. In both cases, calibration is locked before the untouched final validation is opened.

The architecture is intentionally different for filed and non-filing months because the available information and the rarity of negative non-filing outcomes differ. Non-filing months do not have a current VAT return and negative outcomes are much rarer, so they require a separate modeling approach.

Stage 2 reproduced the aggregate audited adjustment

Aggregate gross-positive validation on audited observations

Observed = Rp1.5T | Predicted = Rp1.6T | Aggregate error = +8.2%



Validation is based on audited observations because true VAT gaps are not observed for non-audited taxpayers.

+8.2%
Gross-positive error
Audited validation

0.471
Signed-log Spearman
moderate ability to rank taxpayers from lower to higher audit adjustment.

1.1%
Net abs. error / gross
When positive and negative adjustments are combined, the overall signed aggregate error is small relative to the gross amount.

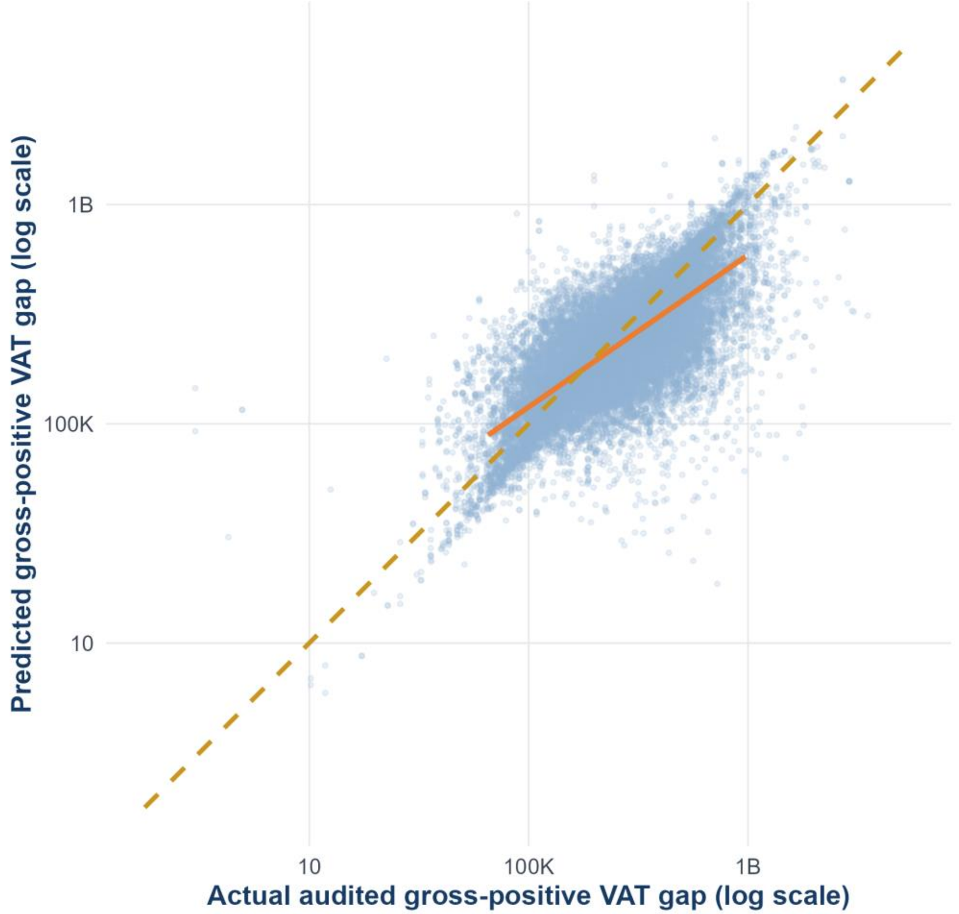
81.8%
Sign accuracy
The model correctly predicts whether the outcome is negative, zero, or positive about 82% of the time.

The audited validation sample shows how well the model ranks and predicts observed audit outcomes, but it cannot directly verify the national total.

