Untargeted Serum Metabolic Profiling by GC×GC-HRTOF-MS

Supporting Information

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S-1. Samples.

(A) Sample collection

The applied conditions, originally developed from proteomic studies but close to general biobanking SOPs, are quite strict concerning the collection, processing and conservation of samples. They meet the protocols reviewed in a white paper from the Metabolomics Society Initiative^{S-1} as well as their guidelines concerning blood derived products. In brief, Venosafe (Terumo, NV, EU) 10 mL dry tubes were used for serum collection. Clotting time was set at 30 minutes at room temperature before a centrifugation step at 2,000 RCF for 10 minutes at 4 °C. Aliquoting of sera was performed in polypropylene cryotubes. The delay between sample intake and storage (-80 °C) was kept inferior to 2 hours. All patients recruited for the proof of concept study were controlled for IBD or any other known digestive cancer by an endoscopic examination of the bowel (rectum, colon and, when possible, last part of the ileum) performed by a trained endoscopist. When applicable, the diagnosis was confirmed by an anatomopathological examination of the biopsies or specimen resected.

(B) Clinical and analytical metadata for the Crohn's disease study

	Healthy Controls	Low EA	High EA	Quiescent EA		Low EA	High EA	Quiescent EA
Total Number	33	14	12	9	Number	14	12	9
Male/Female (n/n)	14/19	5/9	6/6	3/6	Median CDEIS (range)	1.3 (0.5-2)	9.1 (6-28)	0 (0-0)
Mean age at diagnosis (range) in years	44 (26-70)	39 (28-54)	38 (22-71)	51 (37-65)	Median CRP (range / NA, in mg/l)	1 (1-10 / 6)	21.9 (1-67 / 7)	2 (1-14 / 4)
Mean BMI (range) in kg/m ²	25 (16-37)	26 (22-42)	22 (15-26)	27 (24-39)	Nedian Faecal calprotectin (range / NA, in µg/g)	190 (38- 1282 / 8)	474 (63- 1935 / 4)	138 (25-538 / 6)
Current smoker (n)	6	6	5	2	Disease location			
Current alcohol consummers (n)	7	3	1	4	Ileal disease	3	2	5
Medication for gastro- oesophage reflux	9	4	4	2	Colonic disease	2	4	0
L-Thyroxin	6	3	1	3	Ileocolonic disease	6	3	0
CD specific treatments anti- Anti-TNFα	0	10	6	2	Pancolitis	2	1	1
Immunosuppressor	0	0	4	1	Montreal			
					A1	1	1	0
Mean drying batch	4.5	4.3	5.3	5.7	A2	8	9	6
Mean extraction batch	1.5	1.7	1.5	1.8	A3	3	0	3
Mean injection order (range)	43 (3-94)	59 (16-93)	47 (8-92)	53 (9-91)	B1	8	7	7
					B2	3	1	2
					B3	2	3	1
					L1	4	2	5
					L2	1	2	2
					L3	7	6	3
					L4	0	1	0
					p-	6	7	7

Table S-1. Clinical metadata for the samples of the proof of concept study. Endoscopic activity (EA) indices include Montreal classification at diagnosis, Crohn's disease endoscopic index score (CDEIS), C-reactive protein and faecal calprotectin. NA indicates the number of samples for which the information was not available.

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S-2. Security precautions for the sample preparation.

Working with serum samples represent a potential infection risk. In addition, some of the chemicals used are toxic, flammable, corrosive or irritant (methanol, hexane, pyridine, MSTFA and MeOX). Therefore, the staff was properly vaccinated^{S-2} and all manipulations were conducted in a fume hood, with appropriate personal protection equipment including gloves and glasses^{S-3}, in a laboratory with restricted access.

S-3. Box-Behnken design of experiment.

Regarding the DoE, a Box-Behnken design was preferred to a central composite face-centered one because it considered the interactions between the variables as well as their quadratic variations and it required less experimental points. Moreover, the extreme regions were not crucial in the range tested⁸⁻⁴. MSTFA and MeOX temperatures of 20, 40 and 60 °C were tested along with MSTFA volumes of 10, 20 and 30 uL while the MeOX volume and duration of reaction remained constant at 10 μ L and 30 min. The experimental plan consisted in 17 serum aliquot samples, including 5 center points. The *m*/*z* = 73, specific to TMS groups, was maximized for both the whole chromatogram (at the exclusion of the highly concentrated d-glucose and urea) and the most derivatized forms of amino acids that are representative of less reactive groups such as amines. Because the optimum was obtained for the lowest volume of MSTFA, a second DoE was conducted that tested the six combinations of MSTFA (5 and 10 μ L) and MeOX volumes (5, 10 and 15 μ L). Finally, four durations (0.5, 1, 2 and 4 hours) were evaluated at the optimized volumes and temperatures. Additional tests were made at low and high temperatures (4, 80 and 100 °C).

S-4. List of the metabolites monitored in the internal QC samples. Intra and inter-batch variations.

					Intra-Batch			Inter-Batch			
QC Samples		Mean Values				RSD (%	%)		RSD (%)	
Automatic ID	Chemical class	¹ t _R (min)	$^{2}t_{R}(s)$	Normal. V	$^{1}t_{R}$	$^{2}t_{R}$	Normal. V	¹ t _R	$^{2}t_{R}$	Normal. V	
/	/	16.8	2.9	1.1E+6	0.2	1.1	5.4	0.2	0.6	18.2	
Leucine	Amino acid	16.8	1.0	1.5E+6	0.2	1.8	5.1	0.2	2.0	9.5	
Glycine*	Amino acid	24.3	1.9	1.7E+6	0.2	3.3	0.0	0.2	1.7	0.0	
Pentanoic acid. 3-methyl	Organic acid	19.9	2.1	4.1E+4	0.2	3.2	42.2	0.1	2.1	60.6	
Succinic acid*	Organic acid	25.1	2.1	4.3E+6	0.1	1.6	0.0	0.1	1.0	0.0	
/	/	28.9	2.4	3.1E+5	0.1	2.0	19.0	0.1	0.8	54.2	
Benzoic acid	Organic acid	33.2	3.0	5.9E+4	0.0	1.4	25.1	0.0	0.5	20.7	
Glutamic acid	Organic acid	34.1	2.9	4.4E+5	0.1	1.7	8.3	0.1	0.7	13.3	
Cysteine	Amino acid	35.1	1.6	2.7E+5	0.1	2.1	34.6	0.1	1.3	60.7	
/	/	38.5	1.8	4.0E+4	0.1	2.1	23.8	0.1	1.6	45.3	
4.4'-Dibromooctafluorobiphenyl*	Injection standard	39.6	3.1	1.4E+7	0.1	1.1	0.0	0.1	2.6	0.0	
Ribitol	Sugar alcohol	41.8	3.3	6.0E+5	0.1	1.2	3.0	0.1	1.3	10.6	
Tetradecanoic acid	Fatty acid	45.1	2.1	1.4E+6	0.1	1.4	6.0	0.1	3.0	7.6	
Allofuranose	Sugar	46.2	0.5	1.2E+5	0.1	1.0	10.1	0	2.4	22.2	
Tyrosine	Amino acid	48.8	2.1	4.5E+6	0.1	1.6	11.1	0	1.7	14.2	
Gulose	Sugar	52.2	0.7	3.8E+6	0.1	0.8	12.5	0	2.2	12.5	
Heptadecanoic acid	Fatty acid	54.3	2.3	1.5E+5	0.1	2.3	9.2	0	1.1	13.9	
Linoleic acid	Fatty acid	56.3	3.0	4.1E+6	0.1	0.8	3.7	0	1.0	5.9	
Tryptophan	Amino acid	57.0	0.6	2.6E+6	0.1	0.9	33.5	0.1	1.7	32.2	

Table S-2. List of the 19 representative metabolites monitored in the internal QC samples. Intra and inter-batch variations (RSD) are given for the normalized peak volume and the retention time in both dimensions. The values with a natural variability > 30% are in bold.

The monitored metabolites had various retention times in the two dimensions and various volumes. They also represented the main biological classes^{S-5}: amino acids (5), organic acids (4), fatty acids (3), sugars (2) and sugar alcohols (1). For both intra and inter-batch observations, all RSD₁ were ≤ 0.2 %, which is equivalent to 2 times the P_M, and even < 0.1 % for 15 out of 19 metabolites followed (Table S-2). All RSD₂ were ≤ 5 %, even < 2 % for 14 metabolites out of the 19. This is in agreement with previously reported GC×GC performance^{S-6,7}.

S-5. List of the metabolites assessed in the NIST SRM 1950^{S-8}.

	Mass (m	Molar Concentration (µmol/L)				
Alanine	26.2	±	2.2	300	±	26
Glycine	18.0	±	1.2	245	\pm	16
Histidine	11.04	\pm	0.55	72.6	\pm	3.6
Isoleucine	7.13	±	0.42	55.5	±	3.4
Leucine	12.90	±	0.82	100.4	±	6.3
Lysine	20.0	±	1.9	140	±	14
Methionine	3.26	±	0.26	22.3	±	1.8
Proline	19.9	±	1.1	177	±	9
Serine	9.87	±	0.44	95.9	±	4.3
Threonine	13.94	±	0.70	119.5	±	6.1
Tyrosine	10.17	±	0.53	57.3	±	3.0
Valine	20.9	±	1.2	182.2	±	10.4

Table 4. Certified Values for Amino Acids

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Table 5. Reference Values for Amino Acids

	Mass (n	Mass Fraction (mg/kg)			Molar Concentratio (µmol/L)					
Arginine	13.89	±	0.40	81.4	±	2.3				
Cysteine	5.26	±	0.81	44.3	±	6.9				
Cystine	1.83	±	0.08	7.8	±	0.4				
Glutamic Acid	9.7	±	2.5	67	±	18				
Ornithine	6.7	±	0.4	52.1	±	2.8				
Phenylalanine	8.2	±	1.1	51	±	7				

Table 9. Certified Values for Selected Clinical Markers

	Mass Concentration (mg/dL)				Molar Concentration (mmol/L)					
Creatinine	0.6789	±	0.0108	0.0600	±	0.0009				
Glucose	82.16	±	1.00	4.560	±	0.056				
Urea	23.45	±	0.49	3.90	±	0.08				
Uric Acid	4.274	±	0.089	0.254	±	0.005				

Table 2. Certified Values for Fatty Acids

Lipid Name	Chemical Name (Common Name)	Mass (J	ction	Molar Concentration (µmol/L)			
C12:0	Dodecanoic Acid (Lauric Acid)	1.86	±	0.11	9.47	±	0.57
C16:0	Hexadecanoic Acid (Palmitic Acid)	594	±	19	2364	\pm	77
C16:1 n-7	(Z)-9-Hexadecenoic Acid (Palmitoleic Acid)	53.5	±	6.4	215	±	26
C18:0	Octadecanoic Acid (Stearic Acid)	179	±	12	644	\pm	41
C18:3 n-3	(Z,Z,Z)-9,12,15-Octadecatrienoic Acid (α-Linolenic Acid)	14.9	±	1.0	54.6	±	3.6
C18:1 n-9	(Z)-9-Octadecenoic Acid (Oleic Acid)	447	±	43	1614	±	154
C18:2 n-6	(Z,Z)-9,12-Octadecadienoic Acid (Linoleic Acid)	780	±	39	2838	±	143
C22:0	Docosanoic Acid (Behenic Acid)	15.9	\pm	1.5	47.8	±	4.6

Table 3. Reference Values for Fatty Acids

Lipid Name	Jame Chemical Name (Common Name) Mass F (µg		Fraction µg/g)		Molar Con (µmol		centration I/L)	
C14:0	Tetradecanoic Acid (Myristic Acid) ^(a,b)	17.9	±	3.8	80.1	±	17.0	
C14:1	(Z)-9-Tetradecenoic Acid (Myristoleic Acid)(c,d)	1.57	±	0.03	7.1	±	0.1	
C15:0	Pentadecanoic Acid ^(b,e)	1.08	±	0.01	4.56	±	0.04	
C17:0	Heptadecanoic Acid (Margaric Acid ^(d,e)	4.7	±	0.2	17.6	±	0.7	
C18:3 n-6	(Z,Z,Z)-6,9,12-Octadecatrienoic Acid (γ-Linolenic Acid) ^(a,b)	10.9	±	2.3	39.9	±	8.5	
C18:1 n-7	(Z)-11-Octadecenoic Acid (Vaccenic Acid) ^(c,d)	37.7	±	0.9	136	±	3	
C20:0	Eicosanoic Acid (Arachidic Acid) ^(c,d)	5.5	±	0.2	18.0	±	0.5	
C20:1	(Z)-11-Eicosenoic Acid (Gondolic Acid ^(c,d)	3.5	±	0.1	11.5	±	0.5	
C20:2	(Z,Z)-11,14-Eicosadienoic Acid ^(c,d)	5.7	±	0.2	18.8	±	0.6	
C20:3 n-6	(Z,Z,Z)-8,11,14-Eicosatrienoic Acid (Homo-γ-Linolenic Acid) ^(c,d)	41.8	±	1.1	139	±	4	
C20:4 n-6	(Z,Z,Z,Z)-5,8,11,14-Eicosatetraenoic Acid (Arachidonic Acid) ^(a,b)	293	±	54	984	±	180	
C20:5 n-3	(Z,Z,Z,Z,Z)-5,8,11,14,17-Eicosapentaenoic Acid (EPA) ^(c,d)	11.4	±	0.1	38.6	±	0.5	
C22:1	(Z)-13-Docosenoic Acid (Erucic Acid) ^(c,d)	1.1	±	0.4	3.4	\pm	1.3	
C22:4 n-6	(Z,Z,Z,Z)-7,10,13,16-Docosatetraenoic Acid ^(c,d)	8.3	±	0.2	25.5	±	0.6	
C22:5 n-3	(Z,Z,Z,Z,Z)-7,10,13,16,19-Docosapentaenoic Acid (DPA) ^(c,d)	12.5	±	0.2	38.5	±	0.7	
C22:5 n-6	(Z,Z,Z,Z,Z)-4,7,10,13,16-Docosapentaenoic Acid ^(c,d)	6.3	±	0.1	19.5	\pm	0.4	
C22:6 n-3	(Z,Z,Z,Z,Z,Z)-4,7,10,13,16,19-Docosahexaenoic Acid (DHA) ^(a,b)	37.9	±	6.8	118	±	21	
C24:0	Tetracosanoic Acid (Lignoceric Acid) ^(c,d)	16.8	±	0.9	46.6	±	2.6	
C24:1	(Z)-15-Tetracosenoic Acid (Nervonic Acid) ^(c,d)	25.6	±	1.2	71.3	±	3.2	

Figure S-1. Extracts from the NIST SRM 1950 (Metabolites in Frozen Human Plasma) certificate. The metabolites evaluated at the validation step are framed in blue.

