Gambling problems in the general Danish population: Survey evidence

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Pathological and problem gambling prevalence

- As with other syndromes based on the DSM, PG screens designed for clinical use have typically been deployed in public health research to try to estimate prevalence in populations.
- DSM screens essentially count symptoms – that is, they are 'reflective constructs'.
- DSM IV (1994/200) explicitly welcomed tolerance for overestimation of prevalence. DSM 5 (2013) purports in general to reduce this tolerance, but in the case of PG doesn't attempt to do so.

Probing formative constructs: FLAGS

- Whereas DSM screens aim to estimate the probability ("risk") that a person is currently a PG, FLAGS aims to identify the extent of the "risk" that someone will *become* a PG given current manifestations and traits. Use of the same word in these screens thus doesn't signify measurement of the same latent construct.
- FLAGS probes 10 constructs: (1) risky cognitions - beliefs; (2) risky cognitions - motives; (3) preoccupation – desire; (4) impaired control – continue; (5) risky practices – earlier; (6) risky practices – later; (7) impaired control – begin; (8) preoccupation – obsessed; (9) negative consequences; (10) persistence. Only some of these are formative; and there is room for debate about some, e.g. (8).

Methodology I: objectives across disciplines

- Clinicians and psychologists focus on predicting which individuals should be allocated to treatment, and to which treatments.
- Public health researchers focus on predicting prevalence, and patterns of spread and contraction, given varying social / policy environments.
- Economists focus on predicting welfare consequences of varying prevalence and severity, to enable decisions about the relative resources that should be allocated to PG and to assess overall costs and benefits of different regulatory regimes.

Methodology II: statistical issues

Interesting modeling and estimation issues arise when reflective and formative constructs are jointly used in measurement. Properties probed by reflective constructs should *accumulate* for identification of the syndrome. By contrast, some formative constructs (e.g., perhaps, preoccupation) might be sufficient for identification.

Preliminary steps in Denmark

- We obtained 8,405 (12.8%) completed survey responses from a sample frame of 65,592 Danish adults.
- The sample was stratified according to sex and age across three regions: (i) greater Copenhagen, (ii) Jutland and (iii) Funen and Zealand.
- Higher weight (50%) on sample from greater Copenhagen for later recruitment into experiments.
- Among subjects that completed, all self-administered FLAGS plus 2-3 other instruments in varying orders.

Other administered instruments

- Problem Gambling Severity Index (PGSI)
- the DSM-IV problem gambling screen
- Gambling Craving Scale (GACS)
- Gambling-Related Cognitions Scale (GRCS)
- Gambling Urge Screen (GUS)
- Alcohol Use Disorders Identification Test (AUDIT)
- Beck Anxiety Index (BAI)
- Beck Depression Index (BDI)
- Barratt Impulsivity Scale (BIS)

Survey sub-pools with tests for order effects

- 1A: **FLAGS**, PGSI, BIS
- 1B: PGSI, **FLAGS**, BIS
- 2A: **FLAGS**, DSM-IV, BAI, AUDIT
- 2B: DSM-IV, **FLAGS**, BAI, AUDIT
- 3A: **FLAGS**, GACS, AUDIT
- 3B: GACS, **FLAGS**, AUDIT
- 4A: **FLAGS**, GUS, BDI, AUDIT
- 4B: GUS, **FLAGS**, BDI, AUDIT
- 5A: **FLAGS**, GRCS, AUDIT
- 5B: GRCS, **FLAGS**, AUDIT

FLAGS treatments

- The 10 sub-blocks in FLAGS are mapped into 3 groups
  - Group 1: risky cognitions – beliefs (RCB); risky cognitions – motives (RCM); and preoccupation – desire (POD)
  - Group 2: impaired control – continue (ICC); risky practices – earlier (RBE); and risky practices – later (RBL)
  - Group 3: impaired control – begin (ICB); preoccupation – obsessed (POO); negative consequences (NGC); and persistence (PST)

FLAGS treatments

- The baseline FLAGS administration used the standard block order as in Slide 3 and 8 above.
  - Treatments with random order of questions within each of the 3 FLAGS groupings.
- The baseline FLAGS frame probed lifetime events and experiences.
  - Treatments probed events and experiences in the preceding 12 months.

Raw responses: FLAGS

FLAGS Risk Level	Frequency	Percent	Cumulated
No Detectable Risk	6,698	79.7	79.7
Early Risk	1,010	12.0	91.7
Intermediate Risk	328	3.9	95.6
Advanced Risk	274	3.3	98.9
Problem Gambler	95	1.1	100.0
Total	8,405	100.00	

Raw responses: FLAGS and DSM

FLAGS Risk Level	DSM Risk Level		
	Non-Gambler	Problem Gambler	Pathological Gambler
No Detectable Risk	1,353	7	0
Early Risk	174	3	0
Intermediate Risk	64	2	0
Advanced Risk	48	7	1
Problem Gambler	3	6	1
Total	1,644	25	2

Raw responses: FLAGS and PGSI

FLAGS Risk Level	PGSI Risk Level			
	Non-Gambler	Low Risk	Moderate Risk	Problem Gambler
No Detectable Risk	1,291	93	14	1
Early Risk	161	53	15	0
Intermediate Risk	27	25	10	0
Advanced Risk	13	12	19	3
Problem Gambler	0	0	2	18
Total	1,492	183	60	22

Predicted FLAGS levels: No sample weights

FLAGS Risk Level	Prediction (%)	95% Confidence Interval (%)	
No Detectable Risk	79.7	78.9	80.5
Early Risk	12.0	11.3	12.7
Intermediate Risk	3.9	3.5	4.3
Advanced Risk	3.3	2.9	3.6
Problem Gambler	1.1	0.9	1.3

Predicted FLAGS levels: Sample weights

FLAGS Risk Level	Prediction (%)	95% Confidence Interval (%)	
No Detectable Risk	76.0	74.9	77.2
Early Risk	13.2	12.3	14.2
Intermediate Risk	4.2	3.6	4.8
Advanced Risk	4.6	3.9	5.3
Problem Gambler	1.9	1.3	2.4

Predicted FLAGS levels: Sample weights and sample selection

FLAGS Risk Level	Prediction (%)	95% Confidence Interval (%)	
No Detectable Risk	95.7	94.5	96.9
Early Risk	2.7	1.9	3.6
Intermediate Risk	0.8	0.5	1.0
Advanced Risk	0.6	0.5	0.8
Problem Gambler	0.2	0.1	0.2

Figure 1: Marginal Effect of Being Female
on Probability of *FLAGS* Gambling Risk Level