Stage 2 reproduced the aggregate audited adjustment

Actual and predicted VAT gaps show meaningful rank association

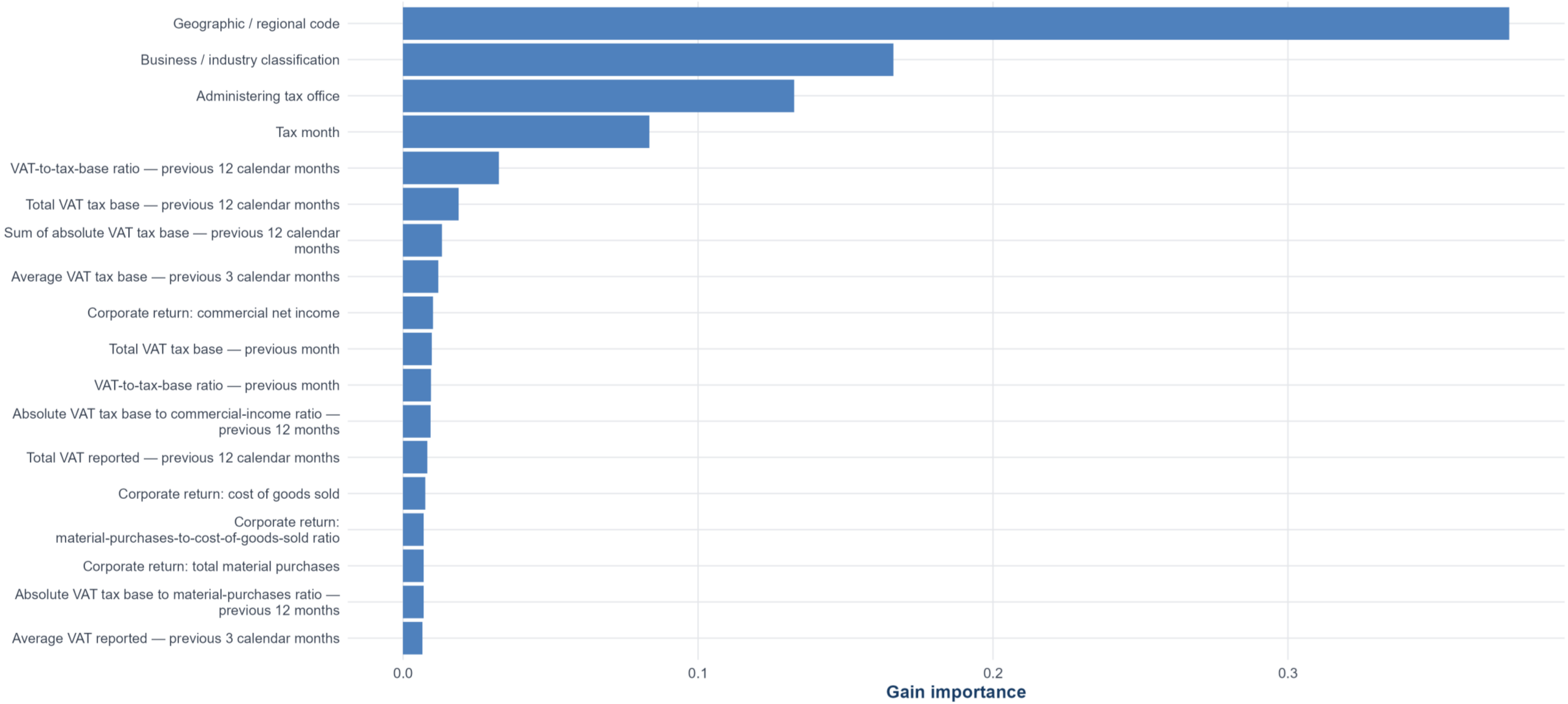
Positive audited validation outcomes | Spearman = 0.727 | fitted log R^2 = 0.551 | strict log R^2 = 0.471



Orange line = fitted relationship between observed and predicted positive gaps; dashed gold line = exact prediction (45-degree line).

