Who is Bogus? Using One-Sided Labels to Identify Fraudulent Firms from Tax Returns

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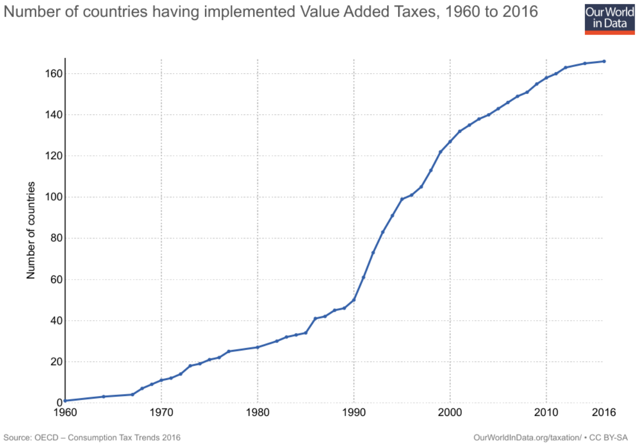
Rapid Increase in Value Added Tax Adoption Since 1960



- 1 country in 1960 → 50 in 1990 → 160 in 2015.
- Tax levied at each stage of production or distribution (contra sales tax).

Evasion under VAT: Bogus Firms

- VAT requires buyer & seller to independently report each transaction.
  - Opposing incentives should reduce scope for collusion and evasion.
  - Whether this occurs, particularly in emerging economies, is an open question. (Limited) evidence.
    - In related work, we show that digitization enabled cross-checking of buyer and seller reports increased collections but only from better monitored firms.[1]
  - VAT example
- Alternative evasion strategy – "Bogus" firms.
  - Bogus firms are shell firms created to enable firms to lower tax bills.
  - Create (fake) paper trails of transactions with genuine firms.
  - Bogus firms example
- Precise extent and magnitudes largely unknown.
  - Media reports estimate the loss, in Delhi alone $\approx$ \$300m.[2]
- Commonly reported in many VAT systems.
  - Still relevant for the newly launched Goods and Services Tax (India).
  - Early conversations in Mexico, Dominican Republic, and Zambia.

[1] Mittal and Mahajan (2017)

[2] India today article, TOI article, BS article

Detecting Bogus Firms: Current Practice

- Physical inspections gold standard, but resource intensive.
  - Audit resources limited (particularly in low-income countries).
- Key problem: How to identify firms for inspection?
  - More of them with less effort
- Officials in the central office create a list of "risky" firms.
  - Based on (limited set of) variables: low (VAT deposited/turnover), high turnover, high revisions, invalid address.
- Local inspectors sent out for inspections.
  - Firms deregistered ("cancelled") if inspection fails.

Our Work

We apply a random forest classifier to the value added tax (VAT) returns from Delhi (India) to increase tax compliance by identifying bogus firms which can be further targeted for physical inspections.

Highlights

- One sided labels and in-sample predictions $\Rightarrow$ Cross-validation.
- Precision, recall, F1 score not ideal $\Rightarrow$ Focus on top recommendations.
- Non-RCT evaluation (for now) $\Rightarrow$ Point-in-time simulation.
- Multiple firm-quarter observations but class timeless $\Rightarrow$ Aggregate the predictions.

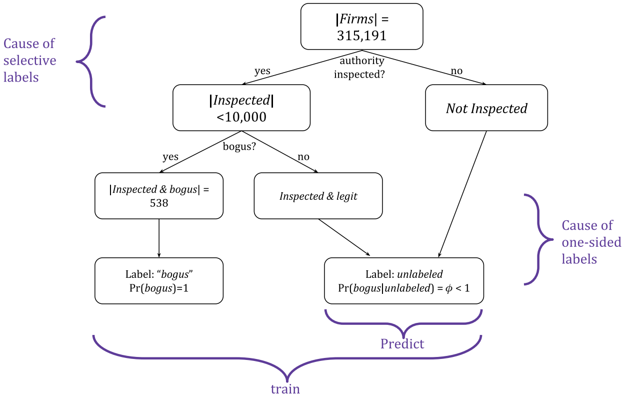
Delhi and Taxation

- Population: 16.8 million (2011 census)
- Real GSDP of NCT of Delhi for 2015-16: ₹4,560 billion (US$ 71 billion)
  - Tax to GSDP ratio: 5.7%
- VAT accounts for 52.4% of total government revenues