Ordinal Probit Model, population weights, with sample selection correction
Point estimate of effect and 95% confidence interval

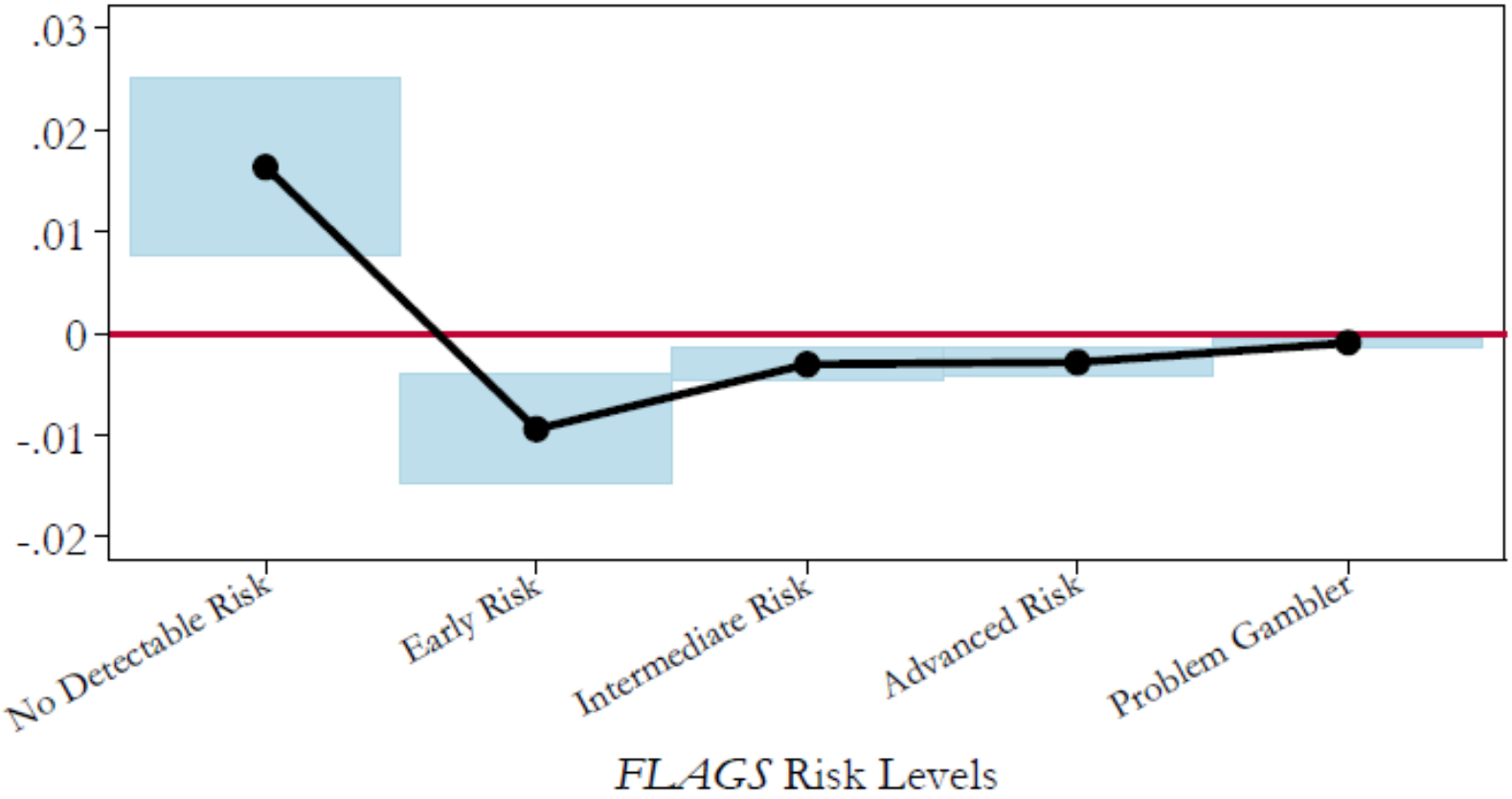
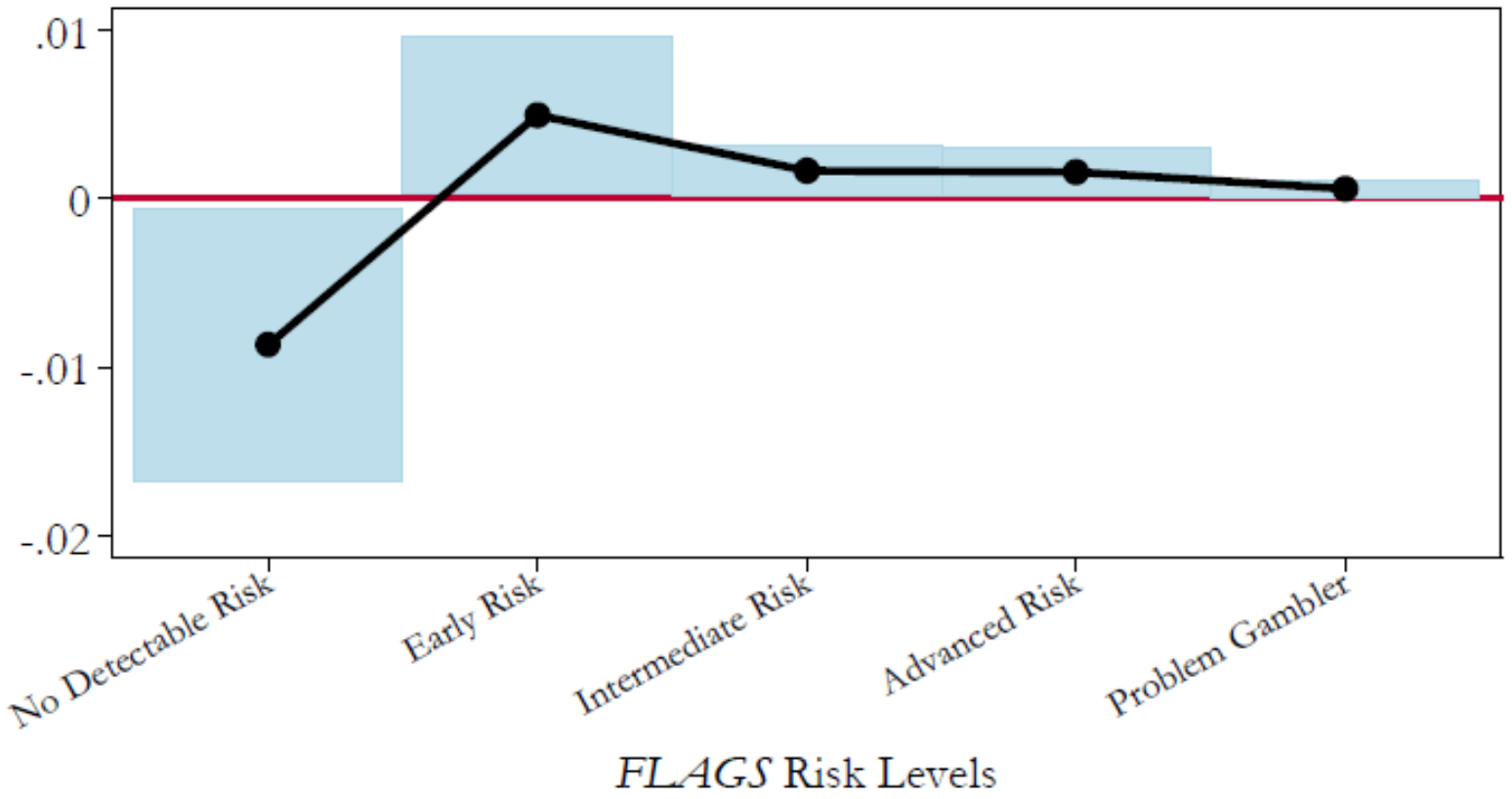