The model ranks taxpayers meaningfully, although very small and very large rupiah outcomes are pulled toward the center.

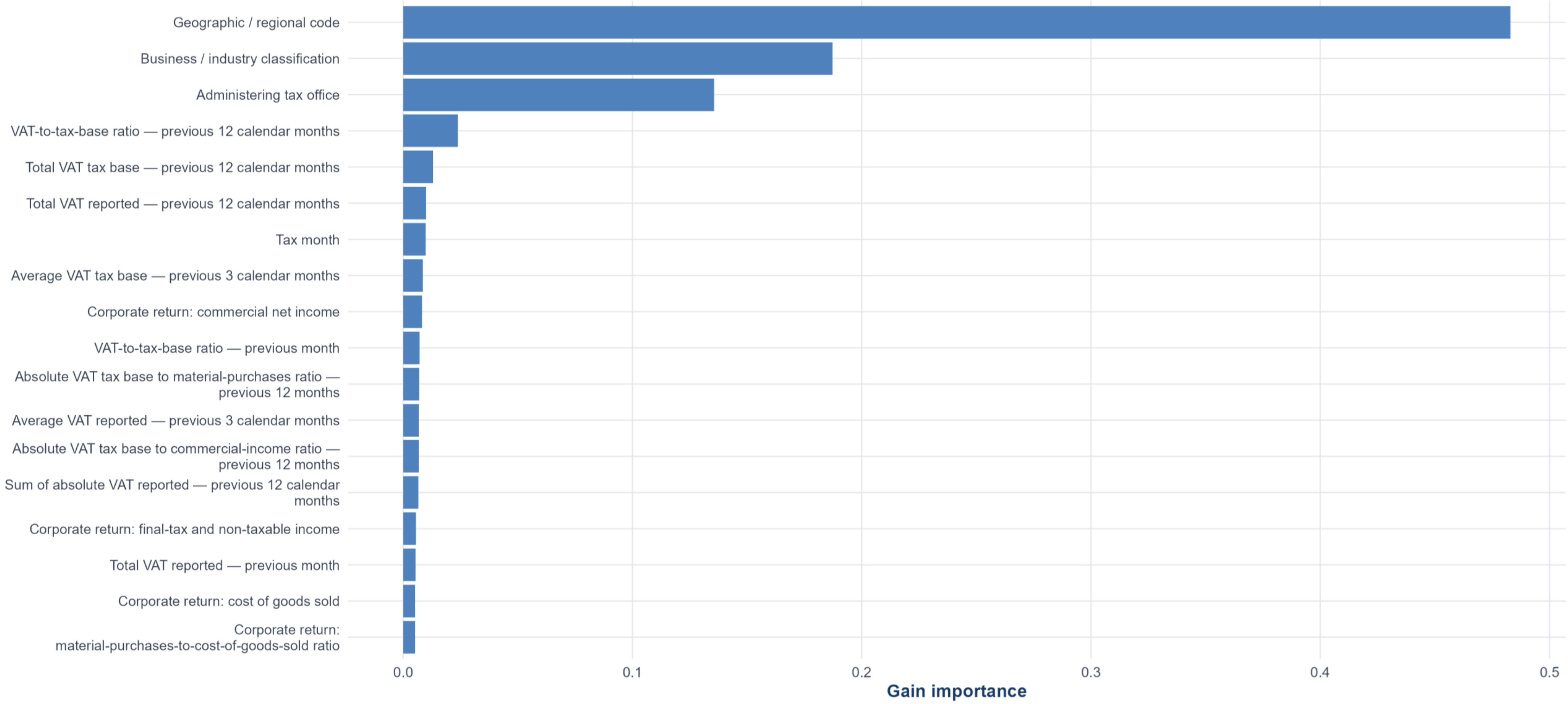
Variables Most Influential in Sign Classification



Feature importance does not identify causal effects.

