Fenton Reactions Drive Nucleotide and ATP Syntheses in Cancer

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A. SUPPLEMENTARY RESULTS

1. Observations from data analyses of cytosolic Fenton reactions

Extracellular superoxide is found to make substantial contributions to cytosolic Fenton reactions in BRCA, COAD, ESCA, HNSC, KIRC, KIRP, STAD, and THCA while mitochondrial superoxide has considerable contributions in BRCA, ESCA, KIRC, KIRP, LUAD, LUSC and STAD, based on our co-expression analyses. For the other four cancer types, contributions from either source is moderate.

Regarding the source of superoxide, we noted that the gene-expression levels of the NADH oxidases NOX1 and NOX4 in all cancer types correlate negatively with the predicted tumor purity of each sample with high statistical significance, as shown in Supplementary Figure S3, hence suggesting that these genes are expressed in immune or stromal cells rather than cancer cells. In addition, the expression levels of the VDAC genes significantly positively correlate with that of the mitochondrial superoxide dismutase SOD2 in the cancer types with significant contribution of mitochondrial superoxide in the fitted regression model, namely BRCA (p-value =1.62e⁻⁴), KIRC (p-value = 3.71e⁻⁷), KIRP (p-value = 4.28e⁻⁸), LUAD (p-value = 1.64e⁻⁷), and LUSC (p-value = 1.21e⁻⁶), indicating that superoxide from mitochondria gets to cancer cell cytosols. Figure S4 shows the levels of correlation between the endogenous superoxide genes and the predicted level of cytosolic Fenton reaction as well as between the mitochondrial superoxide genes and the level of cytosolic Fenton reaction across the 14 cancer types. We can see from the figure that some cancers have higher correlations for the former while other cancers have higher correlations for the latter.

Gene-expression levels of cytosolic transferrin, ferritin and ferric reductases all show significant contributions to the strong correlation between the two sides of Eq. 13, indicating that a substantial amount of unreduced $Fe³⁺$ from cytosolic Fenton reactions is accumulated in cancer cytosol and hence contributing to overwhelming the pH buffer and changing its pH, where the predicted Fe^{3+} accumulation is consistent with published studies (Chen and Paw, 2012). In addition, gene-expression levels of transferrin and ferritin show positive and ferric reductases show negative correlations with the predicted levels of Fenton reactions, all supporting our prediction.

The two outcomes of $Fe³⁺$ as given in Eq. 10 and Eq. 11 that lead to OH accumulation correlate highly negatively with $H⁺$ exporter genes, namely the SLC4A4-11 and SLC9, as shown in Figure S6. In addition, the predicted rates of OH⁻ production (Eq. 9) correlate at least as strongly with the expressions of both acid-loading and acid-extruding transporter genes: SLC4A-3, -4, -5, -s7, -9, -10, ATP2B-3, SLC9A-1, -6, -7, -9 and ATP6V-0A2, -0C, -0D2, -0E1, -0E2, -1A, -1E2, -1F, -1H, all with p-values < 0.05 by Mann Whitney test (detailed in Supplementary Figure S7), as the correlation between the predicted rates of hydroxyl radical production (predicted $\lceil \cdot 0H \rceil'$ in Eq. 13) and the observed rate of $\lceil \cdot 0H \rceil'$ in Eq. 13, measured using the expression levels of the marker genes for hydroxyl radical, all supporting our model.

2. Impact of cytosolic Fenton reactions on intracellular pH

Note from Figure S8 that the three main sources for cytosolic pyruvate production in cancer are glucose, malate originated from glutamine, and serine/glycine; and the five main effluxes from pyruvate are acetyl-CoA; oxaloacetate; amino acids alanine, lysine or aspartate; lactates; and sialic acids. Gene expression data analyses revealed that pyruvate production from glucose and serine is increased across all 14 cancer types, based on up-regulated glucose transporters, glycolytic enzymes, and serine dehydratase genes SDS and SDSL, which is consistent with the literature. In contrast, pyruvate effluxes as well as intracellular concentrations vary substantially across different cancers based on publicly available metabolomics data (Hirayama et al., 2009; Kami et al., 2013).

To assess *if all or only a fraction of the pyruvate produced through glycolysis goes towards lactic acid production and secretion*, we have conducted two random-effect linear regression analyses between the expression levels of the influx enzymes to pyruvate production *vs*. the efflux enzymes from pyruvate: one including the contribution of the gene-expressions of PKM2 & PKLR, and the other not. Lactate producing enzyme, LDHA, is considered as a random effect on the intercept, and the two linear models are compared based on the goodness of the fit.