Figure 2: Marginal Effect of Having Low Income on Probability of *FLAGS* Gambling Risk Level

Ordinal Probit Model, population weights, with sample selection correction
Point estimate of effect and 95% confidence interval

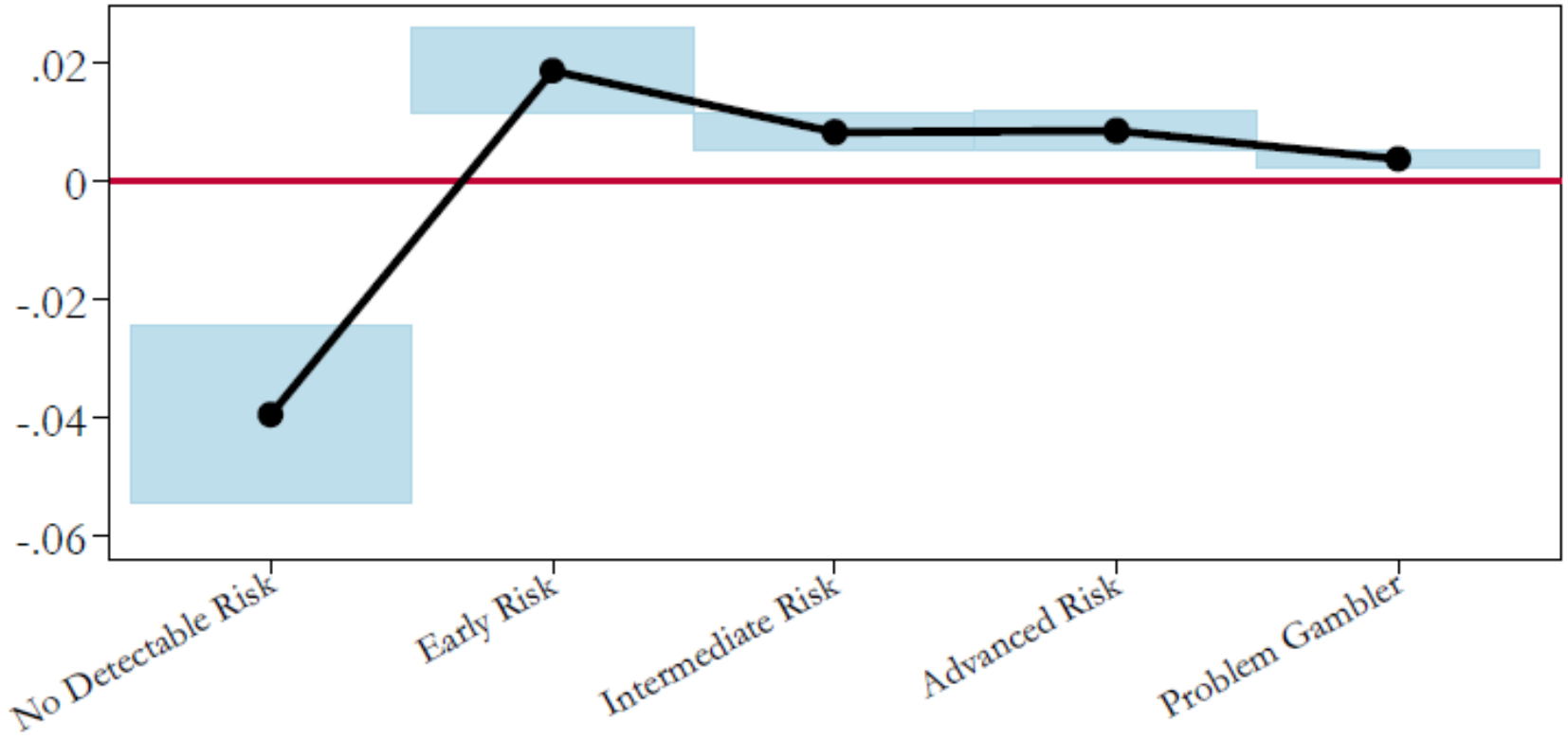


Order effects

Administering FLAGS before other instruments was correlated with higher probability of scoring subjects as having some detectable risk.

Figure 3: Marginal Effect of FLAGS Being First on Probability of FLAGS Gambling Risk Level

Ordinal Probit Model with no sample weights and no sample selection correction
Point estimate of effect and 95% confidence interval