Feature importance is predictive, not causal.

Variables Most Influential in Positive Adjusment Magnitude



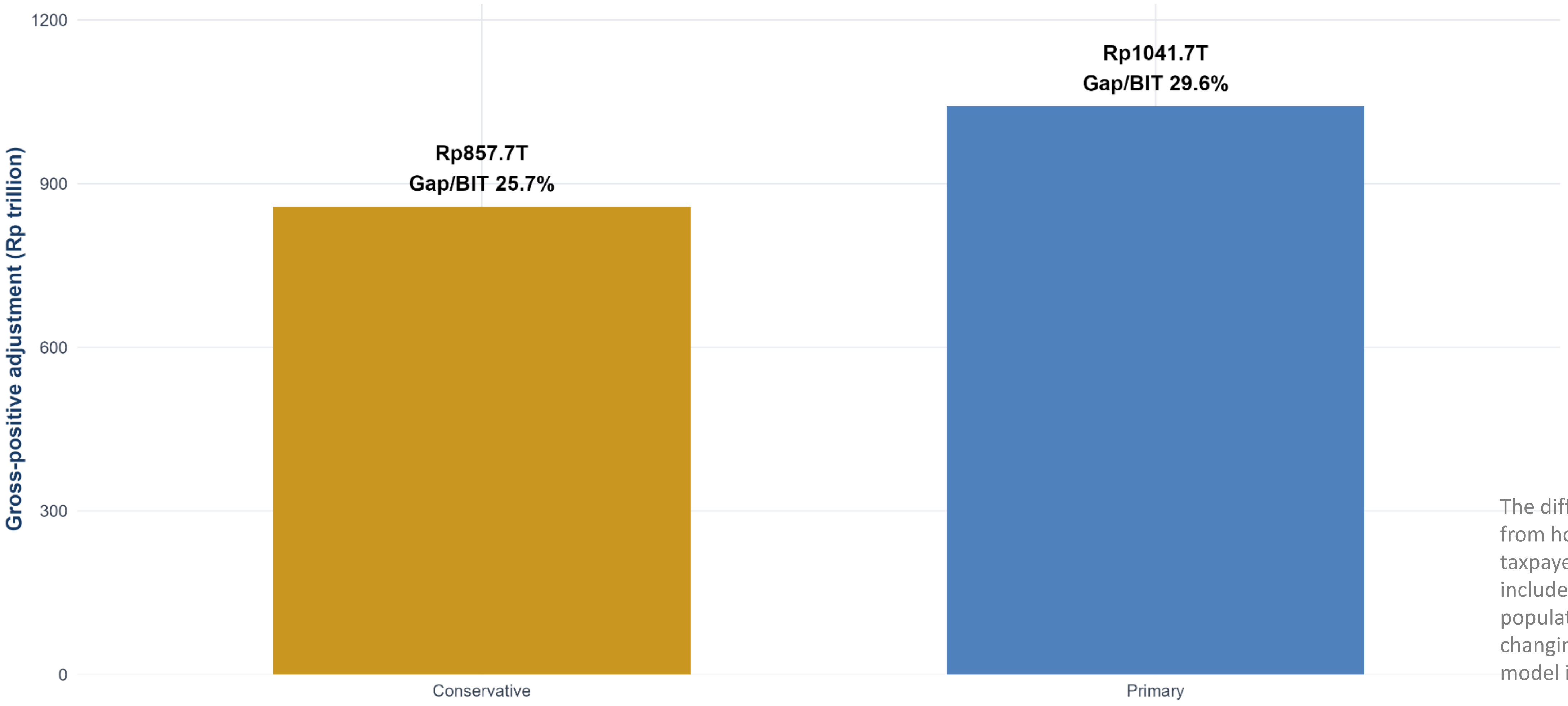
Feature importance does not identify causal effects.

Feature importance is predictive, not causal.