S-6. Method optimization. A. Sample preparation. B. Separation and detection.

(A) Sample preparation

As expected, the optimization led to consequential improvements^{S-9}. Methanol (3:1) *extracted* higher amounts of metabolites than the chloroform/methanol/water mixture (2:1:1:1) (Table S-5). Previously published results were mitigated about methanol^{S-10,S-11,S-12}. Lyophilization, used in a some studies^{S-13}, was not tested, in order to limit the loss of the most volatile compounds^{S-14} such as fatty acids.

As mentioned in the manuscript, the moderate optimal *derivatization* conditions compromised between reaction completion and side-effects that lead to degradation (Figure S-2). This is supported by the incomplete reactions at 4, 80 and 100 °C, with respectively 64, 86 and 71 % of the maximum TIC obtained at 40°C (Table S-3). And 37, 92 and 86 % of the normalized volume of amino compounds at the same temperature. Another observation is that the less reactive groups logically required harder conditions. When derivatization duration went from 30 min to 1 hour, the m/z = 73 was increased, in the total chromatogram and for the less reactive amino-groups. After 2 and 4 hours, however, the gain became marginal. Because the response near the optimal values of temperature and duration was stable, small changes should not affect much the process^{S-11,S-15,S-16}. BSTFA was confirmed^{S-17} to be less efficient than MSTFA, with a decreased global m/z 73 signal. On the contrary, MTBSTFA gave quite similar results and could therefore be appropriate in certain applications. Here, MSTFA was selected because, despite a reported lower stability of adducts^{S-12} and a lower efficiency for the amino groups^{S-} ¹⁸, the TMS groups are lighter and smaller and have lower steric hindrance that would limit the derivatization of carbohydrates^{S-16, S-18}. In addition, MSTFA is the most reported in literature and mass spectral databases^{S-19}. Despite our attempts, and its reported advantages^{S-20}, methyl chloroformate alkylation could not be performed efficiently, thus it could not be compared. To avoid impurities and preserve the syringe, only 15 μ L of the supernatant (out of 25, MeOX + MSTFA) were taken before injection. Regarding the stability of the samples, the storage at -80 °C produced only minor variations, probably because it never exceeded 4 weeks.



Figure S-2. DoE response surfaces for MSTFA and MeOX volumes and temperatures.

Derivatization Agent			V MTSFA /					
			V.					
Putative ID	¹ t _R	$^{2}t_{R}$	MTBSTFA					1
Propanoic acid	14.33	4.21	0.90	Derivatization	MSTFA	MTBSTFA	BSTFA	
DL-3-Phenyllactic acid	14.97	0.83	0.53	Agent				
Butanoic acid	17.24	0.71	0.56	Total Volume	100	102	88	
Aspartic acid	19.70	2.78	1.96	N-groups	100	94	84	J
Ethanedioic acid	25.71	2.14	2.35					-
Aminomalonic acid	32.18	1.59	1.09					
/	36.56	2.62	0.37					
Oxalic acid	37.49	1.23	0.39					
2-Piperidinecarb. acid	37.37	0.79	0.67					
D-Glucofuranose	39.77	0.63	2.21	Tomporatura	Total	N groups		
2-Hexenedioic acid	40.47	1.03	1.23	remperature	Norm. V	IN-groups		
Undecanoic acid	43.09	1.19	0.52	4°C	64	37		
2-Butenoic acid	47.82	1.07	4.71	40°C	100	100		
Dodecanoic acid	48.40	1.55	2.40	80°C	86	92		
Cinnamic acid	49.97	2.70	1.03	100°C	71	86		
Hexadecanoic acid	51.78	1.98	1.07					
Uric acid	54.47	3.06	0.28	Duration	30 min	60 min	120 min	240 mi
Alanine	16.02	0.71	0.66	Total Norm V	100	110	112	108
Isoleucine	24.60	0.87	0.83	N-groups	100	111	113	118
Proline	24.60	1.39	1.30					
Glycine	25.01	0.87	0.76					
Serine	27.69	0.79	0.61	Extraction	MeOH 3:1	$CCI_4/MeOH$		
threonine	28.86	0.67	2.83	Agent		(3.1.1)		
Proline	34.05	3.37	1.16	Total V	100	72		
Ethionine	53.42	2.30	1.55	N-groups	100	75		

Table S-3. Sample preparation optimization. MSTFA and MTBSTFA comparison (left). Derivatization reagents comparison (top right). Influence of the temperature and duration of methoxymation and silylation on the global derivatization (total normalized volume) as well as on less reactive amino groups (middle right). Extraction agents comparison (bottom right). To simplify the comparisons, the peak volumes were normalized to a reference value of 100.

(B) Separation and detection

To assess the *column sets*, in addition to the direct number of unique compounds resolved, parameters linked to resolution, peak shape and peak size (such as symmetry, kurtosis or spread) were measured for 11 compounds representative for chemical classes, retention times and peak volumes (amino, organic and fatty acids, sugars). As a result, the non-polar/semi-polar (normal) set of columns gave the highest number of resolved metabolites (~500 peaks, Figure S-3). The alternative set worked equally well, with a different elution pattern that could be interesting in specific applications^{S-21}. The reverse set (semi-polar/non-polar) gave poor results. Possibly because of a retention of the metabolites in the column due to increased interactions. The two columns used the same diameter and film thickness in order to have an optimal flow in both. The values chosen, 0.25 mm - 0.25 μ m, compromised between sample

loadability and peak capacity in the second dimension, to fit with the objective of an untargeted method. For the same reason, a linear *temperature program* was chosen. It also allowed the use of linear retention indices for compound identification. This parameter revealed to be much more influential than the flow rate, at the tested values (Figures S-4 and S-5). The best resolution was obtained at 1 mL/min, in accordance to the Van Deemter equation, and 3 °C/min, as explained in the manuscript. This low ramp increased the run time to 72 minutes (Table S-4), the price to pay to take full advantage of the instrumentation in an exploratory mode.



Figure S-3. Examples of chromatograms produced by the three sets of columns.







Figure S-4. Separation parameters for various flow rates and temperature ramps. 3 $^{\circ}$ C/min, either with 1 or 1.5 mL/min, provided the best separation, with higher resolution, selectivity and separation despite a higher spread of the peaks.

-



Figure S-5. Chromatograms obtained at 3 and 5 °C/min. The first provided a better use of the separation space, especially in the second dimension, increasing the overall spatial resolution.

Hold time (min) Temp (°C)	1 50	5 300	
Ram Ramp	Ramp 2 Temp		
Ramp 1 Temp (°C/min)	Ramp 1 time (min)	Total Time (min)	(°C/min) 15 °C/min
3	63	73	
5	38	48	
7	27	37	
10	19	29	

Table S-4. Run times for the four temperature ramps evaluated, not including the cooling time of the oven and the columns.

The best *initial temperature* was 50 °C (Figure S-6), in agreement to the good practice rule that suggests to start a run 20 °C below the boiling point of the solvent^{S-22}, here hexane (BP : 69 °C). Indeed, 90 and 70 °C both led to badly focused first eluting compounds. 40 °C did not improve further the resolution.

Once the initial and ramp temperatures were known, the solvent delay was set at 8 minutes to preserve the detector.



Figure S-6. Effect of the initial temperature on the early eluting compounds, that are broadened at 90°C.

The configuration of the *modulation system* depends on the samples to analyze. Here, a modulation period (P_M) of 3.5 seconds was found to maintain the separation of the peaks in the first dimension with minimal empty space and wraparound in the second dimension. Meanwhile, a 700 ms hot jet at 170 °C allowed an efficient reinjection, which is especially important for volatile compounds eluting at low temperatures, and a reduced breakthrough. 500 ms was found too short (Figure S-7), and a temperature of 100 °C too cold. There was no clear improvement at 900 ms and 200 °C.



Figure S-7. Effect of the hot jet duration (P_M 3.5 s) on the resolution in the overloaded zones of urea (above) and glucose (below).

The most effective *injection* temperature was 250 °C (Table S-5). 200 °C was too low to volatilize correctly the heaviest metabolites, especially in a biological matrix^{S-23}. 280 °C was too destructive for the TMS adducts.

Represent.	Compounds	Injection standard				
Injection Temp.	Norm. Volume	Injection Temp.	Norm. Volume			
200	92	200	97			
250	100	250	100			
280	88	280	101			

Table S-5. Influence of the injection temperature on the normalized peak volume, here normalized to 100 at 250°C.

Split mode injection has a reported beneficial effect on peak shape and quantitation^{S-24}. However, negative effects on peak ratios and the stability of amino-groups adducts have also been observed^{S-25}. Here, a split as low as 10 was found too dilutive for untargeted analysis, preventing the detection of trace metabolites, while a split less than 10 was too unstable to be reproducible. The opposite alternative,

i.e. injecting 2 μ L instead of 1 μ L, increased the signals of trace metabolites, but induced an overloading of highly concentrated compounds such as urea and glucose. This resulted in an overall decrease in the number and the chromatographic quality of the metabolites detected in wide areas around them (Figure S-8). Not mentioning the possible backflash that would make the chromatogram unrepresentative of the initial sample. Backflash that likely explained the lower signals detected with the 'Gooseneck' liner which, by design, gives a lower volume to the gas phase to expand (Figure S-9).



Figure S-8. Impact of the injection volume on the chromatographic resolution in an area at risk of overloading (urea).



Figure S-9. Effect of the liner design on the global chromatogram. Higher number of metabolites and signal intensity were detected with the 'Precision' liner.

EXPERIMENTAL									
<u>S</u> 1	ample Prep . Extraction: metha	nol (3:1)							
2. Derivatization (30 µL serum):									
MeOX 15 µL - 40 °C - 1h									
	MSTFA 10 µL - 40 °C - 1h								
<u>S</u> R E	eparation and detecti Rxi-5 - 30 m / Rxi-17 Both 0.25 mm, 0.25 μr	<u>on</u> - 2 m m							
	1 mL/min flow	50 °C initial T							
	3 °C/min ramp T	3.5 seconds P _M							
	700 ms hot jet	250 °C injection T							
\backslash	Precision Sky liner	1 μL splitless	/						
	3 °C/min ramp T 700 ms hot jet Precision Sky liner	3.5 seconds P _M 250 °C injection T 1 µL splitless							

Figure S-10. Summary of the optimized analytical conditions.

S-7. Accuracy and precision assessment in NIST SRM 1950.

	Mean (umol/L)	Precision - RSD (%)			Accuracy	- Z-score
	NIST	NIST	Intra-Batch	Inter-Batch	Intra-Batch	Inter-Batch
Alanine	300	9	7.4	11.3	4.4	0.5
Valine	182.2	6	2.5	8.1	1.9	6.3
Leucine	100.4	6	4.2	8.7	1.0	2.5
Isoleucine	55.5	6	11.6	7.1	34.8	11.2
Proline	177	5	5.6	13.9	7.9	9.5
Serine	95.9	4	4.5	6.3	4.3	6.6
Threonine	119.5	5	9.8	10.4	0.5	24.4
Phenylalanine	51	14	4.2	10.7	11.3	13.1
Methionine	22.3	8	14.8	20.2	7.7	6.4
Glycine	245	7	4.1	4.2	0.5	0.9
Tyrosine	57.3	5	4.7	11.2	25.0	26.3
Lysine	140	10	11.4	8.4	8.0	9.2
Cystéine	44.3	16	14.4	26.4	5.6	5.7
Ornithine	133.5	4	5.3	8.7	5.8	5.1
Urea	3900	2	7.2	4.9	12.1	7.7
Creatinine	60	2	6.0	5.3	13.0	4.6
Histidine	72.6	5	9.0	7.7	17.8	16.2
Glutamic acid	67	27	3.0	9.2	1.0	1.2
Uric acid	254	2	2.8	16.2	27.9	26.2
Dodecanoic acid	9.5	6	3.7	3.6	13.6	12.0
Myristic acid	80.1	21	3.4	4.3	4.1	3.9
Pentadecanoic acid	4.6	1	7.5	14.7	84.0	72.3
Palmitic Acid	2364	3	7.3	7.7	29.2	28.9
Heptadecanoic acid	17.6	4	9.4	7.8	23.9	23.3
Linoelaidic acid	2838	5	5.1	4.5	19.3	19.7
Oleic Acid. (Z)-	1614	10	3.4	9.9	9.6	9.5
Stearic acid	644	6	3.5	7.1	14.4	14.0
Linoleic Acid	54.6	7	5.7	12.7	14.6	14.4

Table S-6. Accuracy and precision assessment in NIST SRM 1950 through intra and inter-batch measurements.

S-8. Recovery assessment in NIST SRM 1950 and internal QC samples.

	Sample	Preparation	1 Extraction	2. Drying &	
Recovery (76)	Glycine	Succinic acid	1. Extraction	Derivatization	
	73	57	63	-16	
OC Inter betch	74	60	69	-20	
QC Inter-baten	73	60	66	-16	
	75	59	66	-18	
Mean	74	59	66	-17	
RSD (%)	1.1	2.3	4.2	10.7	
	65	53	76	-16	
	61	50	74	-16	
NIST Intra-	63	50	73	-17	
batch	61	50	67	-22	
	61	47	68	-19	
Mean	62	50	72	-18	
RSD (%)	2.9	3.8	5.5	15.3	
NICT Inter	65	46	59	-12	
hatch	61	41	57	-16	
baten	57	40	55	-15	
Mean	61	43	57	-14	
RSD (%)	6.7	7.6	3.2	13.2	
Total Mean	66	51	66	-17	
Total RSD (%)	9.7	13.3	10.1	15.6	

Table S-7. Recovery assessment in NIST SRM 1950 and internal QC in intra and inter-batch measurements.

S-9. Regression methods. Determination of the best fit.