Specifically, under the steady state assumption, we should have the total influx to pyruvate equal to the total efflux out of pyruvate; hence there should be non-negative values $\{a_i\}$ that make the left and the right sides of the following approximately the same

 a_1 [PKM2] + a_2 [PKLR] + a_3 [ME1] + a_4 [SDS]

 $\approx a_5$ [NPL] + a_6 [GPT] + a_7 [PC] + a_8 [PDHA1] + a_9 [LDHA]

where [X] represents the gene-expression level of protein X. For given tissue samples with available gene expression data, this problem can be formulated and solved as a non-negative least square problem. To control for contributions of glycolytic pyruvate to non-lactate efflux, we have discretized for each cancer type the [LDHA] expression values into three levels of equal subpopulations. In our regression model, the discretized LDHA expression is considered as a random effect affecting the linear model intercept.

To examine the contribution of $[PKM2]$ and $[PKLR]$ to the quality of this model, we built two random-effect linear regression models by holding the LDHA expression as a random effect that affects only the intercept: one with [PKM2] and [PKLR] as linear predictors, and the other without. For each cancer type, we compared the two models using Chi-Square test to see if adding the terms [PKM2] and [PKLR] could significantly improve the model fitting. We noted that for 7 out of 14 cancer types ($p < 0.05$) and for 10 out of 14 cancer types (p < 0.07) (Supplementary Table S1), adding the term significantly improves the linear model. Hence we conclude that glycolytic pyruvate makes substantial contributions to non-lactic metabolite syntheses in Figure S8.

To assess the amount of time needed for the protons associated with the glycolytic pyruvate to overwhelm the pH buffer, we have estimated the number of net protons needed to change the intracellular pH for one pH level, say, from 8.0 to 7.0. We assume that the

volume of a cancer cell is 100um 3 , which is consistent with the published human cell data. For the intracellular pH to change from 8.0 to 7.0, the concentration of the H⁺ needs to change from $10^{-8.0}$ to $10^{-7.0}$ mol/L. The following calculates the number of protons needed to make such a change for each such cell, assuming that the pH buffering coefficient of the cell is 2.0 x 10⁵ for this pH range (Saleh et al., 1991):

 $(10^{-7.0} - 10^{-8.0}) \times 100 \times 2 \times 10^5 \times 10^{-15} \times 6.02 \times 10^{23} \approx 1.1 \times 10^9$.

where 1L = 10^{15} um³ and 6.02×10^{23} is the Avogadro constant. Hence, it takes 1.1×10^{9} protons to make the desired pH change. It is known that proliferating human fibroblasts consume \sim 5 \times 10⁷ glucose/second per cell (Flamholz et al., 2014). Using a conserved estimate, we assume that a cancer cell uptake 5×10^7 glucose/second, 50% of which goes to pyruvate but not involved in electron transport chain and at least 20% of these is not used towards lactate synthesis (and extracellular secretion). By putting these numbers together, we get: it takes ~220 seconds for such a cell to reach the desired pH change. While our estimate here might be crude, it highlights that it will not take long for Fenton reaction-infected cytosol to overwhelm the pH buffer and start to change the cytosolic pH.

3. Intracellular nucleotide concentration may drive cancer cell division?

It is not unthinkable that increased nucleotide concentration can drive DNA synthesis and cell division by cancer or cancer-forming cells, knowing that proliferation of prokaryotic cells and possibly all unicellular eukaryotic organisms such as yeast is driven by increased nucleotide or nucleotide-sugar concentration (Wang and Levin, 2009). For example, once ATP synthesis rate is higher than its consumption rate, the intracellular ATP concentration will continue to increase in such unicellular cells, resulting in slowdown of their ATP production and increase of nucleotide synthesis as the cells continue to consume the available nutrient. Cells like *E. coli* and yeast use intracellular nucleotide or nucleotide-sugar concentration as cue to activate DNA synthesis and cell-cycle progression. Hence we speculate that cancer cells may have utilized a similar program to activate the cell-division process to rid of their nucleotides (manuscript in preparation).

To probe further this issue, we have conducted a co-expression analysis between nucleotide synthesis and a few downstream pathways: DNA repair, DNA replication, RNA POL I synthesis, aminoacyl-tRNA synthesis and cell cycle in the six cytosolic Fenton reaction harboring inflammatory diseases discussed and all 14 cancer types. The key information gained includes: (i) nucleotide synthesis is not strongly correlated with cell-cycle progression in the six inflammatory diseases; (ii) while they are more correlated in cancers, the correlation level spans a wide range across different cancers and is not nearly as strong as that with DNA repair, strongly suggesting that nucleotide synthesis, DNA synthesis and cell-cycle progression are not coordinated through regulation as in normal proliferating cells in human tissues; and (iii) nucleotide synthesis strongly correlates with DNA repair in both inflammatory diseases and cancers, suggesting that DNA repair may be a key inducer of nucleotide synthesis. Hence, we posit that it is DNA repair processes that may induce nucleotide synthesis rather than DNA replication, which is clearly different from the typical proliferation process where the need for DNA replication drives nucleotide synthesis. The details are given in Supplementary Table S3.