The non-filing universe materially changes the estimate

Cumulative gross-positive VAT gap is materially sensitive to the non-filing universe

Primary Gap/BIT = 29.6% | Conservative Gap/BIT = 25.7%

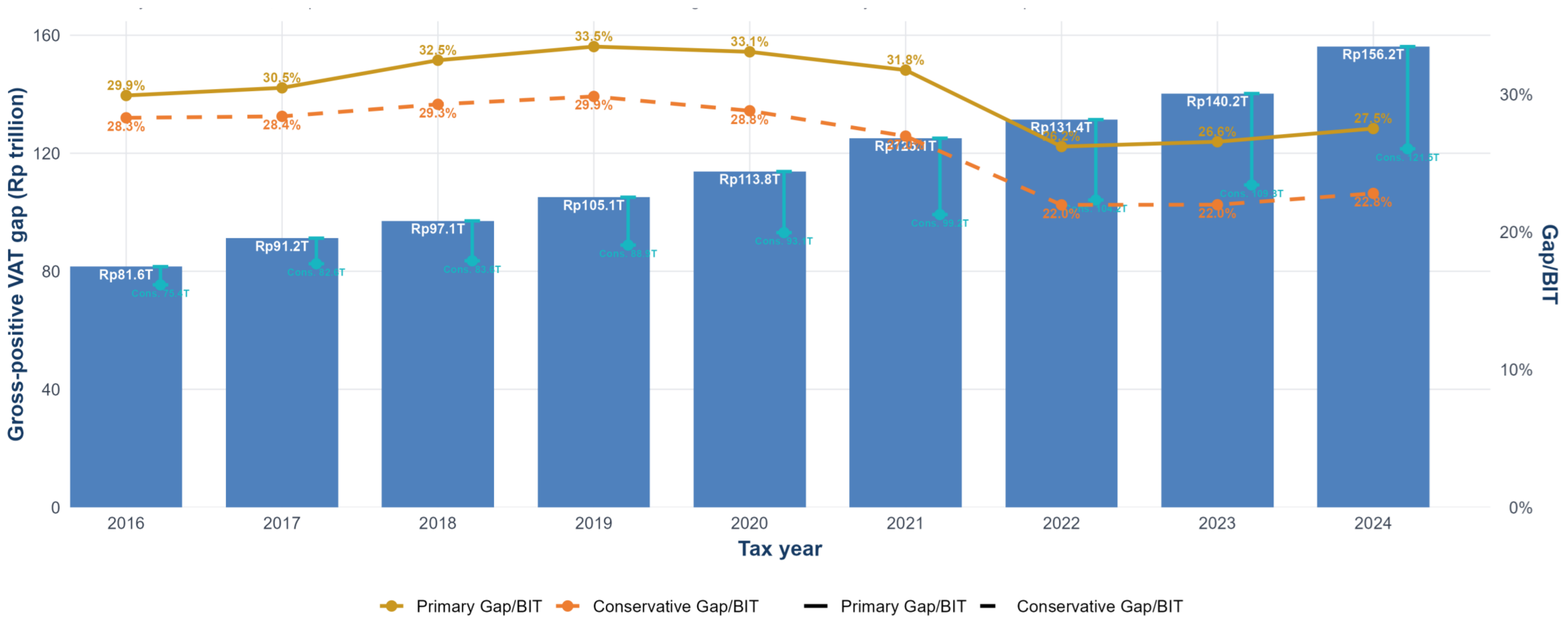


The difference comes mainly from how many historical taxpayer-months are included in the non-filing population, not from changing the prediction model itself.Main take

The difference between the two bars shows how much the national estimate depends on the assumed historical PKP population.

The non-filing universe assumption has a material effect on the national gross-positive VAT-gap estimate and should be considered when interpreting the headline result.

The estimated VAT gap rose from Rp82T to Rp156T



Teal segments show the Primary–Conservative population-definition sensitivity; gold solid line = Primary Gap/BIT; orange dashed line = Conservative Gap/BIT. The teal range is a scenario sensitivity, not a statistical confidence interval.