Data Description

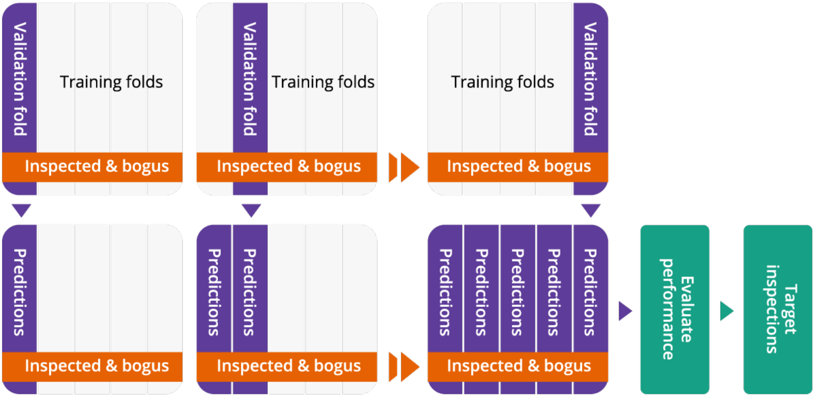
- Entire universe of registered firms from Delhi, India (315,191 firms, unbalanced).
- 3 years of quarterly VAT returns - 2012-13, 2013-14, 2014-15.
- 3 years of quarterly firm level interactions - 2012-13, 2013-14, 2014-15.
- Firm profile data.
- Bogus firm data: 531 bogus firms identified (2012-2015).

Bogus Firms: Our Challenge



- Inspection is based on the tax authority's discretion and so biased (selective labels).
- Class labels are known only for firms both inspected and found to be bogus, not for the rest (one-sided labels).
- We use all for training, but want to predict for those firms still unlabeled (in-sample predictions).

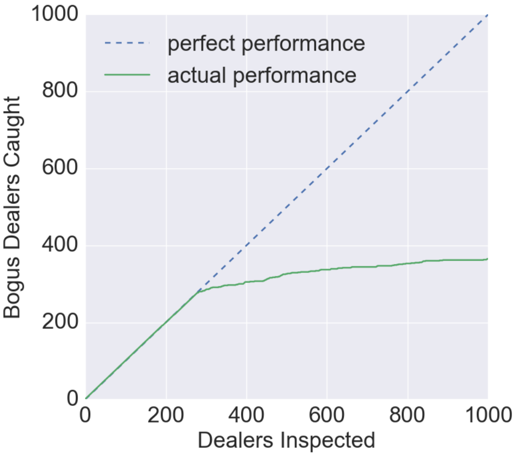
Cross-validated Prediction Procedure



Multi-Period Model

Wide Model

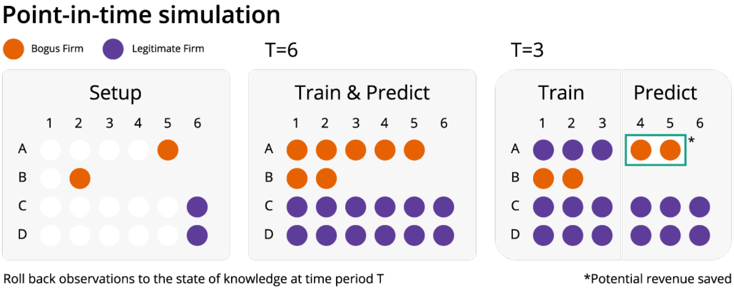
Random Forest Model Performance on Top 1000 Recommendations



- Results similar when we control for revenue size.