4. Observations from data analyses of mitochondrial Fenton reactions

The mitochondrial NADH and superoxide contribute strongly to the reduction of $Fe³⁺$ from mitochondrial Fenton reactions, hence driving the continuous Fenton reactions. In parallel, significant Fe³⁺ accumulation and its correlation with mitochondrial Fenton reactions are also observed based on the up-regulated mitochondrial iron importer genes SLC25A28 and SLC25A37, heme synthesis gene ALAS1 and their significant correlations with protein damages in mitochondria, indicating that some OH⁻ produced by mitochondrial Fenton reactions are not naturalized by Fenton or associated reactions, hence leading to consumption of protons inside mitochondria.

The expression levels of Complexes I and III both show strong correlations with our predicted levels of the mitochondrial Fenton reactions when $Fe³⁺$ being reduced by superoxide or unreduced. Interestingly, higher correlations were observed in cancer tissues with higher levels of hypoxia, measured using the expression levels of hypoxia marker genes EGLN1 and EGLN3, as detailed in Supplementary Methods and Figure S12.

The expression levels of ATP-ADP exchanger genes SLC25A4, SLC25A5 and SLC25A6 all show strong correlations with the predicted rates of mitochondrial Fenton

reactions when $Fe³⁺$ being reduced by superoxide or unreduced, strongly suggesting that such Fenton reactions contribute to ATP syntheses. Similarly, higher correlations are observed in cancer tissues that are more hypoxic, which are particularly so for cancer types with significant levels of mitochondrial Fenton reactions, namely BRCA, COAD, KICH, KIRC, KIRP, LUAD and PRAD, suggesting that some aerobic respiration may take place in $O₂$ rich environment as in normal cells.

One evidence for unreduced $Fe³⁺$ in mitochondria is the increased synthesis of iron-sulfur clusters as reflected by the HSCB gene and the ABCB6 gene, the former of which transfers a newly synthesized iron-sulfur to specific proteins and the latter removes iron sulfur from the mitochondria, as shown in Figure S14. The rationale is that a damaged iron-sulfur cluster indicates that Fenton reaction already takes place, hence Fe^{2+} is oxidized to Fe^{3+} and then the iron-sulfur cluster is replaced by a new one while the $Fe³⁺$ ions along with the damaged iron-sulfur cluster will be removed from mitochondria using the ABCB6 transporter (Richardson et al., 2010). From the figure, we can see both genes are up-regulated in majority of the cancer types, indicating the number of unreduced $Fe³⁺$ is increased.

5. Additional evidence for UCP5 being used for ATP production

Strong positive correlations between UCP5 and mitochondrial iron importer genes SLC25A28 and SLC25A37 while negative correlation between UCP5 and the rate-limiting gene ALAS1 of heme synthesis are observed in BRCA, HNSC, KIRC, KIRP, LUAD, PRAD and THCA but not in normal tissues. These observations suggest that the activation of UCP5 is associated with the accumulation of Fenton reaction-produced Fe^{3+} , but not Fe^{2+} .

Furthermore, the malate importer gene SLC25A11 of the malate-aspartate shuttle is largely up-regulated and strongly co-expressed with $Fe³⁺$ accumulation rather than the aspartate anti-porter SLC25A12 in cancer. Noting that previous studies have discovered that malate accumulation in cancer cells of multiple cancer types where malate serves as a chelator of Fe³⁺ (Hamada et al., 2005). Hence, we posit that the unreduced Fe³⁺ produced by mitochondrial Fenton reactions are chelated with malate and accumulated in mitochondria, which directly contribute to cross-membrane proton gradients and ATP synthesis.

B. SUPPLEMENTARY METHODS

1. Comparative analyses of Fenton reactions in cancer *vs.* **inflammatory disease**

Comparitive analyses of the differentially expressed genes in 16 types of inflammatory diseases and the 14 cancer types are made. Differentially expressed genes are identifed in each dataset by using Mann-Whitney test with FDR < 0.05 as the significance cutoff. Considering that the cancer transcriptomic data are all measured using RNA-seq while only microarray data are avialable for the inflammatory diseases, we have also included 12 of the 14 cancer types measured by the same micorarray platform to assure that most of the differentially expressed genes discussed in this study are consistantly identified in both data types.

2. Differential gene expression and pathway enrichment

Differential gene expression is assessed by using the Mann-Whitney test on the RSEM (or RPKM) normalized RNA-seq data collected from cancer *vs*. control samples of each cancer type. FDR is applied to control false discoveries and FDR < 0.005 is used as the significance cutoff for determining differential gene expression.

Pathway enrichment analysis is conducted and the statistical significance of each enriched pathway is assessed by using a hypergeometric test (statistical significance cutoff = 0.005) against pathways retrieved from GO and MsigDB as well as ~40 manually curated Fenton reaction related gene sets (Subramanian et al., 2005).