Juc		Concentration	Predicted	Observed		Relativ
		(ng/µL)	Signal	Signal	% Recovery	Error
Slope	9035	0	8.8E+2	0.0E+0	/	/
Intersect	882	0.05	1.3E+3	3.5E+1	3794	3694
Illumiah (al		0.25	3.1E+3	1.5E+3	210	110
Unweighten		1.67	1.6E+4	2.1E+4	78	22
\mathbb{R}^2	0.9957	10	9.1E+4	9.1E+4	101	1
						3827
Slope	9148	0	4.0E+0	0.0E+0	/	/
Intersect	4	0.05	4.6E+2	3.5E+1	1312	1212
		0.25	2.3E+3	1.5E+3	153	53
V3		1.67	1.5E+4	2.1E+4	75	25
		10	9.1E+4	9.1E+4	101	1
						1292
Slope	9136	0	-8.7E+0	0.0E+0	/	/
Intersect	-9	0.05	4.5E+2	3.5E+1	1275	1175
S		0.25	2.3E+3	1.5E+3	152	52
3		1.67	1.5E+4	2.1E+4	74	26
		10	9.1E+4	9.1E+4	101	1
						1253
Slope	6649	0	-1.4E-1	0.0E+0	/	/
Intersect	0	0.05	3.3E+2	3.5E+1	945	845
S2		0.25	1.7E+3	1.5E+3	111	11
5-		1.67	1.1E+4	2.1E+4	54	46
		10	6.6E+4	9.1E+4	73	27
						929
Slope	1145	0	-2.2E-4	0.0E+0	/	/
Intersect	0	0.05	5.7E+1	3.5E+1	163	63
C ³		0.25	2.9E+2	1.5E+3	19	81
3		1.67	1.9E+3	2.1E+4	9	91
		10	1.1E+4	9.1E+4	13	87
						322
Slope	746	0	-4.9E-7	0.0E+0	/	/
Intersect	0	0.05	3.7E+1	3.5E+1	106	6
S ⁴		0.25	1.9E+2	1.5E+3	12	88
3		1.67	1.2E+3	2.1E+4	6	94
		10	7.5E+3	9.1E+4	8	92
						279
Slope	709	0	-1.5E-9	0.0E+0	/	/
Intersect	0	0.05	3.5E+1	3.5E+1	101	1
S ⁵		0.25	1.8E+2	1.5E+3	12	88
ø		1.67	1.2E+3	2.1E+4	6	94
		10	7.1E+3	9.1E+4	8	92
					Γ	275

Table S-8. Determination of the most efficient regression for succinic acid. The framed cells indicate the sum of relative errors. The bold values are between 80 and 120% of recovery (ideal case). The lowest sums, in grey, were obtained with the S^5 and S^4 weights (standard deviation at the fifth and fourth power, respectively). The latter was chosen because it gave, for a very similar error, a simpler model. As showed in the percentage of recovery, this regression fitted well only at low concentrations, the ones used for the sensitivity assessment.

Fu	naric acid					
		Concentration (ng/µL)	Predicted Signal	Observed Signal	% Recovery	Relative Error
Slope	43158	0	7.0E+3	1.0E+1	67822	67722
Intersect	6964	0.05	9.1E+3	1.6E+3	577	477
		0.25	1.8E+4	1.2E+4	147	47
Unweighted	0.9948	1.67	7.9E+4	1.0E+5	77	23
R ²		10	4.4E+5	4.3E+5	101	1
						68271
Slope	43379	0	1.0E+3	1.0E+1	10203	10103
Intersect	1048	0.05	3.2E+3	1.6E+3	204	104
1~		0.25	1.2E+4	1.2E+4	98	2
٧S		1.67	7.3E+4	1.0E+5	71	29
		10	4.3E+5	4.3E+5	100	0
					ſ	10237
Slope	44162	0	3.2E+1	1.0E+1	315	215
Intersect	32	0.05	2.2E+3	1.6E+3	142	42
~		0.25	1.1E+4	1.2E+4	92	8
S		1.67	7.4E+4	1.0E+5	72	28
		10	4.4E+5	4.3E+5	102	2
					ſ	295
Slope	44021	0	8.8E+0	1.0E+1	86	14
Intersect	9	0.05	2.2E+3	1.6E+3	140	40
c)		0.25	1.1E+4	1.2E+4	91	9
S ²		1.67	7.4E+4	1.0E+5	71	29
		10	4.4E+5	4.3E+5	101	1
						93
Slope	37180	0	1.0E+1	1.0E+1	100	0
Intersect	10	0.05	1.9E+3	1.6E+3	118	18
c?5		0.25	9.3E+3	1.2E+4	77	23
S ^{2.5}		1.67	6.2E+4	1.0E+5	60	40
		10	3.7E+5	4.3E+5	86	14
					ſ	96
Slope	32201	0	1.0E+1	1.0E+1	100	0
Intersect	10	0.05	1.6E+3	1.6E+3	103	3
c1		0.25	8.1E+3	1.2E+4	67	33
S ³		1.67	5.4E+4	1.0E+5	52	48
		10	3.2E+5	4.3E+5	74	26
						110
Slope	30993	0	1.0E+1	1.0E+1	100	0
Intersect	10	0.05	1.6E+3	1.6E+3	99	1
64		0.25	7.8E+3	1.2E+4	64	36
5*		1.67	5.2E+4	1.0E+5	50	50
		10	3.1E+5	4.3E+5	71	29
					ſ	116

Table S-9. Determination of the most efficient regression for fumaric acid. The framed cells indicate the sum of relative errors. The bold values are between 80 and 120% of recovery (ideal case). The lowest sum, in grey, was obtained with the S^2 weight (square standard deviation). The obtained regression fitted well at all concentrations.

	Glycine					
		Concentration (ng/µL)	Predicted Signal	Observed Signal	% Recovery	Relative Error
Slope	16841	0	5.0E+4	4.3E+4	116	16
Intersect	49606	0.05	5.0E+4	4.9E+4	104	4
There is a based		0.25	5.4E+4	5.0E+4	107	7
Unweighted	0.9866	1.67	7.8E+4	9.2E+4	84	16
\mathbb{R}^2		10	2.2E+5	2.2E+5	101	1
						44
Slope	295307	0	-3.1E+5	4.3E+4	-722	822
Intersect	-307991	0.05	-2.9E+5	4.9E+4	-602	702
		0.25	-2.3E+5	5.0E+4	-465	565
v s		1.67	1.9E+5	9.2E+4	200	100
		10	2.6E+6	2.2E+5	1226	1126
					l l l l l l l l l l l l l l l l l l l	3316
Slope	313520	0	-1.9E+5	4.3E+4	-445	545
Intersect	-189820	0.05	-1.7E+5	4.9E+4	-357	457
e.		0.25	-1.1E+5	5.0E+4	-222	322
3		1.67	3.3E+5	9.2E+4	361	261
		10	2.9E+6	2.2E+5	1366	1266
						2851
Slope	161166	0	-2.5E+4	4.3E+4	-58	158
Intersect	-24919	0.05	-1.7E+4	4.9E+4	-35	135
S ²		0.25	1.5E+4	5.0E+4	31	69
3		1.67	2.4E+5	9.2E+4	264	164
		10	1.6E+6	2.2E+5	736	636
						1162

Table S-10. Determination of the most efficient regression for glycine. The framed cells indicate the sum of relative errors. The bold values are between 80 and 120% of recovery (ideal case). The unweighted regression gave the lowest sum and fitted very well at all the concentrations tested.



Figure S-11. Residual plots for the three IS using unweighted (blue points) and weighted (orange points) regressions. The complete plots are on the left. For succinic and fumaric acids, the plots on the right zoom-in in order to neglect the very high recovery percentage of the blank in the unweighted regression. The efficiency gain produced by weighting was especially important at low concentrations, where the limits of detection and quantification (LOD and LOQ) were assessed.



Figure S-12. Unweighted and weighted linear regression for succinic acid, fumaric acid and glycine with zoom-in to the lowest concentrations (right). The experimental values are encircled in red.

S-10. Sensitivity assessment. A. Methods. B. Calculation of LOD and LOQ.

(A) Methods

The selective m/z considered were: 247 for fumaric acid-2,3-d₂, 251 for succinic acid-2,2,3,3-d₄, 104 (2 TMS), 250 and 278 (3 TMS) for glycine-2,2-d₂.

Sensitivity was assessed in three ways. In the first, the analytical signals for LOD and LOQ, named vLOD and vLOQ, were defined as^{S-26,S-27,S-28}:

$$yLOD = M_{blank} + 3.S_{blank}$$
$$yLOQ = M_{blank} + 10.S_{blank}$$

Where M is the mean signal and S the standard deviation. The regressions obtained earlier are of the (linear) form y = ax + b, where y is the analytical signal at the analyte concentration x. Therefore:

$$LOD/LOQ = \frac{yLOD / yLOQ - b}{a}$$

In the second, the signal from the blank was compared to the signal at the lowest concentration injected^{S-29}.

$$LOD = yLOD. \frac{Lowest Conc}{Mean Signal_{Lowest conc}}$$
$$LOQ = yLOQ. \frac{Lowest Conc}{Mean Signal_{Lowest conc}}$$

In the third, the LOQ was defined as the minimal amount really injected with a RSD below $30 \%^{S-30}$ and a signal over 5 times the blank signal^{S-31}. S/N ratios were not tested because of the artificial loss of signal due to the early centroidization of the chromatograms that accounted for a factor around 2 despite optimization.

(B) Calculation of LOD and LOQ

	LOD (pg/uL) 1.	LOQ (pg/uL) 2.	LOD (pg/uL) 3.	LOQ (pg/uL) 4.	30% RSD & > 5*Blank Signal	Sensitivity (e- /pg.ul)
Fumaric Acid	1.6	5.2	2.2	7.3	50	44.0
Succinic Acid	4	13	4.5	14	250	7.5
Glycine	125	1375	53.1	75	10000	16.8

	On-column					
	LOD (pg/uL)	LOQ (pg/uL)	LOD (pg/uL)	LOQ (pg/uL)		
	1.	2.	3.	4.		
Fumaric Acid	1.9	6.3	2.7	8.8		
Succinic Acid	5	16	5.4	17		
Glycine	150	1650	63.7	90		

1. LOD = 3 SD blank / slope regression
2. $LOQ = 10 SD blank / slope regression$
3. LOD = Min.Conc*yLOD / y Min.Conc
4 IOD – Min Conc $*$ vIOO / v Min Conc

Table S-11. LOD, LOQ and sensitivity assessment (in pg/uL injected) using three different methods: regression applied to the blank (1 and 2), blank and minimal concentration tested (3 and 4) and minimal concentration tested having RSD < 30% (5).

Because of the high signal of its blank, glycine had a lower sensitivity. It also exhibited higher variations from one method of evaluation to the other. Therefore, only the method that compared, and in a way corrected, the blank to the signal at the lowest concentration injected worked well (Table S-11). To achieve that, the blank had to be reliably measured, which was the case here with a RSD of 7%. This procedure seemed the most consistent overall, presumably because it uses signals from real injections while the regression curves modelize an approximated behavior. Nevertheless, these results also emphasize the need for m/z that are very specific of the IS, therefore the need for highly deuterated standards, to reliably quantify compounds at low concentrations. Because it is based on real amounts injected, here the third method suffered from the low number of concentrations tested near the LOQ and thus was not very informative.

Overall, the discrepancies observed between the three IS as well as the deviations from an ideal behaviour, for both linearity and sensitivity, show that the capacity to quantify, even when limited to semi-quantitation, cannot be systematically achieved. Hence, it is important, when establishing a method, to evaluate these parameters for compounds representative of the various metabolites present in the samples in terms of chemical classes, signal intensities and retention times.

The sensitivity value is based on the working principle of the microchannel plate (MCP) detector used in the TOF spectrometer. It makes the assumption that each unity of the signal (given by the slopes of the regressions) corresponds to an electron produced through the electron amplifier of the detector. Thus, theoretically 7, 17 and 44 electrons were produced at the detector per pg of compound (respectively succinic acid, fumaric acid and glycine) per μ L of sample.

S-11. QC system. A. Acceptance/rejection criteria. B. Effect of the QC correction

(A) Acceptance / rejection criteria

<u>Any injected sample</u> was rejected if the raw peak volume of any standard –internal or injection- was outside the QC mean value ± 30 %.

A whole <u>batch</u> of 5 study samples was rejected if the following QC sample was rejected or if at least 2 study samples were rejected.

A QC sample was rejected if:

- The raw peak volume of any standard –internal or injection- was outside the QC mean value $\pm 30\%$.
- Any retention time of any representative metabolite (out of 19) was outside the action limits, or at least
 3 of the same kind (first or second dimension) were outside the warning limits.
- The corrected peak volume was outside the action limits for at least 2 representative metabolites (out of 16, IS excluded), was outside the warning limits for at least 4 of them, or was outside the action limits for at least 1 of them and outside the warning limits for at least 2 of them.

No trends criteria were used in this study but could be interesting in others.

Any study or QC sample rejected was directly reinjected. A second rejection, in the absence of any other clue, was considered a derivatization failure. In this circumstance, a biological replicate was prepared and injected. Another rejection was considered a system failure and stopped the sequence of injection. Once the issue had been found and fixed, and the system reconditioned, the sequence started again. In the case of a study sample, a biological replicate was prepared and injected. In the case of a QC sample, the whole batch was rejected and biological replicates were prepared and injected.

(B) Effect of the QC correction



Figure S-13. Effect of the LOESS (partial) correction on the QC samples for two metabolites of the final dataset.


Figure S-14. QC (blue points) and study samples (orange points) signals before (above) and after (below) the LOESS (partial) correction.

The LOESS procedure corrected, albeit not completely, the analytical variations measured in the QC samples (Figure S-4, blue points in Figure S-5), while maintaining the biological variation (orange points in S-5). Indeed, the RSD in the QC samples went respectively from 48 and 25% to 12 and 11%. However, whatever the effectiveness of the procedure, the analytical variations cannot be totally corrected a posteriori. Trying to do so is risky because it would most probably lead to overfitting and to the reduction of the biological variation of interest. Since it is also more effective and less risky to correct for small variations, a prior optimization of the analytical method is very advisable.

S-12. Data Scaling.



Figure S-15. HCA plots for the various scaling methods. Healthy controls are in red, high endoscopic activity samples in green, low endoscopic activity samples in royal blue and quiescent samples in light blue. The red circles emphasize the potential outliers and their dissimilarity.



Figure S-16. PCA 3D plots for the various scaling methods. Healthy controls are in red, high endoscopic activity samples in green, low endoscopic activity samples in royal blue and quiescent samples in light blue. The red circles emphasize the potential outliers. The yellow lines emphasize an early separation.



Figure S-17. PCA 2D plots for level scaling with all samples (left) and without the two alleged outliers (right), where new ones appear. Healthy controls are in red, high endoscopic activity samples in green, low endoscopic activity samples in royal blue and quiescent samples in light blue.



Figure S-18. PLS-DA 3D plots for the various scaling methods. Healthy controls are in red, high endoscopic activity samples in green, low endoscopic activity samples in royal blue and quiescent samples in light blue. The yellow lines emphasize an early separation.