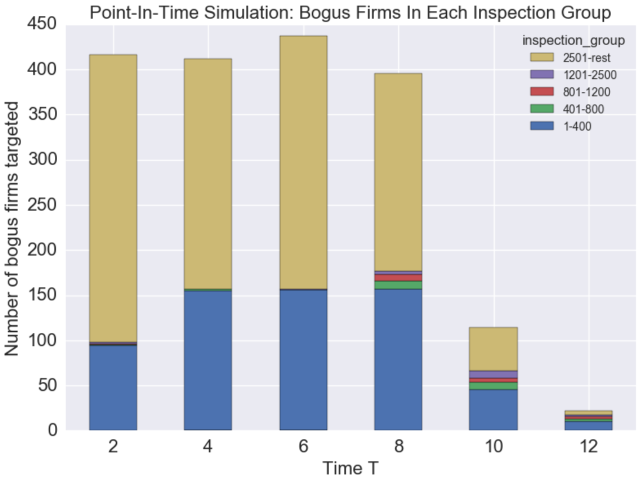
Different Classifiers Different Feature Sets All Recommendations Important Features

Illustration of Point-in-time Simulation at T=3



- In a real-world scenario, do not have access to all returns by all firms and not required to predict retroactively.
- Blind the model to information obtained after time "T" - do not consider "future" tax returns after T.
- Only use bogus firms that were already classified by time T.

Point-in-time Simulations Performance



Revenue Saved

Conclusions and Challenges

- Used digitized tax returns to create a ML tool to identify potentially fraudulent firms.
  - Next: Tax authority inspects most suspicious firms (create training data).
  - Finally: Compare revenue implications against current practices.
- Challenge: Firms will respond to better targeting – e.g. by creating more bogus firms faster.
  - ML tool will require regular updating (more training data).
  - Real world example of adversarial ML.
- Interest from many tax authorities, potentially useful tool in the hands of high level officials.

Thanks!

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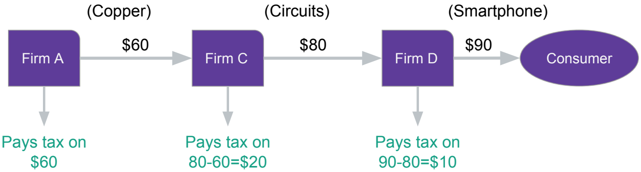
VAT: Example



Government receives tax on $90 value added.

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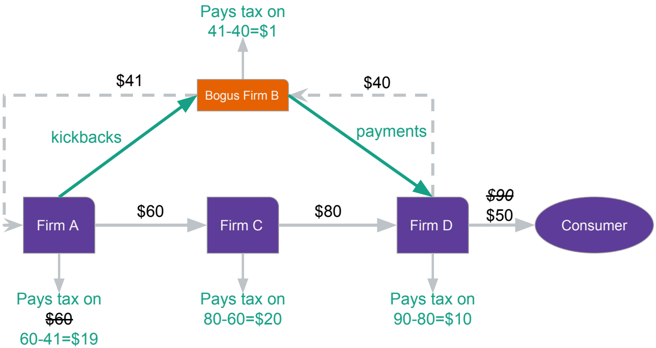
Bogus Firms: Example



Government receives tax on $50 value added. Surplus is divided between offenders.

- Firms A, C and D not necessarily in the same chain.
- Bogus firm can make sales to any firm which needs input credits.

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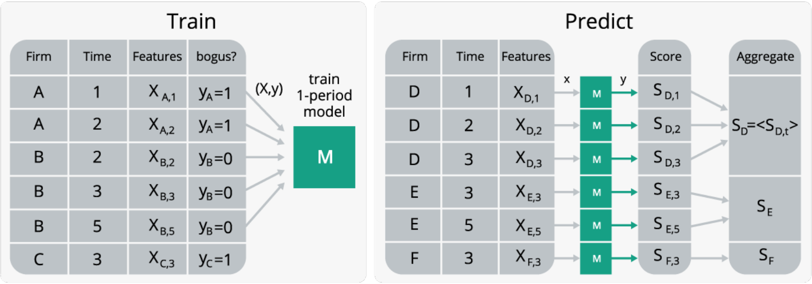
Firm Level Predictions from Firm-quarter Data Points