3. Genes selected for estimation of Fenton reactions in mitochdondria and ECM

Mitochondrial Fenton reaction: The gene-expression levels of up-regulated protein-degradation enzymes in mitochondria, specifically CLPP, LONP1, THOP1, HTRA2, PMPCA, PMPCB, SPG7, CLPX, and AFG3L2 are used to estimate the mitochondrial [⋅ OH]. All mitochondrial iron-sulfur proteins are used as the source of F_e^2 accessible to mitochondrial Fenton reactions; and hence $[Fe^{2+}]$ is estimated by using a linear model of expressions of the synthesis genes of iron-sulfur clusters, namely CIAO1, BRIP1, HSPA9 and ACO2. Mitochondrial $[H_2O_2]$ is estimated using a linear model over the expressions of mitochondrial anti-oxidation reductases such as GPX4 and TXN. The level of reducing agents, [RA], is

estimated by using the expression data of mitochondrial dehydrogenases. The level of superoxide, $[0^-_2]$, is estimated using the gene-expressions of mitochondrial superoxide dismutase SOD2. Fe $3+$ accumulation is estimated using mitochondrial iron transporter genes SLC25A28 and SLC25A37, the rate-limiting enzyme of iron-sulfur cluster synthesis ISCU and the rate-limiting enzyme of heme synthesis ALAS1.

Extracellular matrix Fenton reaction: [∙ OH] is estimated using ECM degradation genes MMPs (Supplementary Table S1) via a regression model over $\rm [H_2O_2]$ and $\rm [C_u^{\ 1+}]$ since $\rm C_u$ instead of F_e is involved in such Fenton reactions. $[H_2O_2]$ is estimated using the expressions of NOX2, NOX3 and GPX7 while $[C_u¹⁺]$ is estimated by using the expressions of two extracellular copper-dependent enzymes: lysyl oxidase (LOX) and lysyl oxidase like 2 (LOXL2). It has been reported that the copper(I) ions in lysyl oxidase are involved in Fenton reaction and the produced copper(II) ions can be further reduced by superoxide: $Cu^+ + H_2O_2 \rightarrow$ Cu^{2+} + $·$ OH + OH⁻; Cu²⁺ + O⁻₂ -> Cu⁺ + O2; and Cu⁺ + O₂⁻+ 2H⁺ -> Cu²⁺ + H₂O₂ (Brown Jr, 1997). It is noteworthy that all the genes used to assess extracellular Fenton reactions are genes expressed in stromal and local immune cells rather than cancer cells.

4. Inference of subcellular location of selected proteins

The subcellular location of a protein is first predicted based on the annotation in Genecards, which uses a number between 0 and 5 to represent the reliability of a prediction, with 5 being the most confident and 0 being the least. We have used 4 as the cutoff in assessing the subcellular localization for a protein (Safran et al., 2010).

5. Hypoxia level prediction

We have previously developed a computational method to estimate the oxidative stress level of a tissue sample based on expression levels of ~40 genes whose proteins either contribute to the generation of oxidative stress or respond to it (Cao et al., 2015). Here, a similar approach is applied to train a predictor for the hypoxic level in the given tissue based on its gene expression data. Specifically, we have collected 10 gene-expression datasets of 24 samples with known hypoxia levels and 30 control samples as the training data (see Supplementary Table S4) to train a predictor for the microarray data (Affymetrix UA133 plus

2.0 array). 180 genes are selected as hypoxia responsive genes, including known hypoxia induce factor I and II (HIF1 and HIF2) and genes directly regulated by them, retrieved from the *Transfec* database (Wingender et al., 1996) and genes annotated by GO to be hypoxia responsive. The predictor is trained by using a logistic regression model with variable selection by using L1 regularization(Park and Hastie, 2007). "glmnet" in the R package is applied to train the predictor and the model parameters are selected that achieve the highest prediction accuracy with 10-fold cross-validation. Five genes, namely EGLN1, EGLN3, MAT2A, PFKFB3 and PFKFB4, are selected and used in the final predictor, which achieves 96.1% prediction accuracy in 10-fold cross validation.

To predict the hypoxia level of a tissue sample based on the RNA-seq data, we have selected gene EGLN3 (Egl-9 Family Hypoxia Inducible Factor 3) with the highest F score among the five selected genes in the logistic regression-based prediction model. A higher expression level of EGLN3 implies a more hypoxic condition. We have used the expression level of EGLN3 to classify the samples of each cancer type into *hypoxic* (top 30% EGLN3 expressed samples), *aerobic* (bottom 30% EGLN3 expressed samples) and *intermediate* groups.

The non-linear model for Fenton reaction in each subcellular location is fitted with gene-expression data in each hypoxia group, respectively. The predicted mitochondrial Fenton reaction levels in each group strongly correlate with the ETC Complex I and III genes for each cancer type. Consistently higher correlations ($p < 1e-5$ by Mann-Whitney test) between the predicted Fenton reaction level and ETC Complex I and III genes in samples with higher hypoxia levels are observed in all cancer types with significant mitochondrial Fenton reactions, namely BLCA, BRCA, COAD, KICH, KIRC, KIRP, LUAD, LUSC, PRAD, and STAD. Detailed correlations between predicted Fenton reaction level and ETC Complex I and III genes in different hypoxia groups and cancer types are shown in Supplementary Figure S12.