_										
	D	OOB	A 4	OOB	Damata	OOB	Damas	OOB	Veet	OOB
1	Kaw	0.456	Auto	0.426	Pareto	0.426	Kange	0.412	vast	0.397
I	Peak	MDA	Peak	MDA	Peak	MDA	Peak	MDA	Peak	MDA
	56	0.013	144	0.017	144	0.017	144	0.015	144	0.017
	144	0.012	56	0.015	56	0.013	56	0.012	56	0.016
	87	0.008	90	0.010	90	0.010	90	0.010	90	0.010
	114	0.008	87	0.006	11	0.008	11	0.007	81	0.007
	90	0.008	11	0.006	154	0.005	154	0.006	114	0.006
	11	0.007	114	0.006	114	0.005	87	0.005	11	0.006
	154	0.006	154	0.005	63	0.005	63	0.004	87	0.006
	122	0.005	63	0.005	87	0.004	114	0.004	63	0.005
	63	0.004	81	0.004	54	0.004	161	0.004	109	0.005
	29	0.004	122	0.004	122	0.004	14	0.003	154	0.005
	14	0.004	14	0.004	14	0.003	69	0.003	122	0.004
	81	0.003	54	0.003	161	0.003	81	0.003	161	0.003
	109	0.003	136	0.003	182	0.003	105	0.003	29	0.002
	136	0.003	68	0.003	81	0.002	29	0.003	133	0.002
	75	0.002	105	0.003	4	0.002	122	0.002	136	0.002

Table S-12. Effect of scaling on random forests' (RF) ability to highlight the most significant metabolites. All methods gave similar results, either for the significant metabolites or their associated mean decrease accuracy values (MDA). All methods also improved the significance of the potential biomarkers (higher MDA and lower out-of-bag error, OOB) in comparison to the raw data.

	PLS-DA Q ²	PLS-DA R ²
Raw	0.01	0.35
Pareto	0.02	0.47
Auto	0.28	0.77
Range	0.31	0.77
Vast	0.17	0.73
Level	Out	liers

Table S-13. PLS-DA Q^2 and R^2 for the various scaling methods. Auto and range scalings provided the best performances, calculated on all variables.

PCA (%)	PLS-DA (%)
70	61
42	34
24	18
26	20
37	21
Out	liers
	PCA (%) 70 42 24 26 37 Outl

Table S-14. Percentages of variation explained by the first two axis in PCA and PLS-DA plots, that are lower for auto and range scalings. Again, the models were constructed on all variables.

S-13. Statistics for biomarker research. A. Statistical treatment details. B. Significance.

(A) Statistical treatment details

ANOVA consisted of Welch ANOVA and Kruskal-Wallis test. Random forests (RF) produced 500 trees and applied both^{S-32} Gini Index^{S-33} and Gain Ratio in order to improve the splitting and the variable selection^{S-34}. PLS-DA performed cross-validation to define the optimal number of latent variables. PLS-DA and OPLS-DA performed permutation testing (2000 permutations). Naïve Bayes did not assume the homoscedasticity of the variables. SVM used a polynomial kernel that was adapted (often linear) to maximize the separation. Neural network (NN) used no hidden layer because this configuration revealed to be more efficient to limit overfitting as well as to select the significant variables^{S-35}. Multivariate ROC curves used SVM, RF, PLS-DA and logistic regression algorithms, with Monte-Carlo cross-validation. Since the global statistical power is directly linked to the p-value^{S-36, S-37}, it was interpreted in a similar way. Here, it was only partially informative because the calculation implemented in MetaboAnalyst, the only free resource we found, suffered from the non-consideration of the covariance between the biomarkers^{S-38}.

(B) Significance

To be able to simultaneously take into account different statistical tests, thresholds corresponding to moderate and strong significance were defined for each of them, based on general statistical knowledge and specific sources. A variable meeting one or both thresholds was attributed respectively one or two points. The points were summed and the metabolites were ranked and selected accordingly. The thresholds were: 0.05 and 0.01 for any test giving a p-value, such as Pearson r, Spearman ρ , Kendall τ , Welch or Mann-Whitney/Kruskal-Wallis ANOVA and Fisher ratios (FR). 2 and 3 for PLS-DA VIP. 0.0020 and 0.0025 for RF^{S-39}. 0.7 and 0.8 for AUC^{S-40}. 1.5 and 2 for fold change (FC). 70 and 80% for univariate two-tailed statistical power. To be selected and to be selected among the first ten variables for feature selection methods and OPLS-DA. To be among the most significant 10% or 5% based on

weight or distance for Bayes classifier, NN and SVM. For the three CD subgroups separation, the biological proximity of the samples made more difficult their separation and therefore lowered the statistical values. The PLS-DA VIP thresholds were adapted to 1.4 and 1.7. Bonferroni correction for multiple testing^{S-40} was mostly informative. Indeed, it was interesting to see which metabolites met this conservative threshold for significance but we did not want to restrict the selection process. Especially since the ability of the metabolites was further assessed at the following performance assessment step.

S-14. Data control and selection process for the Crohn's disease samples and the healthy controls.



Figure S-19. OPLS-DA plots for the separation between CD (red) and HC (green) samples, constructed on all the 183 metabolites taken in the final dataset.

The good discrimination achieved in Figure S-19 shows the existence, in the data set, of metabolic information capable to separate the Crohn's disease (CD) samples from the healthy controls (HC). Thus the interest to try to extract it through the selection process.

The main statistical values for the candidate biomarkers are given in the article.

15 tests	Score	8 tests	Score	15 tests	Score		8 tests	Score
Peak	/ 30	Peak	/ 16	Peak	/ 30		Peak	/ 16
144	24	144	15	4	7	ĺ	4	4
114	23	114	14	11	14		11	7
29	22	56	13	13	9		13	3
69	21	29	12	29	22		29	12
154	20	63	12	54	12		54	6
56	19	69	12	55	9		55	6
87	19	154	12	56	19		56	13
63	18	87	11	63	18		63	12
81	15	81	10	69	21		69	12
11	14	105	9	81	15		81	10
105	14	11	7	86	5			
54	12	54	6	87	19		87	11
132	12	55	6	90	7		90	5
136	11	90	5	97	6		97	4
109	10	132	5	105	14		105	9
13	9	133	5	109	10		109	4
55	9	136	5	114	23		114	14
122	8	168	5	122	8		122	4
133	8	4	4	124	6		124	3
168	8	97	4	126	7		126	4
4	7	109	4	132	12		132	5
90	7	122	4	133	8		133	5
126	7	126	4	136	11		136	5
97	6	161	4	144	24		144	15
124	6	13	3	154	20		154	12
86	5	124	3				161	4
				168	8		168	5

Table S-15. Global significance scores obtained through the aggregation of the individual statistical significance values (see section S-12). Two cases are compared. In the first, all 15 tests were performed and considered (first and third frames). In the second, only the 8 most effective tests, the ones recommended in the main article, were considered (second and fourth frames): FC, ROC, Pearson/Spearman, Kendall, Welch/Mann-Whitney ANOVA, Stepdisc, PLS-DA, RF. The first two frames are ordered according to the global score while the third and fourth ones are ordered according to the peak number ID to facilitate the comparison. The peak number is the one in the final data set, among the 183 final variables.

Table S-15 shows that using only the 8 most effective tests, instead of all 15 tests, did not change the candidate biomarkers that were selected. The peaks with the highest scores were the same in both cases (peaks 86 and 161 had different rankings but also a low significance). For this reason, these 8 tests are recommended to simplify the selection process. Regarding the Bonferroni criterion, many candidates met it for some of the statistical tests (Table S-16). The most significant even met it for all the 4 tests considered.

Bonferroni	
CB	/ 4 tests
1	4
2	4
3	4
4	3
5	4
6	0
7	1
8	3
9	1
10	1
11	2
12	0
13	0
14	0
15	0
17	0
18	0
19	2
20	3
22	4

Table S-16. Candidates meeting the significance threshold of 0.05 after Bonferroni correction for multiple testing (0.05/183) for four statistical tests: Pearson/Spearman and Kendall correlations, Welch/Kruskal-Wallis ANOVA and FR.

D 1	PLS-DA	OPLS-DA	RF
Peak Number	137	46	161
Number	16	12	14
	46	16	130
	12	182	12
	76	162	75
	182	137	160
	3	143	41

Table S-17. Additional biomarker research through PLS-DA, OPLS-DA and RF. The grey cells indicate the metabolites highlighted multiple times. The peak number is the one in the final data set, among the 183 final variables.

Peak Number	Ranking
46	23
12	27
137	28
16	29
182	86

Table S-18. Ranking of the potential additional candidate biomarkers in the initial selection process.

Regarding the search for additional candidates, some metabolites were highlighted by at least two methods (Table S-17). Nevertheless, their boxplots were not 'better' than the ones of the selected candidate biomarkers (Figures S-21) and they were not selected. This supported the comprehensiveness and efficiency of the selection process. Just as did the comparison of the OPLS-DA plots before and

after the selection where a degradation of the separation indicated that a large part of the relevant information had been successfully extracted (Figure S-20).



Figure S-20. OPLS-DA plots constructed on all 183 metabolites of the final dataset (left) and on the 161 metabolites left after the selection of the candidate biomarkers (right).





Figure S-21. Examples of boxplots for some of the candidate biomarkers (4 boxplots above) and for the potential additional ones (4 boxplots below).



S-15. Data control and selection process for the three subgroups of Crohn's disease samples.

Figure S-22. sPLS-DA plots (latent variables 1 and 2 on the left, 3 and 4 on the right) for the separation between CD subgroups samples. High endoscopic activity samples are in red, low endoscopic activity samples in green and quiescent samples in blue.

Figure S-22 shows the existence of metabolic information capable to separate the CD subgroups. However, the difficulty to completely do so, in comparison to the direct separation with the healthy controls, is obvious. This is supported by the fact that, in the selection process (Table S-19), only the candidate highlighted as the most significant (candidate 11) met the Bonferroni criterion, for only one of the two univariate tests considered. The high endoscopic activity sample outside the 95% confidence ellipse in sPLS-DA will be investigated in a future biological interpretation of the results.

Candidate	Normality	Standisc	Fisher p-	Welch / K-	PLS-DA	RF	Sansa of variation
Calididate	Normanty	Stepuise	value	W	VIP	MDA	Sense of variation
11	0.00		0.00	0.00	1.9	0.0039	High > Quiescent > Low
23	0.00		0.01	0.01	1.7	0.0028	High > Quiescent > Low
1	0.00		0.02	0.04	1.5	0.0099	Low > High > Quiescent
15	0.46		0.04	0.05	1.3	0.0022	High > Quiescent > Low
18	0.20		0.01	0.01	1.8	0.0078	Quiescent > Low > High
24	0.01		0.00	0.04	2.0	0.0012	Quiescent > Low > High
25	0.00		0.01	0.04	1.5	0.0097	Low > High > Quiescent
8	0.00		0.01	0.03	1.5	0.0071	Low > High > Quiescent
5	0.02		0.06	0.04	1.6	0.0008	High > Quiescent > Low
14	0.00		0.16	0.10	1.2	0.0013	Low > Quiescent > High
7	0.15		0.03	0.04	1.3	0.0029	Low > High > Quiescent
26	0.00		0.34	1.00	0.9	0.0014	High > Quiescent > Low
9	0.00		0.02	0.02	1.3	0.0034	High > Quiescent > Low
27	0.00		0.12		1.1	0.0009	Quiescent > High > Low
28	0.00		0.01	0.01	1.6	0.0000	Quiescent > High > Low
6	0.00		0.03	0.03	1.3	0.0033	Quiescent > High > Low
29	0.00	5	0.67	0.59	0.9	0.0000	Quiescent > High > Low
30	0.01	2	0.08	0.23	1.4	0.0003	Quiescent > High > Low
31	0.00		0.05	0.07	1.4	0.0008	Quiescent > High > Low
2	0.00		0.02	0.05	1.4	0.0006	Low > High > Quiescent
32	0.00		0.02	0.06	1.4	0.0039	Low > High > Quiescent
33	0.23	7	0.05	0.10	1.4	0.0003	Quiescent > High > Low
34	0.57		0.05	0.01	1.3	0.0011	Low > High > Quiescent
35	0.01		0.05	0.18	1.4	0.0008	Quiescent > High > Low
36	0.01		0.05	0.03	1.4	0.0005	Quiescent > High > Low
10	0.26	12	0.05	0.08	1.3	0.0038	High > Quiescent > Low
37	0.00	13	0.06	1.00	1.5	0.0003	Quiescent > Low > High
38	0.00		0.03	0.12	1.7	0.0010	Quiescent > High > Low
39	0.00		0.03	1.00	1.5	0.0004	High > Low > Quiescent

Table S-19. Main statistical values for the candidate biomarkers selected to separate the three CD subgroups. The candidates are ordered according to their significance in the selection process. Univariate methods: Welch and Kruskal-Wallis tests, FR. Multivariate methods: Stepdisc feature selection, PLS-DA, RF (mean decrease accuracy). The values meeting the statistical thresholds for significance are in bold.



Figure S-23. sPLS-DA plots constructed on the 183 metabolites of the final dataset (left) and on the 154 metabolites left after selection of the candidate biomarkers (right).

Figure S-23, through the clear degradation of the separation when the candidates were removed, indicates that the information relevant for the biological question studied was successfully extracted from the data set by the selection process.



Figure S-24. Examples of boxplots for some of the candidate biomarkers.

S-16. Bias control for the CD candidates. A. Repartition of the factors between the two biological classes. B. Relationships between the candidate biomarkers and the bias factors. C. Residual separation ability.

The medications considered were the ones with enough representation in the groups or the ones linked to CD: Elthyrone[®] and L-Thyroxine[®] (thyroid regulation), Pantomed[®] (gastroesophageal reflux and ulcer), Remicade[®] and Humira[®] (anti-TNF α) and Imuran[®] (immunosuppression).

(A) Repartition of the factors between the two biological classes

	Gender				Gastro.	L-	Anti-	
%	(F)	Tobacco	Alcohol	Hemolysis	reflux	Thyroxin	TNFα	Immunosupp.
HC	58	18	21	15	27	18	0	0
CD	60	37	23	14	29	20	51	14
				-				
Mean	Inj Order	Age	BMI					
HC	43 ± 27	44 ± 12	25 ± 5					
CD	53 ± 28	42 ± 12	25 ± 5					
	1				1			
Drying				Drying			1	
Number	HC	CD		%	HC	CD		
Batch 1	4	4		Batch 1	12	11		
Batch 2	3	5		Batch 2	9	14		
Batch 3	6	2		Batch 3	18	6		
Batch 4	5	3		Batch 4	15	9		
Batch 5	4	4		Batch 5	12	11		
Batch 6	3	5		Batch 6	9	14		
Batch 7	3	5		Batch 7	9	14		
Batch 8	2	6		Batch 8	6	17		
Batch 9	3	1		Batch 9	9	3		
	1				1			
Extraction				Extraction			1	
Number	HC	CD		%	HC	CD		
Batch 1	16	16		Batch 1	48	46		
Batch 2	17	15		Batch 2	52	43		
Batch 3	0	4		Batch 3	0	11		

Table S-20. Repartition of the bias factors between the CD samples and the healthy controls, given by the numbers of samples, the percentages, means and medians.