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Wide Model

Firm	Time	Features	bogus?
A	1	$X_{A,1}$	$y_A=1$
A	2	$X_{A,2}$	$y_A=1$
B	2	$X_{B,2}$	$y_B=0$
B	3	$X_{B,3}$	$y_B=0$
B	5	$X_{B,5}$	$y_B=0$
C	3	$X_{C,3}$	$y_C=1$

Firm	Features_1	Features_2	Features_3	bogus?
A	$X_{A,1}$	$X_{A,2}$	NULL	$y_A=1$
B	NULL	$X_{B,2}$	$X_{B,3}$	$y_B=0$
C	NULL	NULL	$X_{C,3}$	$y_C=1$

- Entry and exit of firms will result in the dataset having a lot of NULL values

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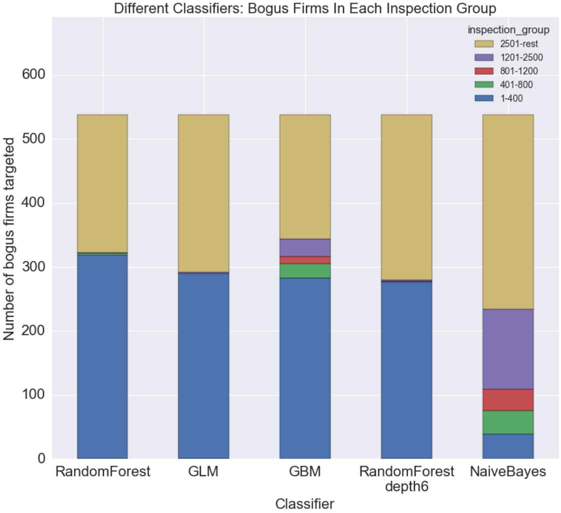
Comparison of Different Classifiers



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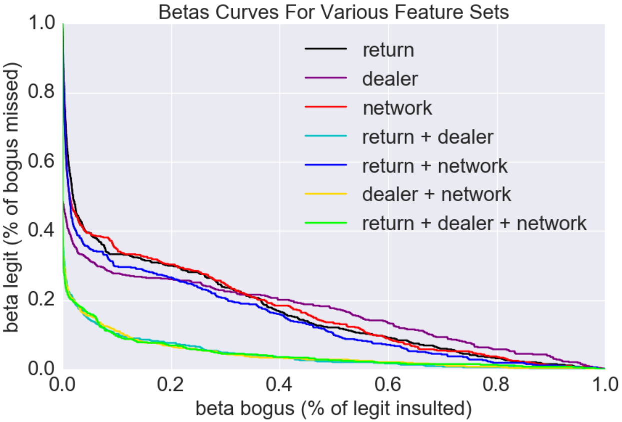
Betas curves for different feature sets



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Model performance on all recommendations

Inspection Group	*Firms Inspected*	*Total Bogus Firms Caught*	*Bogus Firms Caught/Inspection*
1 - 400	400	305	0.76
401 - 800	400	48	0.12
801 - 1200	400	24	0.06
1201 - 2500	1300	29	0.02
2501 - rest	313229	132	0.00

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Point-in-time simulation performance for the 1-400 inspection group

T	*Total Bogus Firms Caught*	*Bogus Firms Caught/Inspection*	*Revenue Gained by Inspecting Entire Group (USD Millions)*	*Revenue Gained per Inspection (USD 000s)*	*Total Bogus Firms in the Sample*	*Revenue Lost from All Bogus Firms (USD Millions)*
2	94	0.24	19.44	48.60	416	49.40
4	155	0.39	43.19	107.97	412	108.38
6	156	0.39	25.48	63.70	437	63.84
8	157	0.39	9.38	23.46	395	26.43
10	46	0.11	1.70	4.24	114	4.52
12	10	0.02	0	0	22	0