6. Prediction of tumor purity

To assure that the analyzed extracellular genes are truly expressed by stromal or immune cells rather than cancer cells, we have selected genes with expression levels

negatively correlated with the cancer purity predicted by ESTIMATE, ABSOLUTE, LUMP, IHC and CPE methods in each of the 14 cancer types (Aran et al., 2015). Detailed correlations between the gene expression and predicted cancer purity are given in Supplementary Figure S3.

7. Validation of saturated malate-aspartate (M-A) shuttle

The net result of M-A shuttle is to regenerate NAD+ in cytosol and produce NADH in mitochondria. In this process, SLC25A11 transports malate into mitochondria and SLC25A12/SLC25A13 transport aspartate out of mitochondria. In normal conditions with balanced NADH and NAD+, there should be a strong correlation between the expressions of SLC25A11 and SLC25A12/SLC25A13. Interestingly, the correlation is insignificant in cancer tissues in general across 14 cancer types. Furthermore, we noted that SLC25A11 strongly correlates with ETC Complex I, which is the first step to utilize NADH to transport electron, but the correlation between SLC25A12/SLC25A13 and Complex I is insignificant. This strongly suggests that the transportation rates of SLC25A12/SLC25A13 reach their maximum, i.e., they become saturated while SLC25A11 remains at a high rate. Previous studies have shown that the efflux of aspartate is irreversible and the rate-limiting step of the M-A shuttle, while the exchange between malate and α-ketoglutarate is driven by the concentration gradients of its substrates. By integrating all these, we predict that malate is being used to chelate Fe $^{3+}$ (Lu et al., 2008; Adam et al., 2015).

8. Variable selection and statistical significance test

"glmnet" in R package is applied to compute each regression model with variable selection by using a L1-penalty (Friedman et al., 2010). Cross-validation is applied to achieve the best λ value for each fitting. To assess the statistical significance of each regression model, we conducted a permutation-based testing by using the following criteria: (i) \mathbb{R}^2 value, (ii) the number of selected variables, (iii) biological explanation of the positive or negative sign of each model parameter, and (iv) biological meaning of each gene used. A p-value < 0.005 is used as the cutoff for the statistical significance.

9. Assessment of statistical significance of Fenton reaction prediction

For each regression model of each Fenton reaction related quantity, statistical significance from three aspects is assessed to demonstrate the occurrence of a Fenton reaction: (i) over expression of each Fenton reaction associated gene; (ii) significance in fitting the reaction equation, Eq. 13 in the main text, calculated using a permutation test on the $R²$ value by randomly choosing the same number of genes with similar expression patterns to those used for estimating [Fe²⁺], [H₂O₂], [•0H], [O₂] and [RA], respectively, for variable selection; and (iii) the sign of each regression parameter, which is assessed using a permutation test on a predefined Sign-Score, and 0.005 was used as the cutoff for the significance values. For (i) and (ii), we have applied a test by permuting the independent variables in the regression model and another test to permute the dependent variables by fitting the regression model against genes with similar over-expression levels but independent of those of the selected marker genes for $\lceil \cdot \text{OH} \rceil$ production.

Our analysis indicates that Eq. 13 is non-linear. Hence a polynomial model based on Tayler expansion of the function is used to capture the non-linear relationship. The non-linear function is first approximated using a linear regression over a set of expanded variables based on the Taylor expansion. Genes deemed to make significant contributions are selected using a linear regression with an L1-penalty. Then a non-linear regression of the selected genes is then conducted.

The sign of the regression parameters is defined by the following function to assess the significance for the occurrence of Fenton reaction in a specific subcellular location:

$$
\text{Sign Score} = \frac{\sum_{\text{RA}} (K_1^{\text{RA}} + K_2^{\text{RA}} + K_3^{\text{RA}} + K_{\text{cat}}^{\text{RA}} + K_5^{O_2^-} + K_6^{O_2^-} + K_{\text{cat}}^{O_2^-})}{\sum_{\text{RA}} (|K_1^{\text{RA}}| + |K_2^{\text{RA}}| + |K_3^{\text{RA}}| + |K_{\text{cat}}^{\text{RA}}| + |K_5^{O_2^-}| + |K_6^{O_2^-}| + |K_7^{O_2^-}| + |K_{\text{cat}}^{O_2^-}|)}
$$

The significance of the Sign Score is assessed using a permutation test. P-value = 0.005 is used as the significance cutoff.