		Chi ²	0.54		Chi ²	0.33
	Drying	GoodKrusk. Tau	0.55	Hemolysis	GoodKrusk. Tau	0.33
		Theil U	0.52		Theil U	0.27
		Chi ²	0.13		Chi ²	0.91
	Extraction	GoodKrusk. Tau	0.13	Gastro. reflux	GoodKrusk. Tau	0.91
		Theil U	0.06		Theil U	0.91
		Chi ²	0.84		Chi ²	0.85
	Gender	GoodKrusk. Tau	0.84	Thyroid	GoodKrusk. Tau	0.85
		Theil U	0.84		Theil U	0.85
		Chi ²	0.08		Chi ²	0.00
	Tobacco	GoodKrusk. Tau	0.08	Anti-TNFα	GoodKrusk. Tau	0.00
		Theil U	0.08		Theil U	0.00
		Chi ²	0.87		Chi ²	0.02
	Alcohol	GoodKrusk. Tau	0.87	Immunosupp.	GoodKrusk. Tau	0.03
		Theil U	0.87		Theil U	0.01
	Norm.	P / Sp	Kendall	ANOVA	Kruskal-Wallis]
Inject. Order	0.00	0.11	0.05	0.11	0.10	
Age	0.03	0.44	0.30	0.44	0.40	
BMI	0.00	0.92	0.80	0.92	0.83	

Table S-21. p-values for the potential imbalances. The grey cells indicate the significant values. The factors with a statistical imbalance are in bold.

Anti-TNF α and immunosuppression medications had p-values < 0.05 and were potential biases for the selected candidates (Tables S-20 and S-21).

Anti- TNFα	Norm.	P / Sp	Kendall	ANOVA	Kruskal- Wallis	Immuno.	Norm.	P / Sp	Kendall	ANOVA	Kruskal- Wallis
1	0.00	0.05	0.01	0.02	0.05	1	0.00	0.07	0.01	0.00	0.07
2	0.00	0.64	0.40	0.65	0.64	2	0.00	0.18	0.11	0.13	0.18
3	0.00	0.08	0.00	0.06	0.08	3	0.00	0.17	0.00	0.00	0.17
4	0.00	0.03	0.02	0.01	0.03	4	0.00	0.05	0.00	0.00	0.05
5	0.00	0.19	0.01	0.24	0.19	5	0.00	0.04	0.01	0.00	0.04
6	0.00	0.44	0.05	0.43	0.44	6	0.00	0.04	0.25	0.31	0.04
7	0.02	0.06	0.02	0.08	0.06	7	0.02	0.05	0.02	0.08	0.05
8	0.00	0.79	0.61	0.79	0.79	8	0.00	0.07	0.00	0.00	0.07
9	0.00	0.06	0.03	0.10	0.06	9	0.00	0.00	0.00	0.09	0.00
10	0.00	0.17	0.03	0.15	0.17	10	0.00	0.30	0.40	0.51	0.30
11	0.00	0.82	0.75	0.83	0.82	11	0.00	0.06	0.00	0.00	0.06
12	0.00	0.08	0.02	0.08	0.08	12	0.00	0.92	0.97	0.94	0.92
13	0.00	0.29	0.08	0.23	0.29	13	0.00	0.26	0.10	0.02	0.26
14	0.00	0.32	0.16	0.25	0.32	14	0.00	0.23	0.04	0.06	0.23
15	0.06	0.66	0.59	0.66	0.58	15	0.06	0.01	0.00	0.01	0.01
16	0.00	0.01	0.01	0.03	0.01	16	0.00	0.49	0.16	0.45	0.49
17	0.82	0.38	0.28	0.38	0.36	17	0.82	0.19	0.11	0.18	0.26
18	0.03	0.46	0.19	0.49	0.46	18	0.03	0.14	0.13	0.23	0.14
19	0.00	0.32	0.07	0.15	0.32	19	0.00	0.52	0.02	0.04	0.52
20	0.00	0.10	0.00	0.02	0.10	20	0.00	0.38	0.08	0.08	0.38
21	0.00	0.52	0.42	0.54	0.52	21	0.00	0.86	0.95	0.84	0.86
22	0.00	0.03	0.00	0.05	0.03	22	0.00	0.24	0.61	0.72	0.24

(B) Relationships between the candidate biomarkers and the bias factors

Table S-22. p-values for the relationships between the candidate biomarkers and both anti-TNF α and immunosuppression medications. The grey cells indicate the significant values. The candidates significantly linked

to the potential bias factors are in bold. P/Sp stands for Pearson or Spearman correlation, according to the normality of the variable.

Candidates 1, 3, 4, 7, 9, 12, 16, 20, 22 and 1, 3-9, 11, 14, 15, 19, respectively, were found to be linked to, i.e. were potentially influenced by, the factors, with p-values < 0.05 or 0.01, % FC < 90 or 80, Δ AUC < -0.05 or -0.1 (Table S-22). The next section aimed to evaluate how the bias factors could affect the separation ability of these candidates.

(C) Residual separation ability

Sample Removal

To equilibrate the classes regarding the potentially active bias factors, different combinations were tested. As a result, despite the fact that it left aside a substantial proportion of the samples, all samples with anti-TNF α or immunosuppression medication were removed. This had the advantage to completely equalize the distributions (resulting p-values = 0). Details are given in Tables S-23 and S-24.

Clinical	Class	Anti-		Dafara	After
ID	Class	TNFa	Number	Belore	Alter
228-VH	CD	Yes	HC	33	33
354-FD	CD	Yes	CD	35	17
356-OL	CD	Yes			
366-AT	CD	Yes			
368-FP	CD	Yes			
390-JT	CD	Yes			
404-AC	CD	Yes			
407-BM	CD	Yes			
425-SM	CD	Yes			
426-CF	CD	Yes			
429-ID	CD	Yes			
434-SLR	CD	Yes			
453-LR	CD	Yes			
458-SDB	CD	Yes			
465-PM	CD	Yes			
466-VLC	CD	Yes			
488-GA	CD	Yes			
508-DJ	CD	Yes			

Table S-23. Samples removed for the anti-TNF α equilibration and summary of the samples left.

Clinical ID	Class	Immunosup.	Number	Before	After
133-MD	CD	Yes	HC	33	33
351-JT	CD	Yes	CD	35	30
228-VH	CD	Yes			
465-PM	CD	Yes			
247-SK	CD	Yes			

Table S-24. Samples removed for the immunosuppressor equilibration and summary of the samples left.

Results

(Order (/	Anti-	Norm.	P / Sp	Kendall	ANOVA	Kruskal-	Partial	Partial	FC Ratio	ROC
	1	1	0.00	0.00	0.00	0.00	0.00	r / Sp	0.00	202	0.06
	1	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	203	0.00
	3	3	0.00	0.03	0.00	0.01	0.01	0.00	0.00	08	-0.04
	4	4	0.00	0.02	0.00	0.02	0.01	0.01	0.00	97	-0.01
	7	7	0.13	0.00	0.00	0.00	0.00	0.00	0.00	115	0.08
	9	9	0.00	0.01	0.00	0.01	0.00	0.02	0.01	100	0.05
	11	12	0.00	0.03	0.00	0.02	0.02	0.06	0.04	103	0.03
	15	16	0.00	0.47	0.31	0.46	0.40	0.35	0.31	85	-0.07
	20	20	0.00	0.90	0.00	0.93	0.00	0.94	0.00	79	-0.03
	22	22	0.00	0.12	0.30	0.21	0.39	0.11	0.29	94	-0.08
(Order (/	Immuno	Norm	D / Cm	Van dall	ANOVA	Kruskal-	Partial	Partial	EC Datia	ROC
2	22)	mmuno.	Norm.	P/Sp	Kendan	ANOVA	Wallis	P / Sp	Kendall	FC Kallo	Difference
	1	1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	87	-0.02
	3	3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	89	-0.02
	4	4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	95	-0.03
	4	5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	97	-0.02
	6	6	0.00	0.00	0.00	0.00	0.00	0.01	0.01	93	0.00
	7	7	0.02	0.01	0.00	0.00	0.00	0.00	0.00	96	-0.02
	8	8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	87	-0.03
	9	9	0.00	0.02	0.00	0.01	0.01	0.02	0.01	90	-0.04
	11	11	0.00	0.05	0.00	0.05	0.05	0.04	0.00	97	-0.03
	14	14	0.00	0.11	0.01	0.09	0.09	0.09	0.02	97	-0.02
	15	15	0.13	0.03	0.01	0.03	0.03	0.02	0.04	95	-0.03
1		40			0.00				0.00	0.7	0.00

Table S-25. Effect of the factors on the separation ability measured through the residual separation capability (p-values for Pearson/Spearman and Kendall correlations, Welch/Kruskal-Wallis test and Fisher ratios) and on the capability variation (fold change percentage and ROC curve delta). The order is the ranking of the candidates in the set of candidate biomarkers. The grey cells indicate the significant p-values (< 0.05) while the candidates in bold are the ones with a low residual separation capability (p-values > 0.1).

	Order	Candidate		Norm.	P / Sp	Kendall	ANOVA	Kruskal- Wallis	FC	FC Ratio	Uni ROC	ROC Difference					
	15	16	Before	0.00	0.03	0.01	0.03	0.03	1.29	85	0.65	-0.07					
		10	After	0.00	0.47	0.31	0.46	0.40	1.10	05	0.58	0.07					
Anti-	20	20	Before	0.00	0.30	0.00	0.29	0.00	1.31	70	0.80	0.03					
TNFα	20	20	After	0.00	0.90	0.00	0.93	0.00	1.03	13	0.77	-0.05					
	22 2		Before	0.00	0.01	0.01	0.01	0.02	1.30	04	0.66	0.09					
	22	22	After	0.00	0.12	0.30	0.21	0.39	1.22	94	0.58	-0.08					
								0.01									
	14	14	Before	0.00	0.05	0.00	0.05	0.03	1.31	07	0.68	-0.02					
T	14	14	After	0.00	0.11	0.01	0.10	0.00	1.27	97	0.66						
1mmuno.	10	10	Before	0.00	0.08	0.00	0.03	0.00	1.88	07	0.75	0.02					
	19	19	19	19	19	19	19	After	0.00	0.12	0.00	0.11	0.03	1.83	91	0.73	-0.02

Table S-26. Comparison of the separation ability (p-values, FC, AUC) before and after the equilibration, for the candidates potentially affected. The grey cells indicate the significant variations. The order is the ranking of the candidates in the set of candidate biomarkers. The candidates with substantial deterioration due to the bias factors are in grey.

The residual separation capability evaluation worked in two steps, with first the direct assessment of the residual ability (Table S-25) and second, for the candidates with p-values > 0.1, an investigation of the variation resulting from the bias effect by comparing the ability with and without the consideration of the possible bias (Table S-26). Here, candidates 16, 20, 22 as well as 14 and 19, respectively, had p-values > 0.1 (Table S-25). Candidate 3, linked to anti-TNF α bias, had a high decrease in fold change but

its other statistical values were quite good. Table S-26 shows that the candidates 16, 20 and 22 were deteriorated in all five tests performed and had a low residual ability. These were therefore removed from the set of candidate biomarkers.

S-17. Bias Control for the three CD subgroups candidates. A. Repartition of the factors between the biological classes. B. Relationships between the candidate biomarkers and the bias factors. C. **Residual separation ability.**

The medications considered were the ones with enough representation in the groups or the ones linked to CD: Elthyrone[©] and L-Thyroxine[©] (thyroid regulation), Pantomed[©] (gastroesophageal reflux and ulcer), Remicade[©] and Humira[©] (anti-TNFa) and Imuran[©] (immunosuppression).

(A) Repartition of the factors between the biological classes

	Gender				Gastro.	L-	Anti-	
%	(F)	Tobacco	Alcohol	Hemolysis	reflux	Thyroxin	TNFα	Immunosupp.
High	50	42	8	8	33	8	50	33
Low	64	43	21	7	29	21	71	0
Quiescent	67	22	44	33	22	33	22	11
				_				
	Inj							
Mean	Order	Age	BMI					
High	47 ± 26	38 ± 16	22 ± 3					
Low	59 ± 28	39 ± 9	26 ± 5					
Quiescent	53 ± 32	51 ± 8	27 ± 5					
	-							
Drying				7				
%	High	Low	Quiescent					
Batch 1	8	14	11					
Batch 2	25	14	0					
Batch 3	0	7	11					
Batch 4	8	14	0					
Batch 5	0	21	11					
Batch 6	17	7	22					
Batch 7	8	14	22					
Batch 8	25	7	22					
Batch 9	8	0	0					
	-							
Extraction				-				
%	High	Low	Quiescent					
А	58	36	44					
В	33	57	33					
С	8	7	22					
Location				_				
%	High	Low	Quiescent					
Ileitis	17	21	56					
Colitis	25	14	0					
Ileocolitis	33	43	0					
Pancolitis	8	14	11					
Other	17	7	33					

Table S-27. Repartition of the bias factors considered between the three CD groups (high, low and quiescent endoscopic activities) given by the numbers of samples, the percentages, the means and the medians.

	Chi ²	0.71		Chi ²	0.17
Drying	GoodKrusk. Tau	0.72	Hemolysis	GoodKrusk. Tau	0.22
	Theil U	0.42	-	Theil U	0.21
	Chi ²	0.54		Chi ²	0.86
Extraction	GoodKrusk. Tau 0.55		Gastro. reflux	GoodKrusk. Tau	0.87
	Theil U	0.58		Theil U	0.85
	Chi ²	0.68		Chi ²	0.36
Gender	GoodKrusk. Tau	0.68	Thyroid	GoodKrusk. Tau	0.40
	Theil U	0.68		Theil U	0.34
	Chi ²	0.56		Chi ²	0.01
Tobacco	GoodKrusk. Tau	0.61	Anti-TNFa	GoodKrusk. Tau	0.01
	Theil U	0.54		Theil U	0.01
	Chi ²	0.15		Chi ²	0.05
Alcohol	GoodKrusk. Tau	0.19	Immunosupp.	GoodKrusk. Tau	0.04
	Theil U	0.15		Theil U	0.03
				Chi ²	0.12
			Disease	GoodKrusk. Tau	0.25
			Location	Theil U	0.06
			<u> </u>		
	Norm.	ANOVA	Kruskal-Wallis		
Inject; Order	0.01	0.56	0.58		
Δge	0.17	0.01	0.01		

Table S-28. p-values for the potential imbalances. The grey cells indicate the significant values. The factors with statistical imbalance are in bold.