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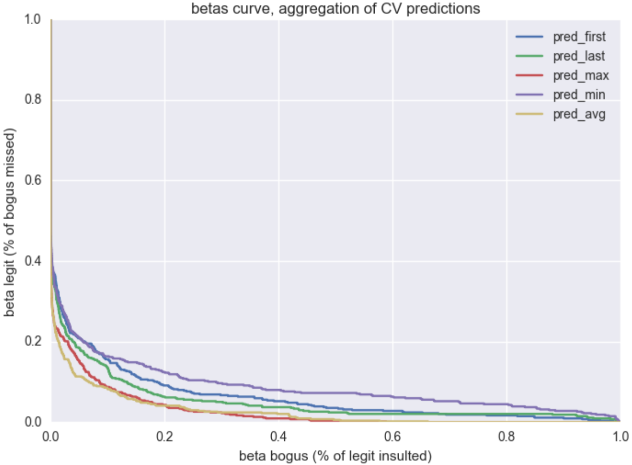
Machine Learning Performance: Aggregation



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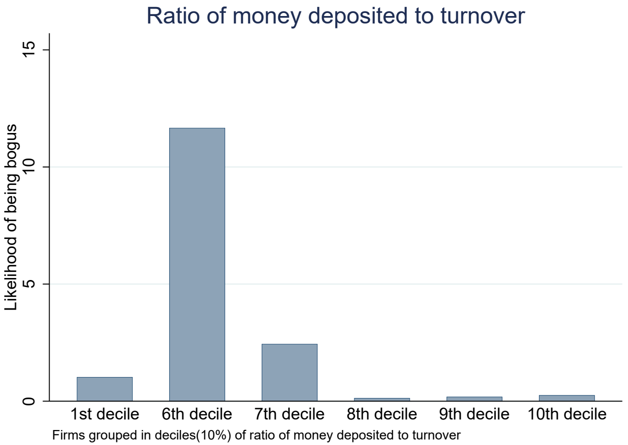
Interpreting Features: Gaming Measures



- Bogus firms likely to have ratio in middle indicates that they know tax authority monitors extreme values so they make sure they are not in extremes.

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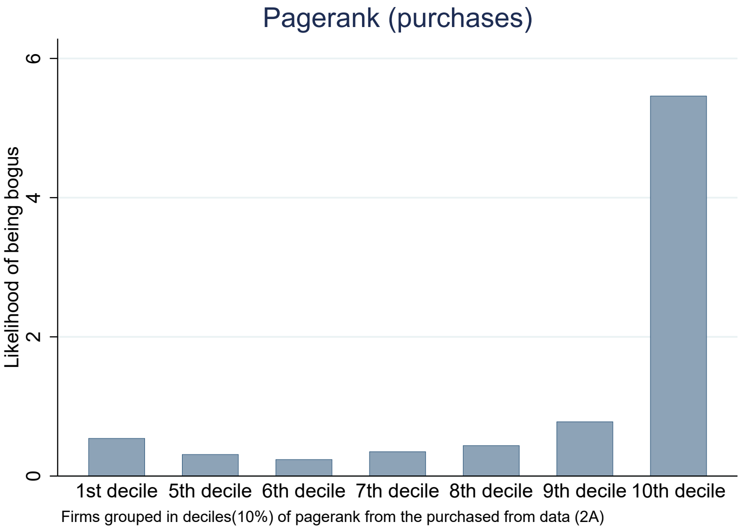
Network feature: Pagerank (2A)