10. Pathway-pathway correlation significance calculation

For two pathways P1 and P2 with p1 and p2 genes, respectively, we have calculated their Pearson correlation and constructed a correlation p1 x p2 matrix. We then counted all the gene pairs which satisfy: (a) p-value \leq 0.01 and (b) correlation value is above 0.1. We have then conducted 10,000 permutations of the two pathways. Let N be the number of such pairs and M the number of times out of these permutation tests with significant gene pairs at least being N. The following is used as the significance value:

Permutation pvalue =
$$
\frac{M}{10000}
$$

11. Validation of up-regulated gene expressions against protein expression data

All the up-regulated genes in cancer tissues used in this study are validated using protein expression data in the relevant cancer type. The staining data for 16,236 proteins in 14 types of human cancers are retrieved from The Human Protein Atlas. For most proteins, they have four staining level: high, middle, low and not detectable, which are scored as 5, 3, 1 and 0, respectively. Since the database also contains the following information: the number of patients for each of these four levels for each protein and the total number of patients included for each cancer type, we can calculate the proportion of this protein in different levels and derive its staining score as defined above.

8 of the 14 cancer types used in our study are included in this database: BRCA, HNSC, LUSC, STAD, COAD, LIHC, PRAD and THCA. For each cancer type, we compared average staining scores for each protein in each cancer type, and consider up-, down-regulation or change for protein in each cancer type, when assessing the consistencies between differential gene expressions and protein abundance data.

C. SUPPLEMENTARY FIGURES AND CAPTIONS

Figure S1: Elevated iron level in cancer *vs.* control across 14 cancer types (the x-axis). The y-axis is the axis of genes involved in iron uptake, usage and storage. Each entry is the log2-transformed fold-change averaged over all samples of cancer *vs.* control, where blue is for up and red for down-regulation with the detailed color scheme given in the top panel. Eight genes are used with TFR2 for transferrin receptor 2; TFRC for transferrin receptor; STEAP3 for STEAP family member 3; SLC25A37 for solute carrier family 25, member 37; FTH1 for ferritin, heavy polypeptide 1; HAMP for hepcidin antimicrobial peptide, and SLC40A1 for solute carrier family 40 (iron-regulated transporter), member 1, an iron exporter.

Figure S2: Elevated H₂O₂ level in cancer *vs.* control across 14 cancer types (the x-axis). The y-axis is the axis of genes reflecting the H_2O_2 level. Each entry is the log2-transformed fold-change averaged over all samples of cancer *vs.* control, where the color scheme is the same as in Figure S1. Thirteen genes are used with GCLC for glutamate-cysteine ligase, catalytic subunit; GPX1 for glutathione peroxidase 1; GCLM for glutamate-cysteine ligase, modifier subunit; GPX5 for glutamate-cysteine ligase, modifier subunit 5; GPX7 for glutamate-cysteine ligase, modifier subunit 7; TXN for thioredoxin; GPX8 for glutamate-cysteine ligase, modifier subunit 8; GPX4 for for glutamate-cysteine ligase, modifier subunit 4; GPX2 for glutamate-cysteine ligase, modifier subunit 2; and TXNRD1 for thioredoxin reductase 1.

Figure S3: Correlation between the expression levels of extracellular genes and the predicted cancer tissue purities. Cancer sample purities predicted by five methods in the public domain are used. Consistent negative correlations between the predicted purity and the expressions of certain extracellular genes are observed. "-" means not available.

NOX4

NOX1

NOX5

LOXL2

GPX7

NCF1

NCF₂

NCF4

NCF1C

NCF1B

Figure S4: Correlations between the endogenous superoxide genes and the predicted level of cytosolic Fenton reaction as well as between the mitochondrial superoxide genes and the level of cytosolic Fenton reaction across the 14 cancer types. The expressions of NOX1 and NOX4 are used to reflect the level of superoxide from the endogenous source; the expression of SOD2 is used to reflect the level of mitochondrial superoxide; and expressions of proteasome genes PSMA7 and PSMB4 are used to reflect the level of cytosolic Fenton reactions. The first CC represents the correlation coefficient between a gene and PSMA7 and the second CC represents the correlation coefficient between a gene and PSMB4. CC in bold represents that Fenton reactions rely more on the corresponding source of superoxide.

Figure S5: Increased accumulation of cytosolic Fe³⁺ in 14 cancer types. Here we use the expressions of FTL in control tissues vs cancer tissues from stage 1 through stage 4 to reflect the increase in the cytosolic $Fe³⁺$ accumulation. Rows highlighted in red represent cancer types with reduced Fe³⁺ accumulation as reflected by FTL.

Figure S6: Negative correlation between estimated Fe³⁺ accumulation and H⁺ exporter genes across the 14 cancer types. (PSMA7, PSMB4), and (FTH1, FTL) are used to represent the level of Fenton reactions and the accumulation of Fe³⁺. And all the SLC genes used here are acid-extruding transporters.