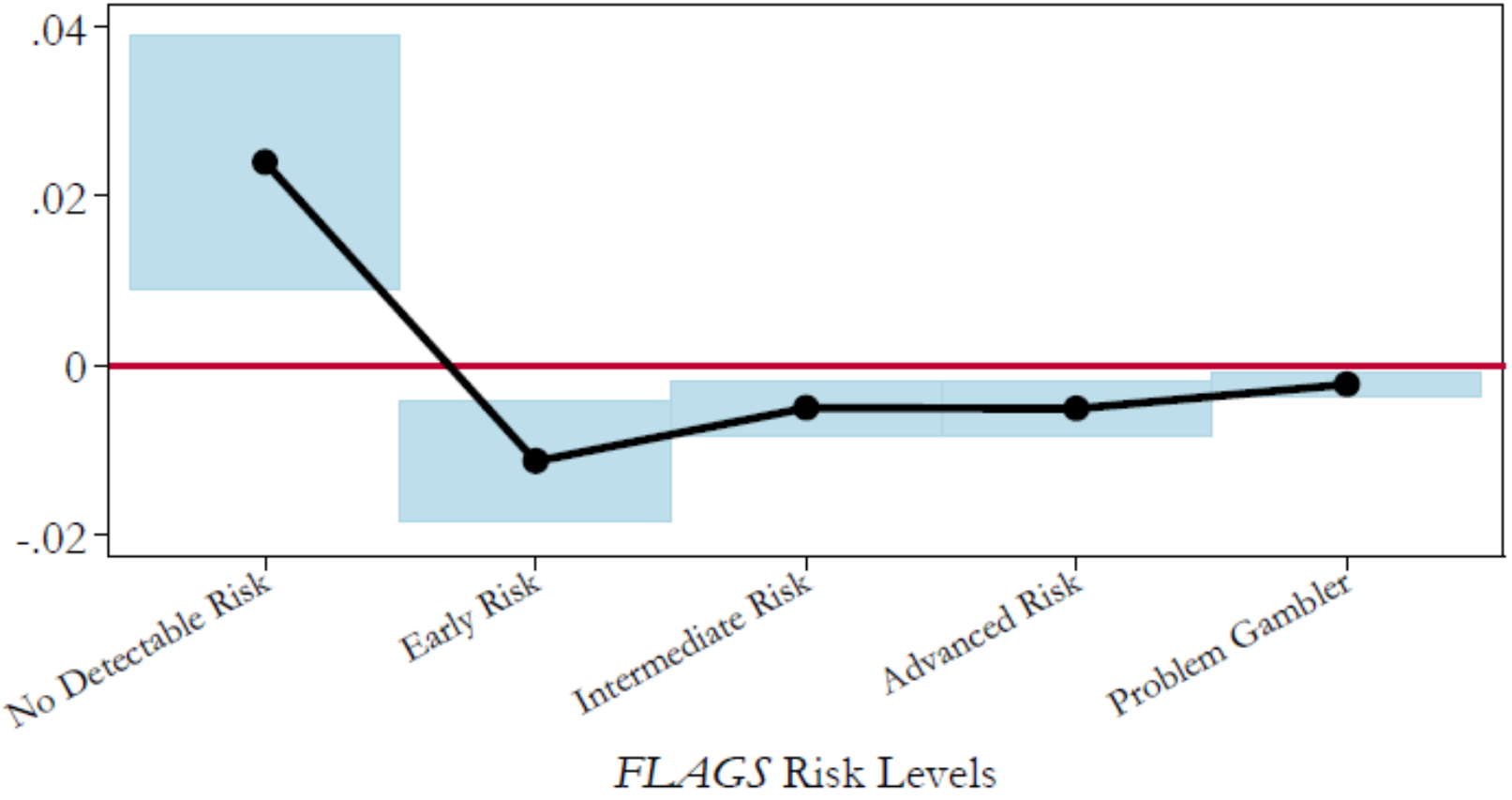


Order effects

Randomizing the order of questions within the three FLAGS blocks was correlated with smaller probability of scoring subjects as having some detectable risk.

Figure 4: Marginal Effect of Randomized Questions on Probability of FLAGS Gambling Risk Level

Ordinal Probit Model with no sample weights and no sample selection correction
Point estimate of effect and 95% confidence interval

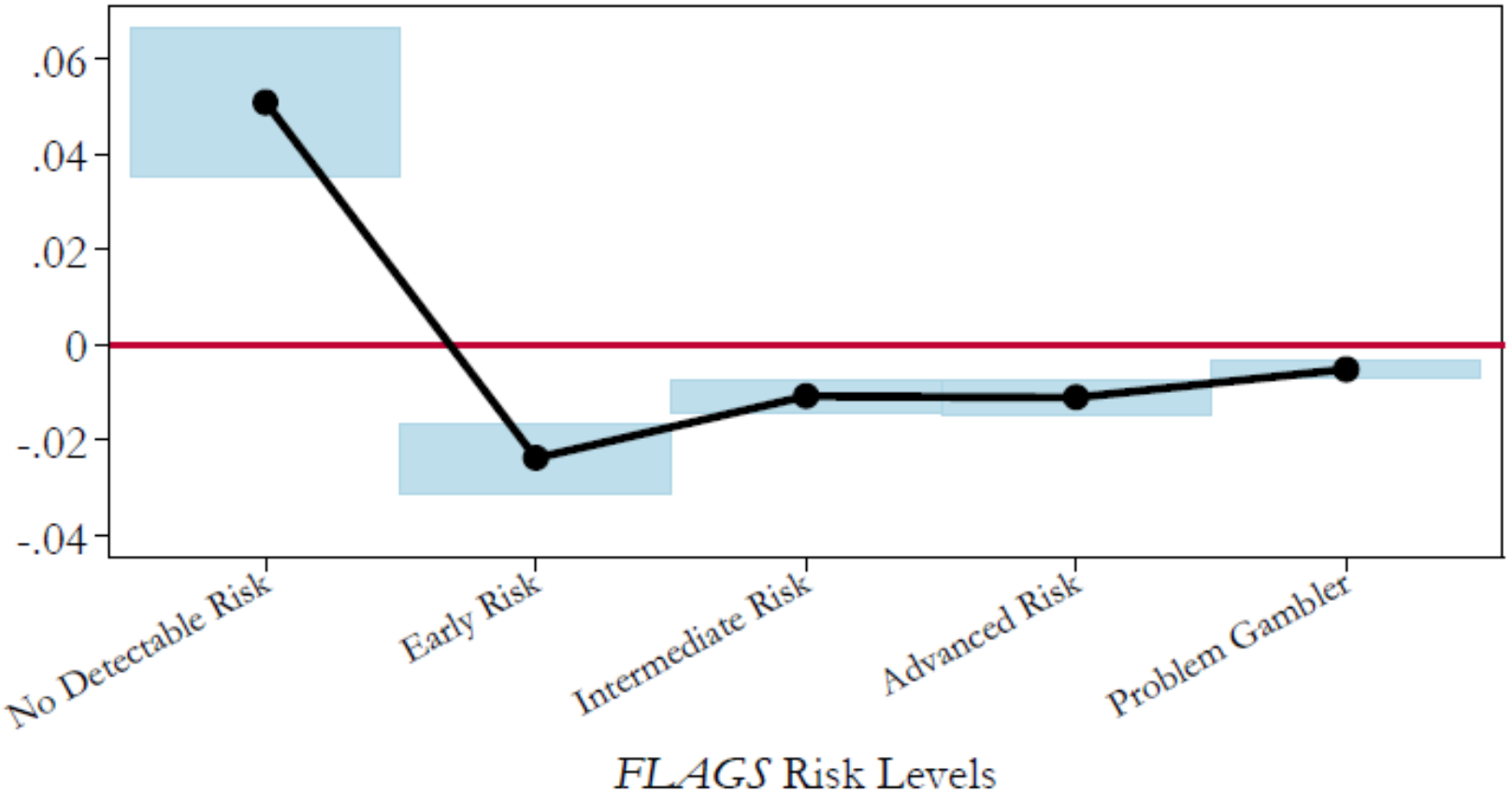


Lifetime frame

Using a lifetime gambling frame was correlated with *lower* probability of scoring subjects as having some detectable risk.