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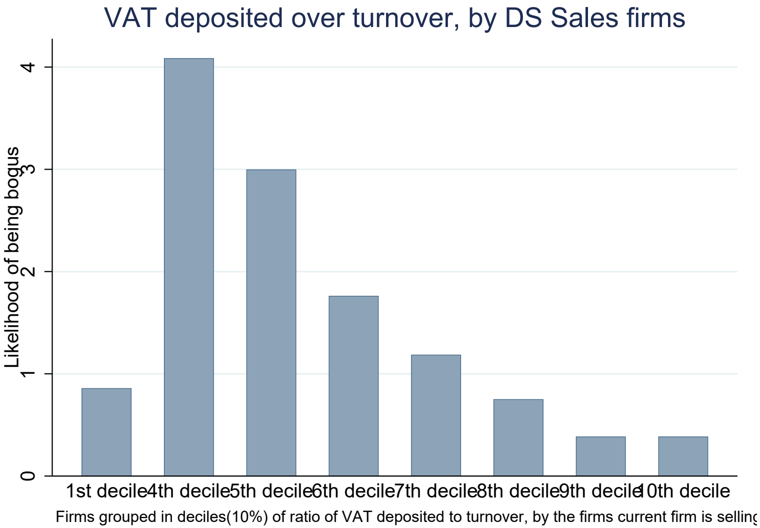
Network feature: VAT deposited ratio by 2B firms



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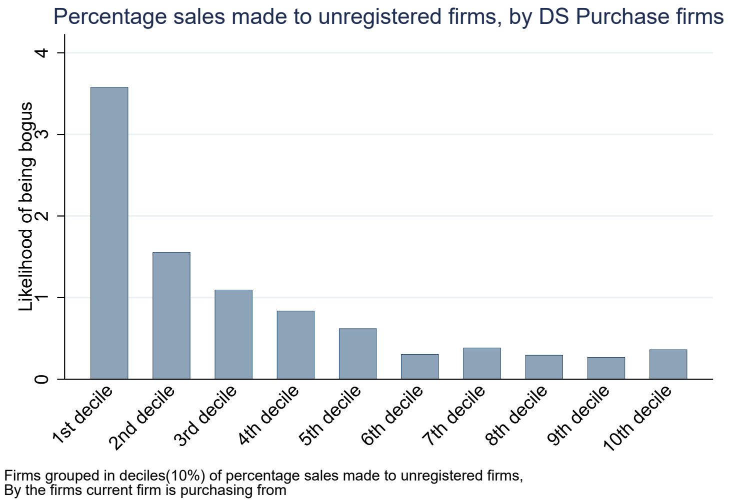
Network feature: Unregistered sales made by 2A firms



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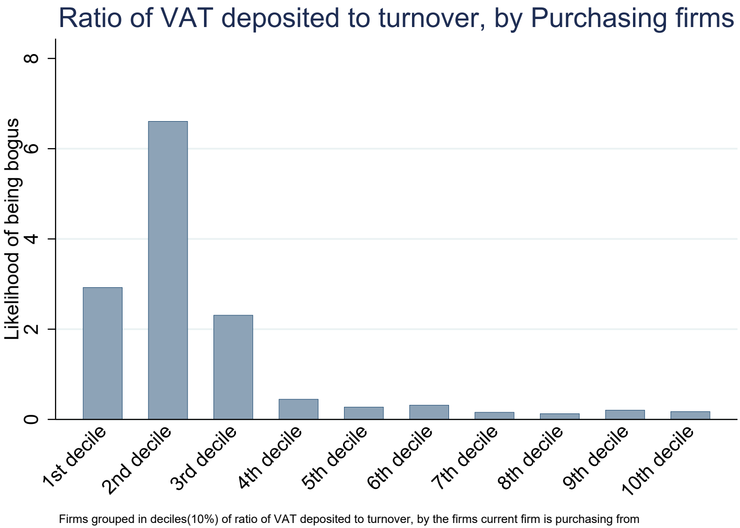
Network feature: VAT deposited ratio by 2A firms