KICH

Figure S7: Correlations between the expressions of acid-loading and acid-extruding transporter genes and the predicted level of cytosolic Fenton reactions as well as with OH⁻-producing cytosolic Fenton reactions. 65 protein damage-responsive genes are selected to be regressed with the Fenton reaction related genes linked via the Michaelis-Menten equation for predicting the occurrence of Fenton reactions. In each panel, the bar on the left shows the correlations between the expressions of selected acid-loading and acid-extruding transporter genes and the level of OH^- -producing cytosolic Fenton reactions predicted by the 65 genes while the bar on the right shows the correlation between these transporter genes and the predicted cytosolic Fenton reaction level. The names of the acid-loading and acid-extruding transporter genes, the cancer type and the p-value of the difference between the correlations tested by Mann-Whitney test are listed above each box-plot.

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SLC4A7 LUAD $p = 0.0163$

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SLC4A9 BLCA $p = 0.0311$

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SLC9A9 LUAD $p = 0.0051$

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Figure S8: The pyruvate metabolism with the name in each box represents a metabolite and the name next to each edge is the name of the enzyme catalyzing the corresponding reaction.

Figure S9: Correlation between the estimated rate of OH⁻ production and the rate of glycolytic ATP synthesis across 14 cancer types. We used a simpler way to estimate the rate of OH⁻ production, specifically using the expressions of ferritin gene FTH1 to represent the accumulation rate of unreduced $Fe³⁺$; proteasome gene PSMA7 to represent the level of cytosolic Fenton reaction; and PKM to represent the level of glycolytic ATP synthesis. For each cancer type, the three values are: the coefficients a_1 and a_2 of FTH1 and PSMA7, plus the correlation coefficient (CC) between PMK and $(a_1 * FTH1 + a_2 * PSMA7)$.

Figure S10: Correlation between glycolysis and aminoacyl-tRNA synthesis, purine synthesis, base excision repair and the glyoxylate and dicarboxylate metabolism, respectively, across six chronical inflammatory diseases. In this plot, PKM is used to reflect the level of glycolytic ATP production, and genes in the four sections along with y-axis, separated by blank lines, are for aminoacyl-tRNA synthesis, purine synthesis, base excision repair and the glyoxylate and dicarboxylate metabolism, respectively. The six disease names to the left of the vertical blank line are six diseases mentioned.

Figure S11: Contribution to mitochondrial Fenton reaction by mitochondrial NADH and superoxide across the 14 cancer types. We use anti-oxidation genes GPX4 and TXN to represent the level of mitochondrial superoxide, MDH1 and MDH2 to reflect the level of mitochondrial NADH level; and CLPP and CLPX to represent the level of mitochondrial Fenton reactions. CC1 represents the correlation coefficient between CLPP and the corresponding gene (on the same row); and CC2 represents the correlation coefficient between CLPX and the corresponding gene. CC values in bold represent strongly correlated mitochondrial Fenton reactions and the relevant NDAH and/or mitochondrial superoxide.

Figure S12: (A) Correlations between the predicted level of mitochondrial Fenton reactions and the expressions of ETC Complex I genes in the more hypoxic and less hypoxic samples, respectively; (B) Correlations between the predicted level of mitochondrial Fenton reaction and ETC Complex III genes in the more hypoxic and less hypoxic samples, respectively. Each box-plot shows the correlations between the level of mitochondrial Fenton reaction predicted by the regression model (tilted in each figure) and the expression levels of Complex I (or III) genes in the more hypoxic samples (left bar, H) and less hypoxic samples (right bar, N).

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Figure S13: Correlation between predicted level of mitochondrial Fenton reactions (represented by CLPP) and Complex I (NDUF) and Complex III (COX) genes depends on the level of exogenous superoxide (reflected by NOX1 and NOX4) and the unreduced $Fe³⁺$ (reflected by FTL). CC represents the correlation coefficient between the expression of CLPP and that of each of the COX and NDUF genes, all averaged over samples of a specific stage.

Figure S14: Unreduced Fe³⁺ in mitochondria as reflected by the HSCB and the ABCB6 genes across 14 cancer types. The ones highlighted in red represent those not up-regulated in cancer compared to the controls.

Figure S15: mitochondrial Fenton reactions contribute to ATP syntheses. We have used CLPP and CLPX reflect the level of mitochondrial Fenton reactions, and ATB5B for ATP synthase, plus UCP5 (SLC25A14) and UCP2 genes. The coloring scheme is the same as in earlier figures, e.g., Figure S10.

Figure S16: Gene-expression levels of SOD3, and extracellular hydrogen peroxide and superoxide producing genes in 16 inflammatory diseases and 14 cancer types. The coloring scheme is the same as in earlier figures, e.g., Figure S10.

Figure S17: Staining score comparison between up-regulated genes and the background genes in eight cancer types. Bar on the left (B_G) is the staining score for background genes and bar on the right (M_G) is the score for the up-regulated model genes.