Audited-sample annual validation error

Held-out model-performance diagnostic; not uncertainty around the national total.

-88.1%	-8.3%	+12.6%	-5.0%	-12.5%	+9.0%	+21.4%	+11.3%	+6.8%

Teal = sensitivity to the historical PKP (VAT-registered taxpayer) universe definition; the validation row = year-specific held-out audited-sample performance. Neither is a statistical confidence interval. The 95% NPWP-cluster (Taxpayer ID-cluster) bootstrap interval is reported separately.

National VAT Gap=Filed component+Non-filing component+other observed components

Downward audit adjustments exceeded upward adjustments

National signed accounting separates upward and downward adjustments

Bars show gross components; the gold line shows the net signed balance.

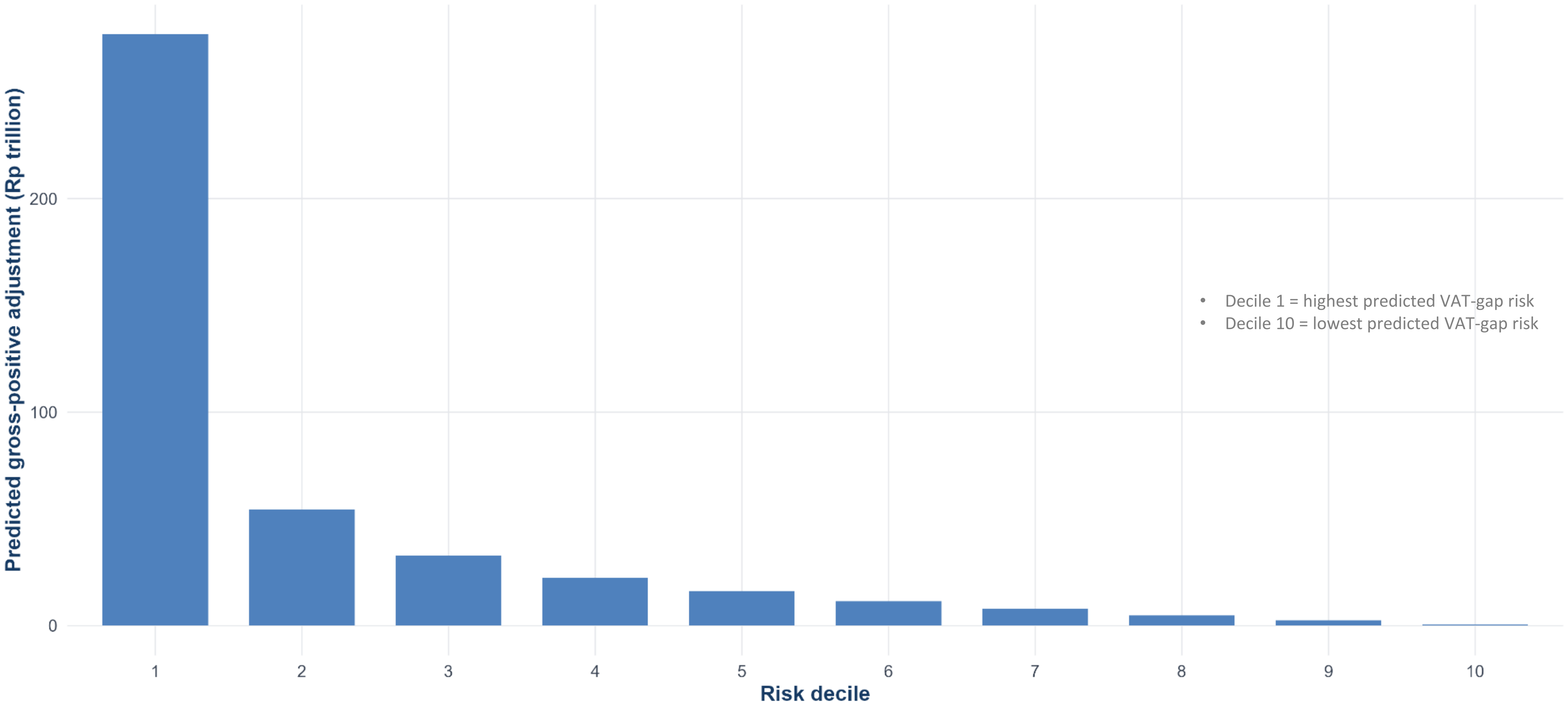
Net signed adjustment equals gross positive additional tax due minus the magnitude of downward audit adjustments.