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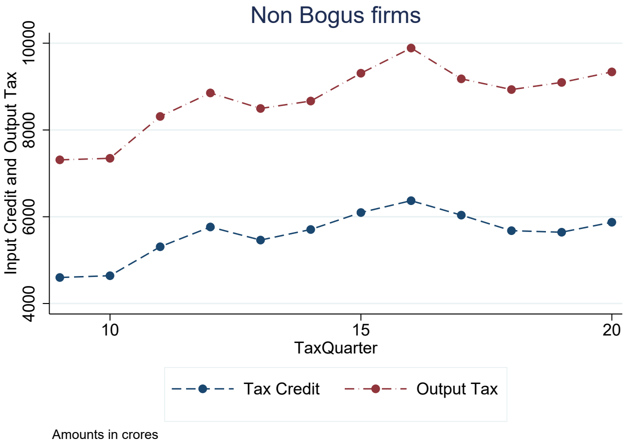
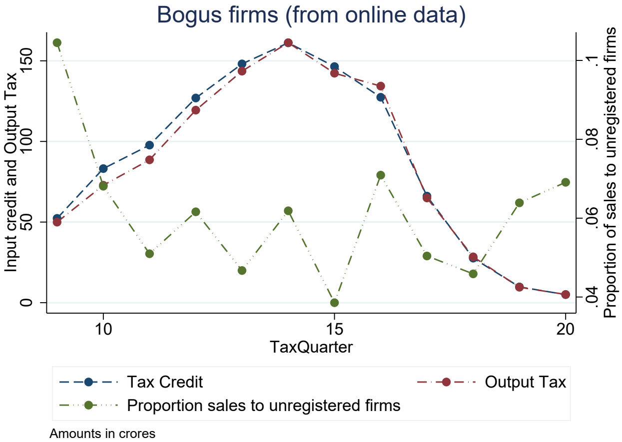
How genuine firms look



- Total output tax reliably larger than input tax credit.

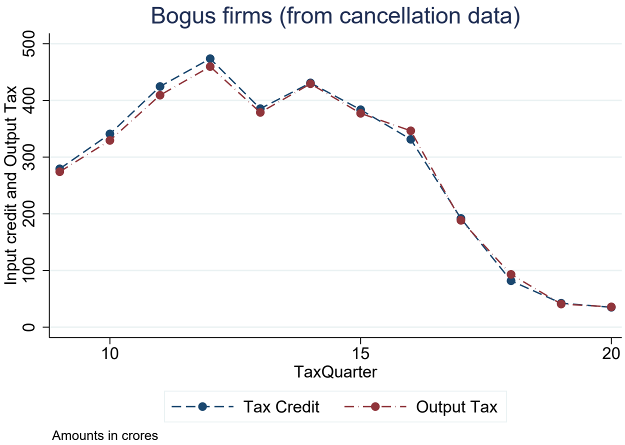
Size of problem: From explicit data



- Input credit claimed weakly greater than output tax declared
- From the limited sample, revenue loss between ₹4-6 billion, annually
- Drop in later quarters due to missing data

From cancellation records

Size of problem: From cancellation records



- From the much bigger sample, revenue loss around ₹15 billion, annually
- Drop in later quarters due to missing data

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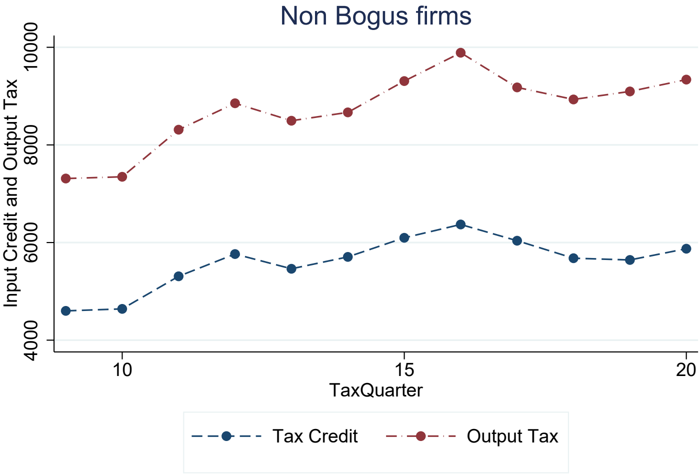
Revenues Non-Bogus Firms



Amounts in crores