0.01

0.01

BMI

0.00

Anti-TNF α and immunosuppression medications as well as age and BMI had p-values < 0.05 (Tables S-27 and S-28).

Unsupervised plots were also drawn to visualize the impact of categorical bias factors, either on all metabolites in the final dataset or on the selected candidates. The one for disease location is given at Figure S-16. Here, only a small effect between ileitis and ileocolitis can be seen. The problem of such plots, however, is that the metabolites are considered together. This dilutes the effect of each metabolite individually.



Figure S-25. HCA and PCA plots constructed on all 183 metabolites (above) and the selected candidates (n=29, below) to see the influence of disease location.

Anti- TNFα	Norm.	P / Sp	Kendall	ANOVA	Kruskal- Wallis	Immuno.	Norm.	P / Sp	Kendall	ANOVA	Kruskal Wallis
11	0.00	0.01	0.01	0.01	0.04	11	0.00	0.20	0.07	0.02	0.13
23	0.00	0.39	0.47	0.41	0.55	23	0.00	0.02	0.40	0.28	0.48
1	0.00	0.13	0.06	0.10	0.15	1	0.00	0.22	0.37	0.00	0.48
15	0.46	0.11	0.05	0.09	0.11	15	0.46	0.02	0.00	0.01	0.02
18	0.20	0.92	0.90	0.95	0.92	18	0.20	0.38	0.28	0.43	0.37
24	0.01	0.07	0.06	0.09	0.11	24	0.01	0.59	0.21	0.70	0.30
25	0.00	0.05	0.02	0.03	0.06	25	0.00	0.28	0.06	0.01	0.12
8	0.00	0.03	0.00	0.01	0.00	8	0.00	0.27	0.01	0.01	0.04
5	0.00	0.34	0.78	0.29	0.82	5	0.00	0.25	0.21	0.06	0.30
14	0.00	0.68	0.22	0.68	0.30	14	0.00	0.36	0.16	0.23	0.24
7	0.15	0.47	0.38	0.35	0.46	7	0.15	0.31	0.21	0.28	0.30
26	0.00	0.41	0.81	0.37	0.84	26	0.00	0.37	0.43	0.05	0.51
9	0.00	0.95	0.94	0.95	0.95	9	0.00	0.01	0.01	0.14	0.03
27	0.00	0.21	0.23	0.26	0.32	27	0.00	0.91	0.69	0.91	0.74
28	0.00	0.10	0.48	0.16	0.56	28	0.00	0.91	0.95	0.89	0.96
6	0.00	0.23	0.38	0.26	0.46	6	0.00	0.31	0.57	0.50	0.64
29	0.00	0.15	0.32	0.20	0.40	29	0.00	0.42	0.53	0.16	0.60
30	0.01	0.39	0.84	0.43	0.87	30	0.01	0.78	0.57	0.87	0.64
31	0.00	0.06	0.14	0.09	0.22	31	0.00	0.66	0.71	0.43	0.76
2	0.00	0.04	0.04	0.02	0.08	2	0.00	0.68	0.78	0.62	0.81
32	0.00	0.05	0.01	0.03	0.04	32	0.00	0.27	0.14	0.02	0.22
33	0.23	0.20	0.12	0.14	0.19	33	0.23	0.78	0.73	0.91	0.78
34	0.57	0.51	0.42	0.76	0.50	34	0.57	0.05	0.02	0.11	0.05
35	0.01	0.39	0.20	0.39	0.29	35	0.01	0.47	0.28	0.54	0.37
36	0.01	0.12	0.05	0.14	0.10	36	0.01	0.58	0.43	0.61	0.51
10	0.26	0.49	0.40	0.37	0.48	10	0.26	0.93	0.91	0.93	0.92
37	0.00	0.17	0.13	0.19	0.21	37	0.00	0.43	0.43	0.24	0.51
38	0.00	0.03	0.13	0.06	0.21	38	0.00	0.60	0.53	0.55	0.60
39	0.00	0.24	0.11	0.20	0.18	39	0.00	0.23	0.09	0.01	0.16

(B) Relationships between the candidate biomarkers and the bias factors

Age	Norm.	P / Sp	Kendall	BMI	Norm.	P / Sp	Kendall
11	0.00	0.89	0.81	11	0.00	0.20	0.01
23	0.00	0.51	0.62	23	0.00	0.31	0.41
1	0.00	0.19	0.50	1	0.00	0.47	0.14
15	0.46	0.48	0.50	15	0.45	0.90	0.77
18	0.20	0.01	0.01	18	0.31	0.00	0.00
24	0.01	0.00	0.00	24	0.01	0.35	0.24
25	0.00	0.89	0.58	25	0.00	0.57	0.12
8	0.00	0.76	0.76	8	0.00	0.47	0.80
5	0.00	0.34	0.09	5	0.00	0.80	0.29
14	0.00	0.16	0.11	14	0.00	0.14	0.63
7	0.15	0.57	0.53	7	0.23	0.67	0.55
26	0.00	0.99	0.62	26	0.00	0.27	0.52
9	0.00	0.49	0.43	9	0.00	0.56	0.39
27	0.00	0.31	0.56	27	0.00	0.03	0.89
28	0.00	0.00	0.02	28	0.00	0.80	0.17
6	0.00	0.61	0.62	6	0.00	0.71	0.86
29	0.00	0.01	0.05	29	0.00	0.31	0.19
30	0.01	0.02	0.15	30	0.02	0.96	0.93
31	0.00	0.01	0.01	31	0.00	0.09	0.38
2	0.00	0.93	0.68	2	0.00	0.97	0.63
32	0.00	0.35	0.87	32	0.00	0.79	0.19
33	0.23	0.09	0.12	33	0.22	0.82	0.91
34	0.57	0.59	0.48	34	0.32	0.05	0.05
35	0.01	0.02	0.11	35	0.03	0.93	0.61
36	0.01	0.05	0.04	36	0.01	0.45	0.47
10	0.26	0.70	0.72	10	0.17	0.22	0.24
37	0.00	0.51	0.68	37	0.00	0.11	0.43
38	0.00	0.03	0.05	38	0.00	0.31	0.89
39	0.00	0.50	0.70	39	0.00	0.01	0.00

Table S-29. p-values for the relationships between the candidate biomarkers and the four potential bias factors. The grey cells indicate the significant values. The candidates significantly linked to the bias factor are in bold.

Candidates 11, 25, 8, 2, 32; 15, 8, 9, 34; 18, 24, 28, 29, 31, 36, 38 and 18, 34, 39, respectively, were found to be linked to the factors (p-values < 0.05; Table S-28). The potential impact was further assessed through the residual ability to separate the biological groups and, for continuous bias factors, through scatterplots (Figures S-26 and S-27). These figures confirmed the links between age or BMI and the candidates. The relationship for candidate 28 seemed due to atypical values (outliers), but it was kept for the remainder of the process since it was significant in Kendall correlation, a non-parametric measure.



Figure S-26. Scatterplots of the candidates' detected signal against age with the corresponding linear regression.



Figure S-27. Scatterplots of the candidates' detected signal against BMI with the corresponding linear regression.

(C) Residual separation ability

Sample Removal

To equilibrate the classes regarding the potentially active bias factors, different combinations were tested. Details of the final results are given at Table S-30, 31, 32 and 33.

	Group	BMI			
390-JT	Quiescent	/			
434-SLR	"Low"	/			
429-ID	"High"	15.4	Number	Before	After
83-ML	"High"	17.5	Quiescent	9	7
508-DJ	"High"	19.6	"High"	12	7
502-SA	"High"	20.7	"Low"	14	11
466-VLC	"High"	20.5			
367-VW	Quiescent	39.2	Ν	W / K-W	Fisher
354-FD	"Low"	30.1	0.98	0.29	0.27
357-WF	"Low"	41.5			

Table S-30. Samples removed for the BMI equilibration (left), summary of the samples left (top right) and p-values for the repartition after the removal (bottom right).

Clinical ID	Class	Anti- TNFa	I	Number	Before	After
404-AC	Low	Yes	Q	Quiescent	9	6
354-FD	Low	Yes		High	12	12
453-LR	Low	Yes		Low	14	8
356-OL	Low	Yes				
426-CF	Low	Yes		Chi ²	0.38	
425-SM	Low	Yes	Go	odKrusk. Tau	0.46	
133-MD	Quiescent	No		Theil U	0.37	
155-PC	Quiescent	No				_
28-CL	Quiescent	No		Norm.	ANOVA	Kruskal- Wallis
				0.00	0.43	0.42

Table S-31. Samples removed for the anti-TNF α equilibration (left), summary of the samples left (top right) and p-values for the repartition after the removal (bottom right).

			Number	Before	After
Clinical ID	Class	Immunosupp.	Quiescent	9	9
465-PM	High	Yes	High	12	10
247-SK	High	Yes	Low	14	14
	Chi ²	0.24	Norm.	ANOVA	Kruskal- Wallis
	GoodKrusk. Tau	0.21	0	0.88	0.25
	Theil U	0.15			

Table S-32. Samples removed for the immunosuppressor equilibration (left), summary of the samples left (top right) and p-values for the repartition after the removal (bottom right).

Clinical ID	Class	Age		Number	Before	After
133-MD	Quiescent	65		Quiescent	9	7
426-CF	Low	28		High	12	9
366-AT	High	22		Low	14	12
390-JT	Low	29				
247-SK	High	26		Norm.	ANOVA	Kruskal- Wallis
228-VH	High	26		0.17	0.13	0.38
28-CL	Quiescent	56]			

Table S-33. Samples removed for the age equilibration (left), summary of the samples left (top right) and p-values for the repartition after the removal (bottom right).

<u>Results</u>

Anti- TNFα	Norm.	ANOVA	Kruskal- Wallis	Immuno.	Norm.	ANOVA	Kruskal- Wallis
11	0.00	0.10	0.01	15	0.58	0.08	0.08
25	0.00	0.30	0.01	8	0.00	0.03	0.00
8	0.00	0.15	0.11	9	0.00	0.03	0.04
2	0.00	0.48	0.65	34	0.63	0.02	0.01
32	0.02	0.28	0.25				
				BMI	Norm.	ANOVA	Kruskal- Wallis
Age	Norm.	ANOVA	Kruskal- Wallis	11	0.00	0.03	0.02
18	0.18	0.16	0.07	18	0.45	0.14	0.05
24	0.01	0.11	0.11	34	0.56	0.12	0.11
28	0.00	0.51	0.34	39	0.00	0.40	0.41
29	0.00	0.54	0.79				
31	0.00	0.19	0.14				
36	0.01	0.08	0.07				
38	0.00	0.28	0.61				

Table S-34. Effect of the factors on the separation ability measured through the residual separation capability (p-values for Pearson/Spearman and Kendall correlations, Welch/Kruskal-Wallis test and Fisher ratios). The order is the ranking of the candidates in the set of candidate biomarkers. The grey cells indicate the significant p-values (< 0.05) while the candidates in bold are the ones with a low residual separation capability (p-values > 0.1).

Order (/ 29)	Anti- TNFα	Norm.	ANOVA	Kruskal- Wallis	Order (/ 29)	Age	Norm.	ANOVA	Kruskal- Wallis
7	25	0.00	0.04	0.01	4	10	0.20	0.01	0.01
	23	0.00	0.30	0.01		10	0.18	0.07	0.14
7	0	0.00	0.03	0.01	4	24	0.01	0.04	0.00
	0	0.00	0.15	0.11		24	0.01	0.11	0.02
20	2	0.00	0.05	0.02	10	20	0.00	1.00	0.55
	2	0.00	0.48	0.25		28	0.00	0.51	0.61
20	32	0.00	0.00	0.02	17	20	0.00	0.59	0.67
		0.02	0.28	0.15		29	0.00	0.54	0.44
					20		0.00	0.07	0.05
Order (/ 29)	BMI	Norm.	ANOVA	Kruskal- Wallis		31	0.00	0.19	0.16
4	18	0.20	0.01	0.01	25	38	0.00	0.12	0.03
	10	0.45	0.05	0.05		50	0.00	0.28	0.17
20	24	0.57	0.01	0.05					
	54	0.56	0.11	0.26					
25	20	0.00	0.13	0.03					
	39	0.00	0.40	0.26					

Table S-35. Comparison of the separation ability (p-values) before and after the equilibration, for the candidates potentially affected. The grey cells indicate the significant values. The order is the ranking of the candidates in the set of candidate biomarkers. The candidates with substantial deterioration due to the bias factor are in bold.

The residual separation capability evaluation worked in two steps. First, the direct assessment of the residual ability (Table S-34). Second, for the candidates with p-values > 0.1, an investigation of the variation resulting from the bias effect by comparing the ability with and without the consideration of the possible bias (Table S-35). Overall, candidates 2, 32, 38 and 39 were considered deteriorated and thus removed from the set of candidate biomarkers. The candidate 18 was impacted by two different factors and was also removed. Candidates 8 and 34, as far as we could evaluate, were significantly

impacted (with initial low p-values, < 0.05) but had remaining p-values around 0.1. It was decided to keep them as biological markers but to leave them aside when evaluating the separation performance.

S-18. Data Processing. A. Meta-markers. B. Testing of potential bias between training and test sets.

(A) Meta-markers

Three meta-markers were considered. The first (CB1) used the most significant candidates for each separation (n=6 for both). The second (CB2) added the very significant ones (n=12 and n=15, respectively). The third (CB3) used all the selected and not biased candidates (n= 19 and n=22).