Figure 5: Marginal Effect of Lifetime Frame
on Probability of FLAGS Gambling Risk Level

Ordinal Probit Model with no sample weights and no sample selection correction
Point estimate of effect and 95% confidence interval



Trigger questions

- It is common in psychiatric and psychological surveys focusing on symptoms of disorder to use 'trigger' questions. That is, questions about extent or severity of symptoms will be asked only if subjects answer 'yes' to a question about a behavior taken to be necessary for *possible* positive diagnosis.
- We asked subjects whether they had ever lost 40 kroner on a single day's gambling, and another treatment group whether they had ever lost 500 kroner on a single day's gambling. This allowed us to compare results we would have obtained had these questions been used as triggers (i.e., had subjects answering 'no' to the 40 kroner trigger and the 500 kroner trigger been scored, respectively, as having no detectable risk).

Figure 6: Comparison of True *FLAGS* Responses and Inferred Responses if Using Gambling History Triggers

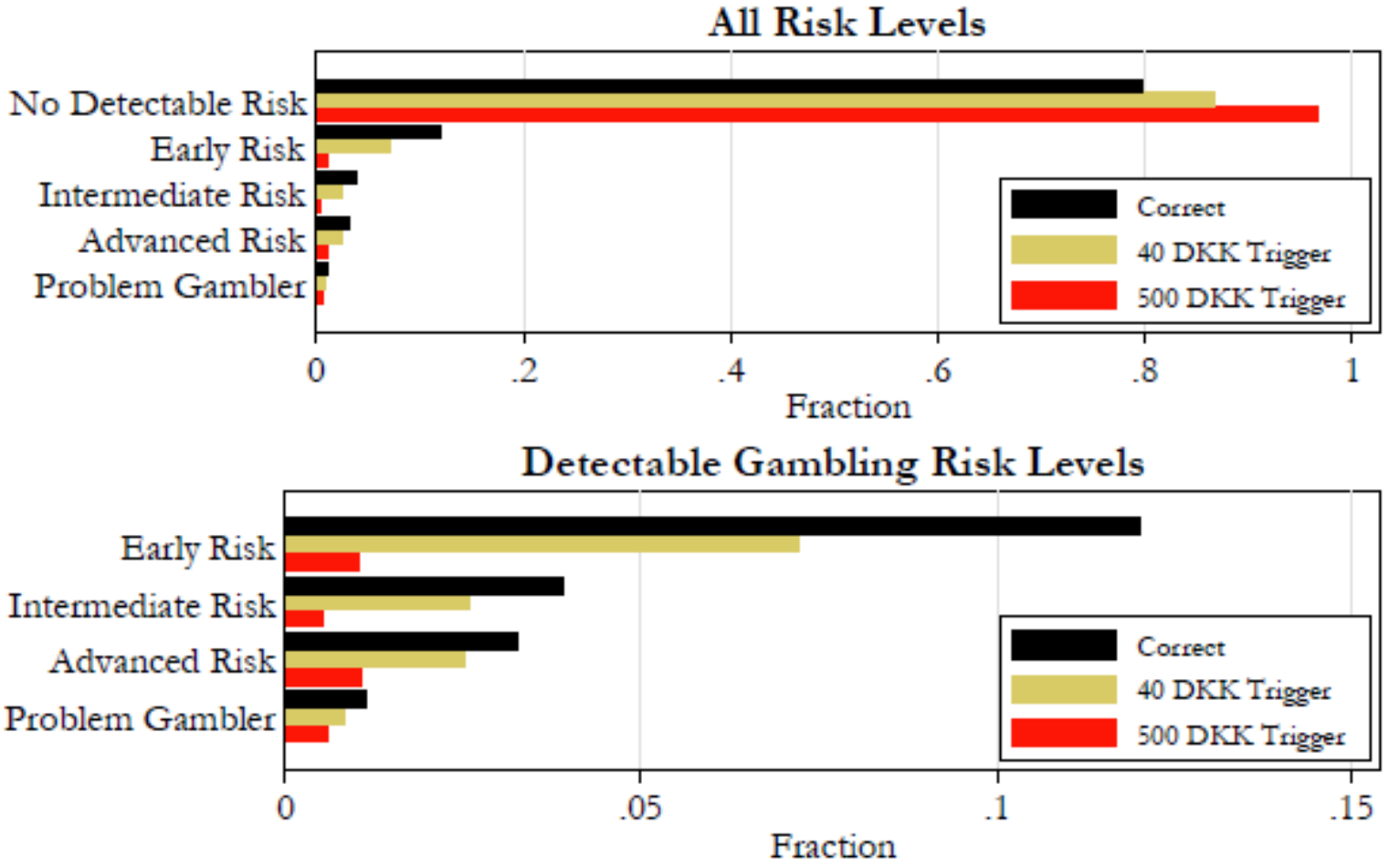


Figure 7: Comparison of True *DSM-IV* Responses and Inferred Responses if Using Gambling History Triggers