D. SUPPLEMENTARY TABLES AND CAPTIONS

TABLE S1: All genes used to demonstrate the occurrence of Fenton reactions in cytosol and mitochondria along with the related analysis results. CY model genes: genes initially used to establish Fenton reactions in cytosol. CY selected genes: genes selected from the model genes that give the optimal R^2 values. CY permutation 1 and 2 are the statistical significance of the derived R^2 values against sets of genes with comparable expression profiles with those in CY selected genes. Similarly defined are for the mitochondrial genes. ECM MMPs, component and glycosaminoglycan are the MMP, glycosaminoglycan and collagen genes used to establish Fenton reactions in extracellular matrix. ECM correlation: correlation between MMP and ECM copper containing genes.

[Table S1 should be here.]

TABLE S2: The first column is cancer type and the second column is the statistical significance of the contribution by glycolytic pyruvate towards non-lactate production in Figure S7.

TABLE S3: Gene-expression analysis data in support of Fenton reaction reactions in cytosol, mitochondria and ECM.

[Table S3 should be here.]

TABLE S4: Differential expression analyses of Fenton reaction-related genes, where a differentially expressed gene is determined by Mann-Whitney Test with FDR < 0.05. In the table, duplicated genes in microarray data refer to different probes of the same gene.

[Table S4 should be here]

REFERENCES

- Adam, F.I., Bounds, P.L., Kissner, R., et al. (2015). Redox Properties and Activity of Iron–Citrate **Complexes: Evidence for Redox Cycling. Chemical research in toxicology 28, 604-614.**
- Aran, D., Sirota, M., and Butte, A.J. (2015). Systematic pan-cancer analysis of tumour purity. **Nature communications 6.**
- Brown Jr, R.H. (1997). Superoxide dismutase and oxidative stress in amyotrophic lateral sclerosis. **Cold Spring Harbor Monograph Archive** *34***, 569-586.**
- Cao, S., Zhang, C., and Xu, Y. (2015). Somatic mutations may not be the primary drivers of cancer **formation. International journal of cancer** *137***, 2762-2765.**
- Chen, C., and Paw, B.H. (2012). Cellular and mitochondrial iron homeostasis in vertebrates. **Biochimica et Biophysica Acta (BBA)-Molecular Cell Research** *1823***, 1459-1467.**
- Flamholz, A., Phillips, R., and Milo, R. (2014). The quantified cell. Mol Biol Cell 25, 3497-3500.
- Friedman, J., Hastie, T., and Tibshirani, R. (2010). Regularization paths for generalized linear models via coordinate descent. Journal of statistical software 33, 1.
- Hamada, Y.Z., Carlson, B., and Dangberg, J. (2005). Interaction of malate and lactate with chromium (III) and iron (III) in aqueous solutions. Synthesis and Reactivity in Inorganic and **Metal-Organic Chemistry** *35***, 515-522.**
- Hirayama, A., Kami, K., Sugimoto, M., et al. (2009). Quantitative metabolome profiling of colon and stomach cancer microenvironment by capillary electrophoresis time-of-flight mass **spectrometry. Cancer Res** *69***, 4918-4925.**
- Kami, K., Fujimori, T., Sato, H., et al. (2013). Metabolomic profiling of lung and prostate tumor tissues by capillary electrophoresis time-of-flight mass spectrometry. Metabolomics 9, **444-453.**
- Lu, M., Zhou, L., Stanley, W.C., et al. (2008). Role of the malate-aspartate shuttle on the metabolic **response to myocardial ischemia. Journal of theoretical biology 254, 466-475.**
- Park, M.Y., and Hastie, T. (2007). L1 regularization path algorithm for generalized linear models. **Journal of the Royal Statistical Society: Series B (Statistical Methodology) 69, 659-677.**
- Richardson, D.R., Lane, D.J., Becker, E.M., et al. (2010). Mitochondrial iron trafficking and the integration of iron metabolism between the mitochondrion and cytosol. Proc Natl Acad Sci **U S A** *107***, 10775-10782.**
- Safran, M., Dalah, I., Alexander, J., et al. (2010). GeneCards Version 3: the human gene integrator. **Database** *2010***, baq020.**
- Saleh, A.M., Rombola, G., and Batlle, D.C. (1991). Intracellular H+ buffering power and its **dependency on intracellular pH. Kidney Int** *39***, 282-288.**
- Subramanian, A., Tamayo, P., Mootha, V.K., et al. (2005). Gene set enrichment analysis: a knowledge-based approach for interpreting genome-wide expression profiles. Proceedings of the National Academy of Sciences 102, 15545-15550.
- Wang, J.D., and Levin, P.A. (2009). Metabolism, cell growth and the bacterial cell cycle. Nature **reviews. Microbiology** *7***, 822-827.**
- Wingender, E., Dietze, P., Karas, H., et al. (1996). TRANSFAC: a database on transcription factors and their DNA binding sites. Nucleic acids research 24, 238-241.