(B) Testing of potential bias between training and test sets for all samples

0.23

Test

0.32

	Number of s	amples					
	Class	Training	Test		Drying	Training	Test
	Healthy Controls	22	11		Batch 1	7	1
	Low	10	4		Batch 2	6	2
	High	8	4		Batch 3	4	4
	Quiescent	6	3		Batch 4	5	3
					Batch 5	5	3
	Extraction	Training	Test		Batch 6	6	2
	Batch 1	21	11		Batch 7	5	3
	Batch 2	23	9		Batch 8	7	1
	Batch 3	2	2		Batch 9	1	3
	Numbe						
	Inj. Order	Gender	Age at sampling	Tobacco	Alcohol	BMI	
Training	48.4	0.39	41.3	0.26	0.24	24.70	
Test	47.4	0.45	46.2	0.27	0.18	25.32	
	Gastro. reflux	L-Thyroxin	Anti- TNFα	Immuno.			
Training	0.30	0.13	0.26	0.11			

]	p-values		P / Sp	ANOVA	Kruskal- Wallis
Drying	Chi ²	0.43	Inj. Order	0.00	0.89	0.89	0,89
	Wilk's Lambda	0.09	Age	0.03	0.11	0.11	0,09
	Good-Krusk. Tau	0.44	Tobacco	0.00	0.92	0.92	0,92
	Theil U	0.41	Alcohol	0.00	0.60	0.59	0,60
	Chi ²	0.64	Gastro. reflux	0.00	0.51	0.50	0,51
Enter of a	Wilk's Lambda	0.00	L-Thyroxin	0.00	0.07	0.11	0,07
Extraction	Good-Krusk. Tau	0.64	Anti-TNFa	0.00	0.91	0.91	0,91
	Theil U	0.65	Immunosupp.	0.00	0.11	1.00	0.11
	Chi ²	0.62					
Gender	Wilk's Lambda	0.00					
	Good-Krusk. Tau	0.62					
	Theil U	0.62					

0.27

0.00

Table S-36. Distribution of the samples (numbers of samples and percentages) and corresponding p-values between training and test sets for the various potential bias factors.

S-19. Separation between healthy controls and Crohn's disease samples. A. Performances. B. Selection order in the models.

(A) Performances

	Predictive		Orthog	onal	Permu	tation	Probability		
OPLS- DA	Q^2	R^2Y	Q^2	R^2Y	Q^2	$\mathbf{R}^{2}\mathbf{Y}$	Q^2	R^2Y	
CB 1	0.45	0.48	0.00	0.03	0.46	0.51	< 0.0005	< 0.0005	
CB 2	0.46	0.49	0.00	0.09	0.46	0.58	< 0.0005	< 0.0005	
CB 3	0.48	0.53	-0.01	0.09	0.47	0.62	< 0.0005	< 0.0005	
						r	T		
PLS-DA	Q ²	R^2Y	Probability	Nber LV		LDA	Rao value	p-value	
CB 1	/	/	/	/		CB 1	10.7	< 0.0001	
CB 2	0.33	0.49	< 0.0005	3		CB 2	7.3	< 0.0001	
CB 3	0.31	0.39	< 0.0005	1		CB 3	4.5	< 0.0001	
	i -			7		1			
Error rates	sPLS- DA	RF	SVM		Error rates	Re- subst.	Re- sampling	Test	
CB 1	/	0.15	/		CB 1	0.19	0.22	0.16	
CB 2	0.16	0.19	0.21		CB 2	0.14	0.20	0.14	
CB 3	0.18	0.15	0.23	J	CB 3	0.11	0.21	0.16	
-									
ROC	Predict.	Holdout	Test	Permut.					
CB 1	0.85	0.90	19	0.01					
CB 2	0.78	0.93	19	0.05					
CB 3	0.75	0.92	17	0.09					

Table S-37. Discrimination performances achieved with the three different meta-markers using OPLS-DA, PLS-DA, LDA, sPLS-DA, SVM and RF models. Plus ROC curves and mean error rates for Bayes classifier, NN, SVM and PLS-DA. The grey cells indicate the best values obtained. Nber LV is the number of latent variables required to obtain the most efficient separation in PLS-DA.

The results summarized in Table S-37 showed that the CD samples were effectively separated from the healthy controls. Rao p-value was < 0.001 for all three potential meta-markers. Mean error rates were around 0.2 (range 0.16-0.29, depending on the meta-marker and the method) and 0.15 (range 0.09-0.23) in re-sampling and test validation, respectively. This was confirmed by sPLS-DA cross-validation (0.16-0.18) and RF out-of-bag error (0.17-0.19). As well as by ROC test validation (between 0.15 and 0.2). The predictive Q² was moderate in PLS-DA model (0.31-0.33) and good in OPLS-DA (0.45-0.48)⁴⁰. Importantly^{S-41}, there was very little overfitting ^{S-42} since Q² was close to R²Y in both PLS-DA and OPLS-DA : 0.39/0.49 and 0.48/0.53 respectively. In OPLS-DA, we observed an explicative power much higher than noise, with the orthogonal Q² equal to 0. Moreover, the permutation Q² was close to the predictive Q² (0.46/0.47) and its p-value was low (< 0.0005), rejecting the hypothesis of a discrimination

due to bare chance. The diagnosis ability measured by ROC AUC was good $^{S-40, S-43}$ with a mean value of 0.80, a range of 0.75-0.85, a confidence interval (CI) mean range of 0.70 - 0.99, a CI global range of 0.57 - 1 and a probability p-value < 0.1. The global statistical power was over 0.8 at FDR 0.1 when all the candidates where employed (Figure S-28). Re-sampling and test validations also indicated the potential ability of the meta-markers to be generalized to new samples. The ratio between the information valuable to separate and the noise can be evaluated by comparing the supervised (that use only mostly the first) and the unsupervised plots (that use both). Here, as in most cases, the successive additions of candidates brought valuable information (better discrimination in supervised plots) but at the cost of noise addition (poorer separation in unsupervised plots; Figure S-30). The performances attained were particularly satisfying, if one considers that the CD samples consisted in three endoscopic activity subgroups, which most probably increased their overall group variance.



Figure S-28. ROC curves (100 cross-validation, SVM algorithm) for an increasing number of candidates (left). Adding candidates to the meta-marker increased the diagnosis capability marginally. Multivariate statistical power for all the candidates at FDR 0.01, > 0.8 for the minimal n (= 33).



Figure S-29. HCA and PCA plots constructed on the most significant candidate biomarkers. The CD samples are in red, the HC in green and the QC samples in blue.



Figure S-30. PCA (left) and OPLS (right) plots constructed on the three different meta-markers (CB1, above, CB2, middle, and CB3, below).

(B) Selection order in the models

СВ	NN	Bayes	PLS- DA	SVM	OPLS- DA	RF	СВ	Mean	Median	Best	Worst	LDA
1	5	2	1	3	1	1	1	2	2	1	5	1
2	11	14	5	16	3	7	2	9	9	3	16	
3	2	1	2	2	7	4	3	3	2	1	7	3
4	6	5	6	4	10	14	4	8	6	4	14	4
5	18	7	3	7	2	3	5	7	5	2	18	
6	4	6	10	8	6	11	6	8	7	4	11	6
7	7	11	8	5	4	6	7	7	7	4	11	
8	17	8	4	9	5	2	8	8	7	2	17	8
9	10	15	14	15	8	9	9	12	12	8	15	
10	12	9	7	6	9	16	10	10	9	6	16	10
11	14	13	12	13	15	5	11	12	13	5	15	
12	3	16	9	10	11	8	12	10	10	3	16	
13	16	12	18	11	16	13	13	14	15	11	18	
14	15	18	16	18	19	12	14	16	17	12	19	
15	13	10	13	14	12	19	15	14	13	10	19	
17	19	19	15	12	17	18	17	17	18	12	19	
18	8	17	17	19	13	17	18	15	17	8	19	
19	9	3	19	17	18	10	19	13	14	3	19	
22	1	4	11	1	14	15	22	8	8	1	15	

221411114152288115Table S-38. Ranking or selection order of the candidate biomarkers in neural network (NN), Bayes classifier,
PLS-DA, OPLS-DA, SVM and RF models. In the far right column, the metabolites found significant in the LDA
model. The grey cells emphasize the highest ranks.

As expected, the candidates selected as the most significant had the highest ranks in the models (Table S-38). As already noticed in the selection process, Bayes classifier, neural network and SVM worked differently, particularly regarding the candidates 19 and 22 (in bold), an issue worth to mention but outside the scope of this study.
S-20. Separation between the three Crohn's disease groups. A. Performances. B. Selection order in the models.

(A) Performances

PLS-DA	Q^2	R^2Y	Probability	Nber LV]	LDA Rao		
CB 1	/	/	/	/		CB 1	3.7	0.000
CB 2	-0.20	0.07	0.003	1		CB 2	1.9	0.032
CB 3	-0.25	0.11	< 0.0005	1		CB 3	1.7	0.069
					-			
Error	sPLS-	DE	7	Error	Do subst	Re-	Test]
Error rates	sPLS- DA	RF]	Error rates	Re-subst.	Re- sampling	Test	
Error rates CB 1	sPLS- DA /	RF 0.29		Error rates CB 1	Re-subst.	Re- sampling 0.36	Test 0.41	
Error rates CB 1 CB 2	sPLS- DA / 0.31	RF 0.29 0.37		Error rates CB 1 CB 2	Re-subst. 0.24 0.11	Re- sampling 0.36 0.45	Test 0.41 0.57	

Table S-39. Discrimination performances achieved with the three different meta-markers using PLS-DA, LDA, sPLS-DA and RF models, and mean error rates for Bayes classifier, NN, SVM and PLS-DA.

Error rates in re-substitution were acceptable, either for sPLS-DA, RF or the mean of SVM, Bayes classifier, NN, and PLS-DA models (0.20-0.30, but as low as 0.07, Table S-39). However, the re-sampling and test error rates increased to 0.36 and 0.41 respectively. And the PLS-DA models were not able to separate effectively the three CD subgroups (negative Q^2). Reasons for this have been mentioned in the manuscript (section 3.3), particularly the difficulty to separate three classes with one rule (section 5.5). To support this, the Rao p-value indicated the possibility to distinguish at least two classes, with a much higher effectiveness (p < 0.0001). And HCA and PLS plots clearly showed that the candidates were able to separate (Figure S-31).

Despite the low number of samples available (n=9 for quiescent CD), the variations of concentration of the candidates were sufficient to achieve a statistical power around 0.8 at FDR 0.1.



Figure S-31. HCA and PLS plots for the separation between the three CD groups (above), constructed on the most significant candidates (CB1) and all the selected and not biased candidates (CB3), respectively. The high endoscopic activity samples are in red, the low endoscopic activity ones in green, the quiescent ones in blue. Statistical power for the 15 most significant candidates (CB2) at FDR 0.1 (below).



Figure S-32. HCA and PCA plots constructed on all the candidate biomarkers. The high endoscopic activity samples are in red, the low endoscopic activity ones are in green, the quiescent ones in light blue, the QC samples in royal blue.

(B) Selection order in the models

СВ	NN	Bayes	PLS- DA	RF	СВ	Mean	Median	Best	Worst	LDA
11	2	6	1	2	11	3	2	1	6	1
23	8	7	3	6	23	6	7	3	8	
1	15	1	7	1	1	6	4	1	15	
15	4	9	9	4	15	7	7	4	9	
25	16	4	6	3	25	7	5	3	16	
5	17	10	8	16	5	13	13	8	17	
14	18	20	15	14	14	17	17	14	20	
7	5	14	4	9	7	8	7	4	14	
26	3	17	17	13	26	13	15	3	17	
9	9	19	16	7	9	13	13	7	19	
27	19	2	18	8	27	12	13	2	19	
28	10	11	19	12	28	13	12	10	19	
6	11	15	14	20	6	15	15	11	20	
29	12	13	20	15	29	15	14	12	20	
30	13	8	13	11	30	11	12	8	13	
33	20	18	10	10	33	15	14	10	20	
35	14	5	11	18	35	12	13	5	18	
36	6	12	5	17	36	10	9	5	17	
10	7	16	12	19	10	14	14	7	19	
37	1	3	2	5	37	3	3	1	5	

371325373315Table S-40. Ranking or selection order of the candidate biomarkers in NN, Bayes classifier, PLS-DA and RF
models. In the far right column, the significant metabolites in the LDA model. The grey cells emphasize the highest
ranks.

Again, the candidates selected as the most significant had the highest ranks in the models, a convergence that tended to support the selection process (Table S-40). Candidate 37, however, seemed important to discriminate despite the fact that it was at first selected in a low position. This discrepancy could again be due to the complexity of separating three groups at once.

S-21. Annotation of the candidate biomarkers.

Candidate	ID	Specific Peaks	Match	Proba.	ΔRT	Δ (ppm)	Criteria Met
1	/	205, 103					0
2	Erythronic acid / Threonic Acid		902	49	57	0.1	2
3	/	259, 198, 167, 139, 114					0
4	/	216, 188, 172					0
5	/	449, 408, 393, 333, 318, 305					0
6	/	205, 147, 117					0
7	Aspartic Acid		758	82	19	0.2	3
8	Threonolactone*		808	57	40	0.6	2
9	Glutamic Acid		853	78	5	0	3
10	Xylose		757	6	28	0.7	2
11	/	203, 156, 112, 89					0
12	/	364, 277, 189, 172					0
13	Methionine		678	86	0	0.1	3
14	2-Hydroxybutyric acid		846	27	1	0.1	3
15	/	249, 233, 207, 175, 133					0
17	1,5-Anhydroglucitol		912	66	11	0.4	3
18	Citric Acid		872	95	12	0.2	3
19	Galactose		739	11	10	34	2
22	/	56					0
23	Erythrose / Threose		572	12	24	0.4	2
24	/	325, 174					0
25	/	203, 188, 172					0
26	Capric acid		795	93	0	0.3	3
27	/	292					0
28	/	384, 369, 327, 266, 237					0
29	/	217, 191, 147					0
30	/	327, 145, 129					0
31	Erythritol / Threitol		823	23	16	/	2
33	Myristic acid		879	96	14	0.1	3
34	Glucose		899	15	7	0.6	3
35	/	255					0
36	Lauric acid		806	90	8	0.1	3
37	Terephthalic acid**		644	0	10	0.2	2

Table S-41. Annotation of the candidate biomarkers. The candidates highlighted in the CD vs HC separation are above. The candidates highlighted in the 3 CD subgroups separation are below. The values that meet the significance thresholds are in bold.