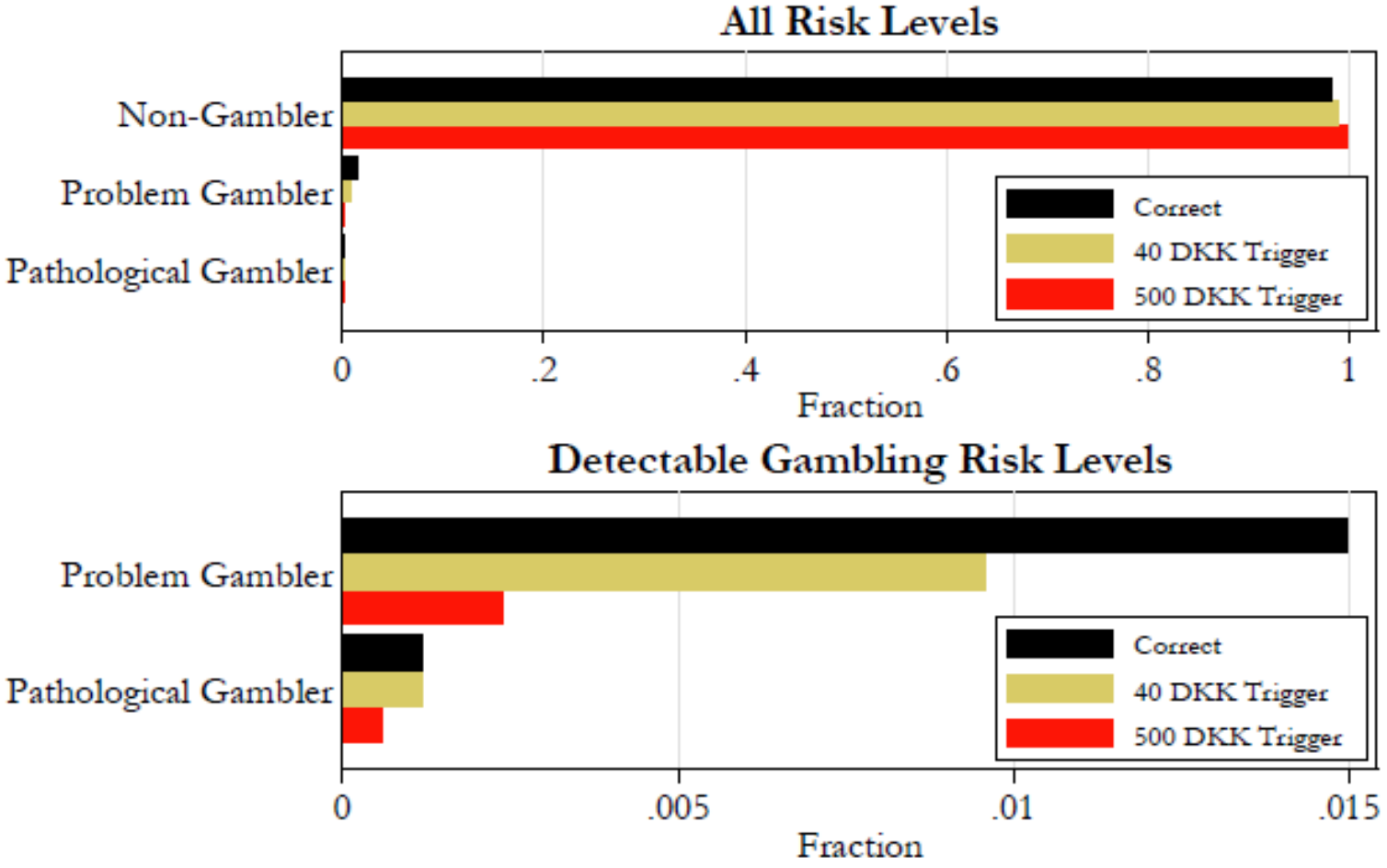
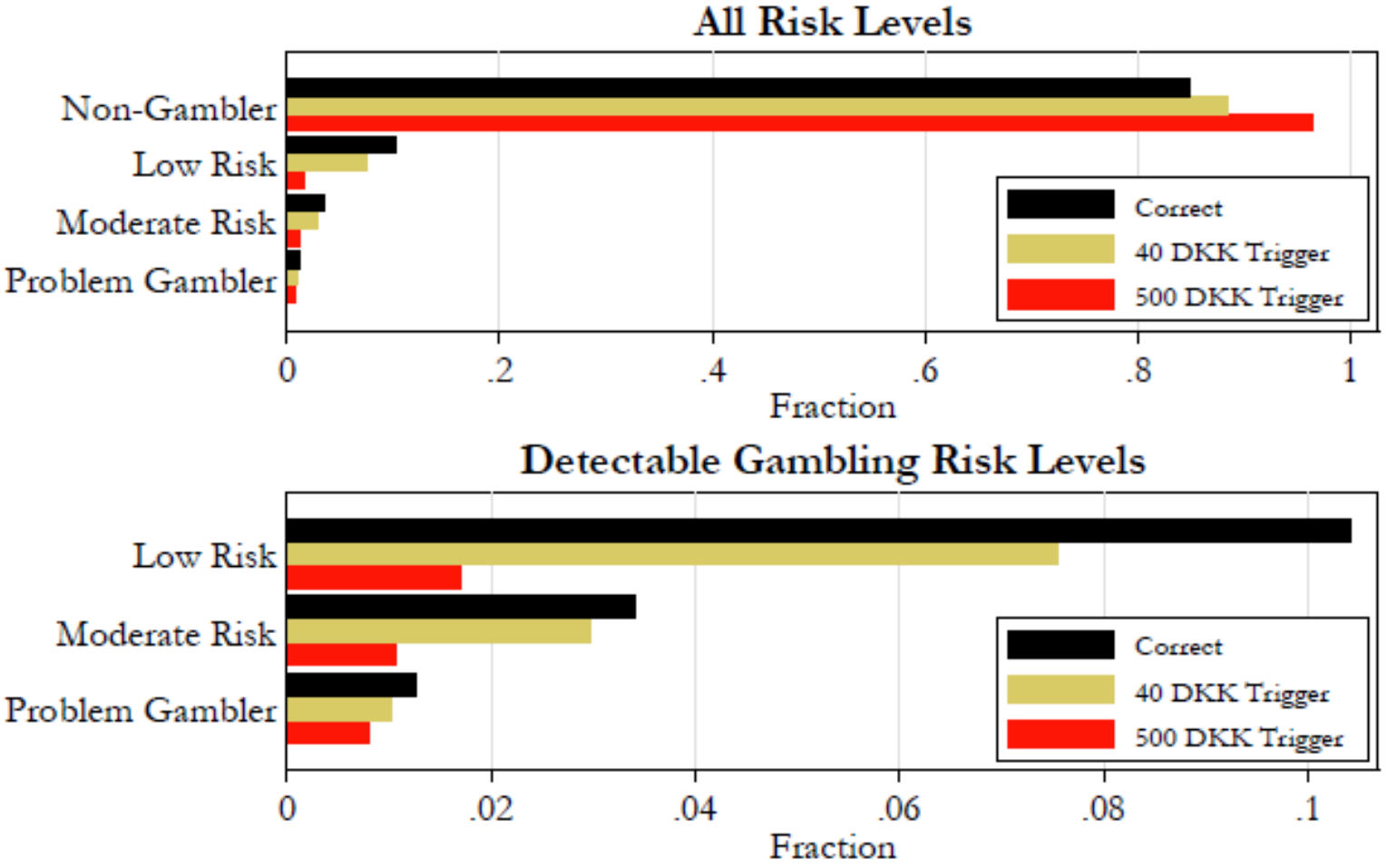