Downward audit adjustments are substantial and are therefore shown separately rather than hidden inside the net balance.

The highest-risk filed decile contains most predicted VAT gap

Predicted positive adjustment is concentrated in the highest-priority filed deciles

Taxpayers are ordered from highest to lowest predicted gross-positive adjustment.



The bars show predicted potential additional VAT, not amounts already collected through audit.

- **Most predicted additional VAT is concentrated in the highest-risk deciles, supporting targeted audit prioritization.**

What we learned

The framework produces a national estimate and a practical risk ranking while making its assumptions visible.

Headline VAT gap

The conventional gross-positive gap rises from about Rp82T in 2016 to Rp156T in 2024. Gap/BIT peaks at 33.5% in 2019 and is 27.5% in 2024.

Audit selection is not random

Audit prevalence declines materially over time and common support is imperfect. Explicit selection modeling and stabilized weighting are therefore central to inference.

Validation is informative but heterogeneous

Ranking is meaningful, yet annual audited-sample error varies substantially. The 2016 validation result is especially weak and should temper interpretation of year-to-year movements.

Non-filing population assumptions matter

The cumulative gross-positive estimate is Rp1,041.7T under the primary universe versus Rp857.7T under the conservative universe, showing material historical-PKP uncertainty.

Risk ranking has operational value

Predicted gross-positive adjustment is strongly concentrated in the highest-risk deciles for both filed and non-filing populations, supporting targeted audit prioritization.

Signed accounting answers a different question

Downward audit adjustments are large, so net signed accounting is negative. Gross-positive VAT gap and signed accounting should be reported together rather than conflated.

4. Conclusion & Challenges

Conculsion

1. Tax gap estimation can be conducted using two approaches, which are top-down using macro-level data, and bottom-up by utilising micro-level data of each taxpayer.
2. Based on the top-down approach, the tax gap estimation results show a decrease in the percentage gap. This decline reflects improvements in taxpayer compliance and enhancements in tax administration and collection. However, in nominal terms, the VAT tax gap shows an increase along with economic growth.
3. On the other hand, tax gap estimation results using the bottom-up method indicate a stagnant trend for the percentage gap. In nominal terms, the estimation shows an increasing tax gap trend. This trend reflects an increase in potential tax revenue derived from audit activities.
4. Both result shows an increase in tax gap nominal but have different result in tax gap percentage.

Challenges

1. Top-down tax gap estimation depends heavily on publication from Statistics Indonesia. Therefore the estimation is less reliable the further the data available from headline year;
2. The bottom-up tax gap estimation for VAT is conducted based on limited audit data. Therefore, increasing the volume of tax audits and establishing sound audit data governance should improve accuracy. Furthermore, bottom-up tax gap estimations do not yet account for the possibility of undetected tax potential during the audit process. Consequently, future estimations should incorporate a non-detection multiplier model, similar to those applied by the IRS, HMRC, and ATO;
3. The VAT tax gap estimation still relies on data sourced from tax returns (SPT), resulting in a limited set of tax gap predictors. Therefore, third-party data or tax return data from other tax types should be utilized as independent variables for more accurate tax gap predictions. For example, identifying taxpayers below the VAT threshold still relies on tax return data. Incorporating external data that accurately reflects the proportion of the VAT threshold and MSME taxpayers is expected to improve estimation.

Thank You

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