S-22. Biological functions of the candidate biomarkers.

r						
Compound	2- Hydroxybutyric	1,5- anhydroglucitol	Citric acid	Galactose	Erythrose / Threose	Decanoic acid
HMDB CHEBI Pubchem KEGG CAS	0000008 1148 11266 C05984 565-70-8	0002712 16070 64960 C07326 154-58-5	0000094 30769 311 C00158 77-92-9	0000143 28061 6036 C00124 3646-73-9	0002649 23956 439574 C01796 1758-51-6	0000511 30813 2969 C01571 334-48-5
Source	Endogenous	Endogenous	Endogenous,	Endogenous, food	Food	Endogenous, food
Tissues and organs	Prostate	Prostate	All Tissues Prostate	Brain Liver Prostate Blood Breast Milk Cellular Cytoplasm Feces Saliva	Cartilage	Liver Prostate Stratum Corneum Thyroid Gland
Biofluid	Blood CSF Feces Saliva Sweat Urine	Blood CSF Saliva Sweat Urine	Blood Breast Milk CSF Feces Saliva Sweat Urine	Urine Extracellular Lysosome	Blood Feces	Blood CSF Feces Saliva Sweat Urine
Cell	Cytoplasm Extracellular	Cytoplasm (predicted)	Cytoplasm Extracellular	na	Cytoplasm (predicted)	Cytoplasm Extracellular
Biological role	Metabolite	na	na	na	na	Membrane (predicted) Membrane stabilizer Energy source Energy storage Nutrient
Biochemical process	na	na	na	na	na	Lipid transport Lipid metabolism Fatty acid metabolism
Cellular process	na	na	na	na	na	Cell signaling
Chemical reaction	na	na	na	na	na	Beta Oxidation of LC Fatty Acids
Environmental role	na	na	na	na	na	Lipid peroxidation
Industrial application	na	na	Pharmaceutical Antimicrobial agent Food and nutrition Personal care products Chelating agent	na	na	Food and nutrition Surfactant Emulsifier Pharmaceutical
Pathways HMDB KEGG	Yes Yes	na na	Yes Yes	Yes Yes	na na	Yes Yes
Biomarker						
CD	na	na	Yes	na	na	na
IBD	na	na	Yes	na	na	na
UC	na	na	Yes	na	na	na

Compound	Erythronic	Threonic acid	Aspartic acid	Threonolactone*	Glutamic acid	Xylose	Methionine
HMDB	0000613	0000943	0000191	0000940	0000148	0000098	0000696
CHEBI	37655	15908	17053	71176	16015	53455	16643
Pubchem	2781043	5460407	5960	2724794	33032	135191	6137
KEGG	/	C01620	C00049	/	C00025	C00181	C00073
CAS	13752-84-6	7306-96-9	56-84-8	21730-93-8	56-86-0	58-86-6	63-68-3
Source	Endogenous	na	Endogenous, food	Endogenous	Endogenous, food	Endogenous, food	Endogenous, food
	na	na	All tissues	na	Adrenal Medulla	Erythrocyte	Fibroblasts
			Prostate		Epidermis	Small Intestine	Kidney
					Fibroblasts		Liver
					Intestine		Muscle
					Kidney		Pancreas
					Muscle		Prostate
					Myelin		Spleen
Tissues and					Nerve Cells		
organs					Neuron		
					Pancieas		
					Placellita		
					Prostate		
					Skeletal Muscle		
					Spleen		
					Stratum		
					Corneum		
	Blood	Blood	Blood	na	Blood	Blood	CSF
	CSE	Feces	Breast milk		Cellular	Feces	Feces
	CDI	1 0005	Diedst milk		Cytoplasm	10003	10003
Biofluid	Feces	Saliva	CSF		CSF	Saliva	Saliva
Diomaid	Saliva	Sweat	Feces		Feces	Urine	Sweat
	Urine	Urine	Saliva		Saliva		Urine
			Sweat		Sweat		
	Cytoplasm	Cytoplasm	Unne		Unne		
	(predicted)	(predicted)	Cytoplasm	na	Extracellular	Cytoplasm	Extracellular
Cell			Mitochondria		Mitochondria	Extracellular	
Cell			Extracellular		Lysosome	Lysosome	
					Endoplasmic		
					reticulum		D
	na	na	Essential	na	Metabolite	na	Drug
			ammo aciu				Essential
					Trace element		amino acid
					Molecular		Waste product
Biological role					messenger		The see product
					Neurotransmitter		Trace element
							(indirect)
							Metabotoxin
							(indirect)
Biochem. proc.	na	na	na	na	na	na	na
Cellular process	na	na	na	na	na	na	na
Chemical reaction	na	na	na	na	na	na	na
Environmental	na	na	na	na	na	na	na
	-	יי ות			Nutritional	Food and	Nutritional
In du-4-1-1	na	Pharmaceutical	Pharmaceutical	na	supplement	nutrition	supplement
application					Pharmaceutical	Personal care	Pharmaceutical
application					i nurnaccutedi	products	i mirmaceutical
D. (I						Pharmaceutical	
	20	***	Vac	20	Vac	20	Vac
KEGG	na	na Ves	i es Ves	na	i es Ves	na Ves	i es Ves
Biomarker	110	103	103	114	100	105	100
CD	na	na	Yes	na	Yes	Yes	Yes
IBD	na	na	Yes	na	Yes	na	Yes
UC	na	na	Yes	na	Yes	na	Yes

Compound	Erythritol	Threitol	Myristic acid	Glucose	Dodecanoic acid	Terephthalic acid*
HMDB	0002994	0004136	0000806	0000122	0000638	0002428
CHEBI	17113	48300	28875	4167	30805	15702
Pubchem	222285	169019	11005	5793	3893	7489
KEGG	C00503	C16884	C06424	C00031	C02679	C06337
CAS	149-32-6	2418-52-2	544-63-8	50-99-7	143-07-7	100-21-0
Crib	Endogenous	Endogenous	511 05 0	Endogenous	115 07 7	100 21 0
Source	food	food	Endogenous, food	food	Endogenous, food	Endogenous
	P '1 '			Adipose	<u> </u>	F 1 11 /
	Epidermis	na	Adipose Tissue	Tissue	Stratum Corneum	Fibroblasts
	Durantata		En: James in	Adrenal		D1-4-1-4
	Prostate		Epidermis	Cortex		Platelet
			D	Adrenal		
			Prostate	Gland		
			C 1	Adrenal		
			Spieen	Medulla		
				Beta Cell		
				Bladder		
				Brain		
				Brain		
				Plaques		
				Epidermis		
				Eve Lens		
Tissues and				Fetus		
organs				Fibroblests		
, i i i i i i i i i i i i i i i i i i i				Conodo		
				Gonads		
				Gut		
				Intestine		
				Kidney		
				Liver		
				Lung		
				Mouth		
				Muscle		
				Myelin		
				Nerve Cells		
				Neuron		
				Pancreas		
				Placenta		
				Prostate	_	
	Blood	Blood	Blood	Blood	Blood	Blood
	CSF	CSF	CSF	Breast Milk	Breast Milk	Saliva
	Feces	Feces	Feces	CSF	Feces	Urine
Biofluid	Saliva	Urine	Saliva	Feces	Saliva	
	Urine		Urine	Saliva	Sweat	
				Sweat	Urine	
				Urine		
	Cytoplasm		C-++1	E-++	E	
	(predicted)	na	Cytoplasm	Extracellular	Extracellular	na
	-		Extractivitar	Lucocomo	Membrane	
Call			Extracentular	Lysosome	(predicted)	
Cell			Membrane	Endoplasmic		
			(predicted)	reticulum		
				Golgi		
				apparatus	<u>.</u>	
	na	na	Membrane stabilizer	Metabolite	Membrane stabilizer	na
Biological			Energy source		Energy source	
role			Energy storage		Energy storage	
			Nutrient		Nutrient	
	na	na	Lipid transport	na	Lipid transport	na
Biochemical			Lipid metabolism		Lipid metabolism	
process					Fatty acid	
-			Fatty acid metabolism		metabolism	
Cellular	20	20	Call signaling		Call signaling	
process	na	118	Cell signating			na
Chemical	na	na	Fatty Acid	na	na	na
reaction		11a	Biosynthesis			
Environmental	na	na	Lipid peroxidation	na	Lipid peroxidation	na
role						
Industrial	na	na	Food and nutrition	Food and	Food and nutrition	na
application				nutition	Personal com	DET plastic
application			Surfactant		products	(manual)

			Emulsifier Surfactant Pharmaceutical Emulsifier Antibacterial Pharmaceutical			
Pathways						•
HMDB	na	na	Yes	na	Yes	na
KEGG	Yes	na	Yes	Yes	Yes	All microbial
Biomarker						
CD	na	na	na	na	na	na
IBD	na	na	na	na	na	na
UC	na	na	na	Yes	na	na

Table 42. Biological functions of the candidate biomarkers. * Threonolactone has been excluded as a product of degradation of L-ascorbic acid. Terephthalic acid is most probably an analytical artefact. Another evidence for it is that all pathways it is involved in are microbial ones.

S-23. Literature review.

Despite the variety of matrices, phenotypes and populations reported, the variations of concentration reported are often in agreement with our observations.

Known Metabolites in IBD						
2-Hydroxybutyric-acid	Galactose	Methionine				
Aspartic Acid	Glucose	Xylose				
Citric Acid	Glutamic acid	Erythronic / Threonic Acid				
Erythritol /Threitol						
Ν	Metabolites unknown in	IBD				
1,5-Anhydroglucitol	Erythrose / Threose	Myristic acid				
Capric acid	Terephthalic acid*	Threonolactone*				
Lauric acid						

Table S-43. Metabolites known and unknown to play a role in IBD. The first ones tend to confirm the results obtained. The others could lead, after validation, to new knowledge that would be helpful in diagnosis and to understand better the CD phenotypes and their functioning. Threonolactone and terephthalic acid are probable artefacts (*).

2-hydroxybutyrate				
Reference	Instrumentation	Matrix	Samples	Variation
Minamoto	GC-TOFMS	Serum, Feces	IBD Dogs	↑
Schicho 2012	NMR	Serum	UC	↑
Schicho 2012	NMR	Plasma	UC	↑
Schicho 2012	NMR	Plasma	CD	↑
Dawiskiba	NMR	Urine	CD & UC	\downarrow
Scoville	UPLC-MS/MS	Serum	CD & UC	\downarrow
Scoville	UPLC-MS/MS	Serum	CD & UC	Ļ

Aspartate				
Reference	Instrumentation	Matrix	Samples	Variation
Ooi	GC-MS	Tissues	CD & UC	1
Scoville	UPLC-MS/MS	Serum	CD & UC	\downarrow
Kolho	UPLC-MS/MS	Feces	CD & UC	Significant
Ponnusamy	GC-MS	Feces	IBS	Significant

Citrate				
Reference	Instrumentation	Matrix	Samples	Variation
Minamoto	GC-TOFMS	Serum, Feces	IBD Dogs	1
Martin	NMR	Plasma	IL-10 mice (vs time)	1
Dawiskiba	NMR	Serum	CD & UC	\downarrow
Dawiskiba	NMR	Urine	CD & UC	\downarrow
Schicho 2010	NMR	Serum	DSS-induced (mice)	\downarrow
Schicho 2012	NMR	Serum	UC	\downarrow
Schicho 2012	NMR	Serum	CD	\downarrow

Schicho 2012	NMR	Urine	UC	\downarrow
Schicho 2012	NMR	Urine	CD	\downarrow
Scoville	UPLC-MS/MS	Serum	CD & UC	\downarrow
Stephens	NMR	Urine	IBD	Significant
Williams 2009	NMR	Urine	CD & UC	Significant
Murdoch	NMR	Urine	IL-10 mice	Significant

Galactose				
Reference	Instrumentation	Matrix	Samples	Variation
Schicho 2012	NMR	Urine	CD	1
Schicho 2012	NMR	Urine	UC	\downarrow

Glucose				
Reference	Instrumentation	Matrix	Samples	Variation
Williams 2012	NMR	Serum	CD & UC	↑
Schicho 2012	NMR	Serum	UC	1
Zhang	NMR	Serum	Early stage colitis	↑
Balasubramanian	1H-MRS	CMT	(In)active CD & UC	↑
Sharma	NMR	CMT	IBD	↑
Le Gall	NMR	Feces	CD & UC	↑
Schicho 2010	NMR	Serum	DSS-induced (mice)	\downarrow
Schicho 2012	NMR	Plasma	CD	\downarrow
Martin	NMR	Plasma	IL-10 mice (vs time)	\downarrow
Dawiskiba	GC-MS	Urine	IL-10 mice	Significant
Scoville	UPLC-MS/MS	Serum	CD & UC	Not Sign.
Lai	LC-QTOFMS	Serum	In(active) CD	Not Sign.

Glutamate				
 Reference	Instrumentation	Matrix	Samples	Variation
Hisamatsu	AA Analyze	Plasma	CD & UC	↑
Dawiskiba	NMR	Feces	CD & UC	1
Bjerrum	NMR	Feces	(In)active CD & UC	\downarrow
Ooi	GC-MS	Tissues	CD & UC	\downarrow
Scoville	UPLC-MS/MS	Serum	CD & UC	Not Sign.
Le Gall	NMR	Feces	CD & UC	Not Sign.

Methionine				
Reference	Instrumentation	Matrix	Samples	Variation
Ooi	GC-MS	Tissues	CD & UC	Ť
Schicho 2012	NMR	Serum	UC	↑
Martin	NMR	Plasma	IL-10 mice (vs time)	Ť
Schicho 2010	NMR	Urine	DSS-induced (mice)	\downarrow
Schicho 2010	NMR	Serum	DSS-induced (mice)	\downarrow
Scoville	UPLC-MS/MS	Serum	CD & UC	Not Sign.
Lai	LC-QTOFMS	Serum	In(active) CD	Not Sign.

AA Analyze	Plasma	CD & UC	Not Sign.
Instrumentation	Matrix	Samples	Variation
GC-TOFMS	Serum, Feces	IBD Dogs	↑
NMR	Urine	CD	1
Erythronic acid / Threonic Acid			
Instrumentation	Matrix	Samples	Variation
GC-TOFMS	Serum, Feces	IBD Dogs	1
	AA Analyze AA Analyze Instrumentation GC-TOFMS NMR / Threonic Acid Instrumentation GC-TOFMS	AA Analyze Plasma Plasma Instrumentation Matrix GC-TOFMS Serum, Feces NMR Urine /Threonic Acid Instrumentation Matrix GC-TOFMS Serum, Feces	AA Analyze Plasma CD & UC Instrumentation Matrix Samples GC-TOFMS Serum, Feces IBD Dogs NMR Urine CD / Threonic Acid Instrumentation Matrix Samples GC-TOFMS Serum, Feces IBD Dogs

Erythritol / Threitol				
Reference	Instrumentation	Matrix	Samples	Variation
Minamoto	GC-TOFMS	Serum, Feces	IBD Dogs	1

Table S-44. Literature review for the selected and annotated potential biomarkers. Comparison of experimental and reported variations. Threonolactone and terephthalic acid are probable artefacts (*). CMT stands for colonic mucosal tissue. The metabolites in grey are the ones with opposite reported variations.

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