Figure 8: Comparison of True *PGSI* Responses and Inferred Responses if Using Gambling History Triggers



Trigger questions bias results

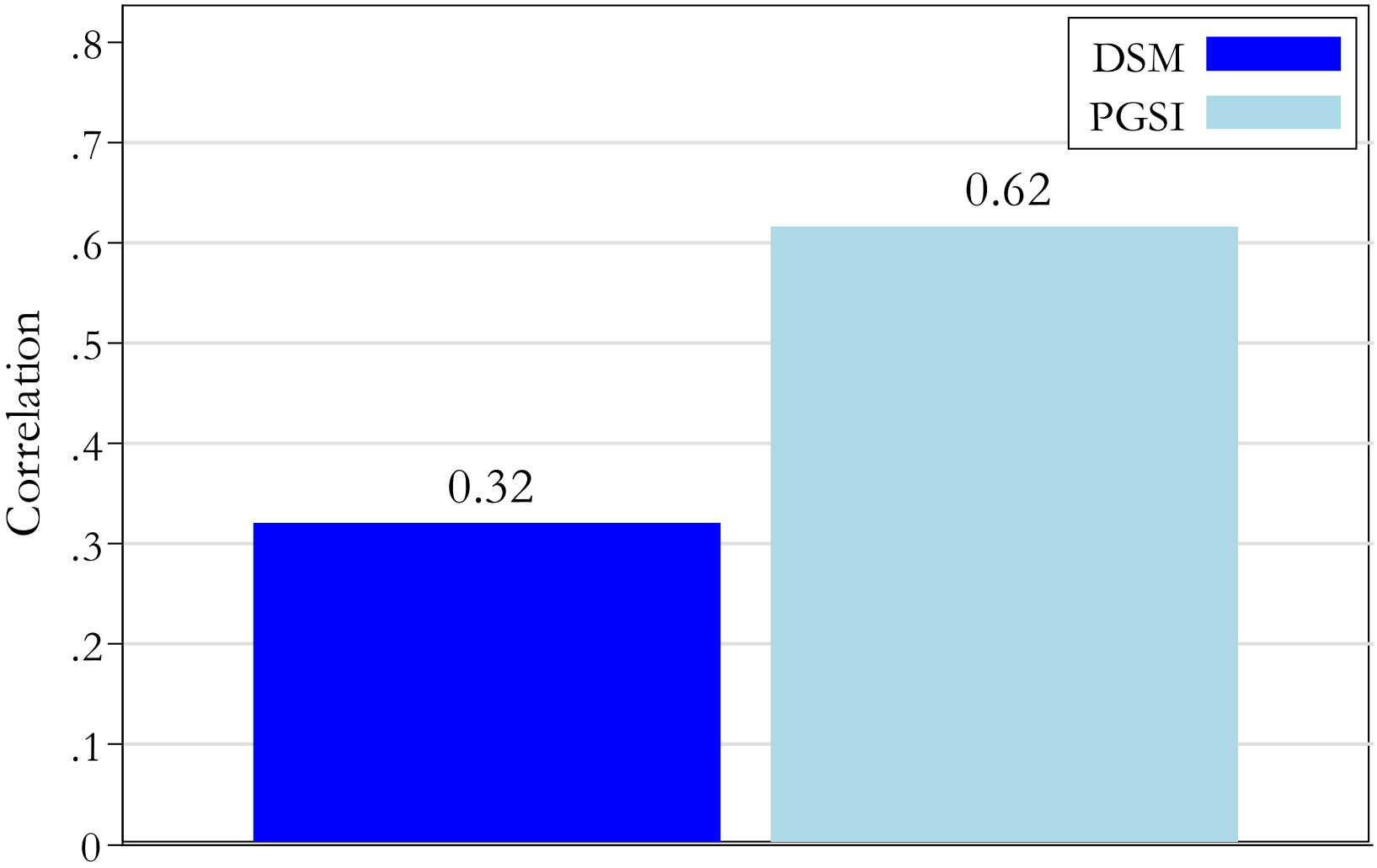
- On all three gambling screens we used (FLAGS, PGSI, DSM-IV), application of trigger questions would significantly increase the proportion of subjects found to have no detectable risk (or be recorded as non-gamblers on the PGSI), and would significantly reduce numbers assigned to each positive risk category.
- We think it unsurprising that trigger questions bias results in this way. There is no basis for assuming that all subjects answer trigger questions accurately, or that false negative responses and false positive responses will typically have similar frequencies.

Correlations

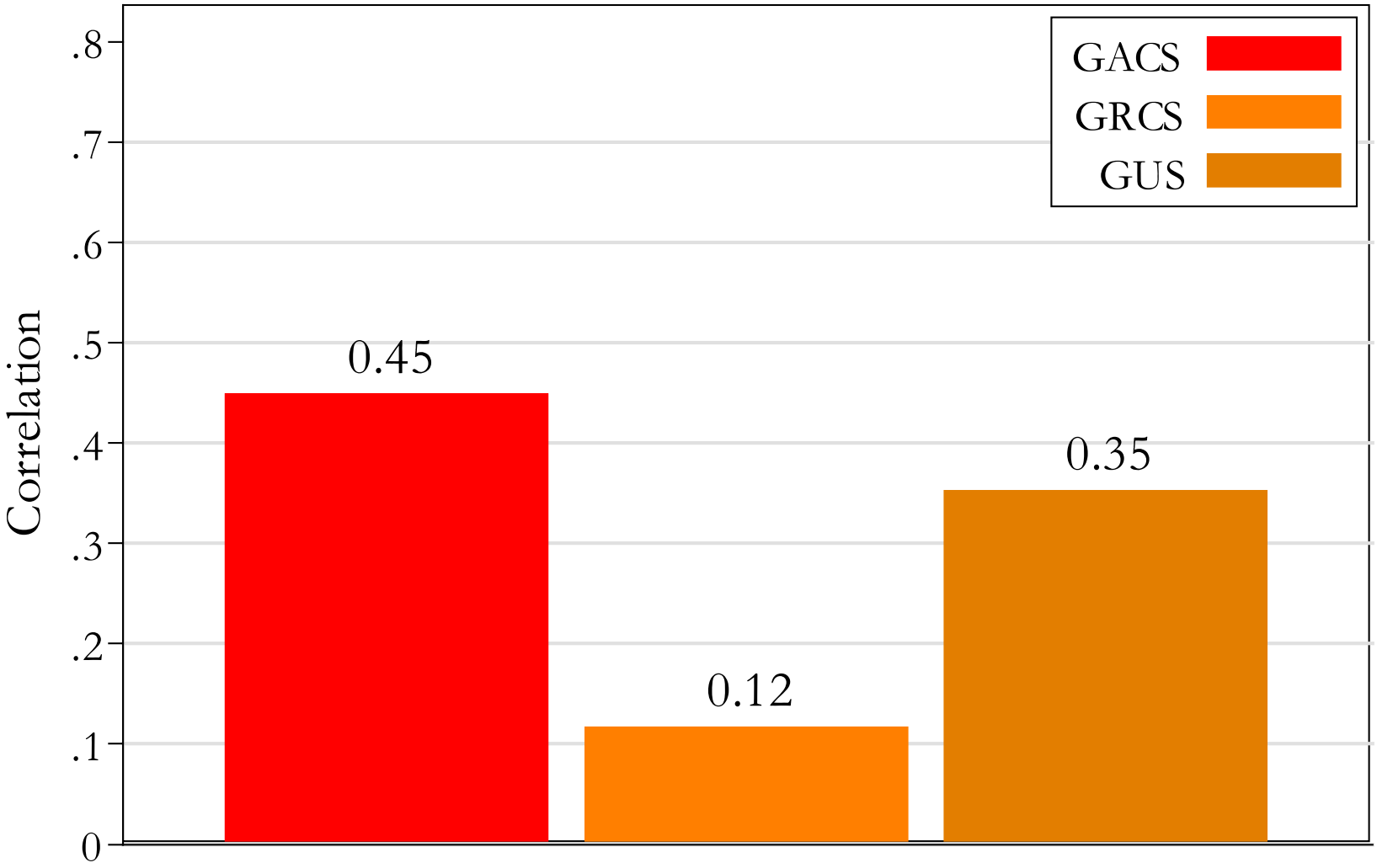
The next figures shows unconditional correlations of the FLAGS gambling risk levels with:

1. Levels of the other gambling risk instruments (PGSI, DSM-IV)
2. Scores on the instruments measuring gambling cravings (GACS), gambling-related cognitions (GRCS), gambling urges (GUS)
3. Measures of alcohol use (AUDIT), anxiety (BAI), depression (BDI) and impulsivity (BIS).

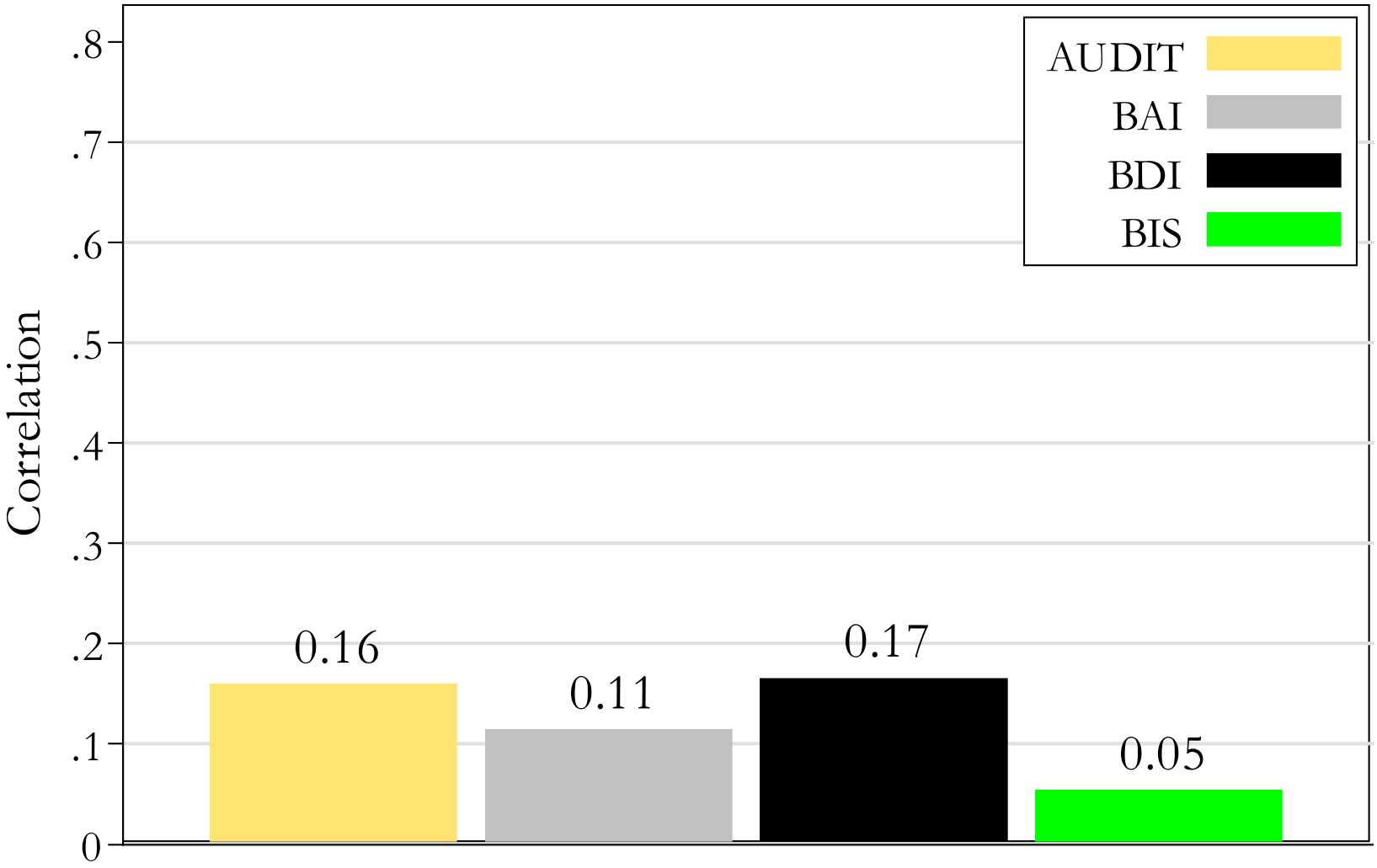
Correlation of FLAGS Scores with Other Instruments - Reflective Constructs



Correlation of FLAGS Scores with Other Instruments - Formative Constructs



Correlation of FLAGS Scores with Other Instruments - Comorbidities



Conclusions

- FLAGS wasn't designed to be administered to non-gamblers, and administering it to them might be contributing to noise (e.g. order effects).
- But if non-gamblers are screened out, then the aims of economists are frustrated, because welfare assessment must accurately pick up all sites of latent risk. And selection bias must be controlled.
- Therefore, we need a combination of measurement instruments that can inform hurdle modeling. This is what we are doing in current work.