Systematic lipidomic analysis of yeast protein kinase and phosphatase mutants reveals novel insights into regulation of lipid homeostasis

Aline Xavier da Silveira dos Santos^{a,b}, Isabelle Riezman^a, Maria-Auxiliadora Aguilera-Romero^{a,b}, Fabrice David^c, Manuele Piccolis^d, Robbie Loewith^{b,d}, Olivier Schaad^a, and Howard Riezman^{a,b} ^aDepartment of Biochemistry, ^bNational Centre of Competence in Research "Chemical Biology," and ^dDepartment of Molecular Biology, University of Geneva, Geneva CH-1211, Switzerland; ^cÉcole Polytechnique Fédérale de Lausanne, Lausanne CH-1015, Switzerland

ABSTRACT The regulatory pathways required to maintain eukaryotic lipid homeostasis are largely unknown. We developed a systematic approach to uncover new players in the regulation of lipid homeostasis. Through an unbiased mass spectrometry–based lipidomic screening, we quantified hundreds of lipid species, including glycerophospholipids, sphingolipids, and sterols, from a collection of 129 mutants in protein kinase and phosphatase genes of *Saccharomyces cerevisiae*. Our approach successfully identified known kinases involved in lipid homeostasis and uncovered new ones. By clustering analysis, we found connections between nutrient-sensing pathways and regulation of glycerophospholipids. Deletion of members of glucose- and nitrogen-sensing pathways showed reciprocal changes in glycerophospholipid acyl chain lengths. We also found several new candidates for the regulation of sphingolipid homeostasis, including a connection between inositol pyrophosphate metabolism and complex sphingolipid homeostasis through transcriptional regulation of *AUR1* and *SUR1*. This robust, systematic lipidomic approach constitutes a rich, new source of biological information and can be used to identify novel gene associations and function.

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INTRODUCTION

Lipids are essential cellular constituents whose functions have been increasingly studied in recent decades. As a class of biomolecules, lipids present a vast diversity of structures (Brown and Murphy, 2009) and functions, with roles as building blocks of biological membranes, as well as in energy metabolism and signaling pathways (Dowhan, 1997; Leonard and Hurley, 2011). Lipids are essential components of

all membranes in living organisms, and despite considerable differences in lipid composition of cells, organelles, and organisms, there is a high degree of conservation in the general framework of lipid metabolism and biological membrane properties throughout the kingdoms (Lykidis, 2007; Dennis *et al.*, 2010; Hannich *et al.*, 2011). In eukaryotic cells, the major membrane lipid components are glycerophospholipids, sphingolipids, and sterols (Daum *et al.*, 1998; Sampaio *et al.*, 2011). Among phospholipid and sphingolipid structures, there are many different combinations of fatty acids with different chain lengths, degrees of saturation, and head groups, giving rise to an extraordinary, although poorly understood, lipid complexity. The generation and maintenance of such diverse lipid compositions imply the existence of complex regulatory mechanisms (Dickson, 2008; Klose *et al.*, 2012; Zhang *et al.*, 2012).

Cells employ coordinated pathways of synthesis/degradation of phospholipids, sphingolipids, and sterols (Carman and Henry, 1999; Carman and Han, 2011; Nohturfft and Zhang, 2009; Gulati *et al.*, 2010; Rajakumari *et al.*, 2010; Gaspar *et al.*, 2011). These interconnected networks constitute a highly dynamic biological core that allows cells not only to adapt their lipid profile to environmental challenges, such as heat stress, osmotic stress, and nutrient

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Address correspondence to: Howard Riezman (Howard.Riezman@unige.ch).

Abbreviations used: GC-MS, gas chromatography-mass spectrometry; IPC, inositol-phosphorylceramide; MIPC, mannose-inositol-phosphorylceramide; M(IP)₂C, mannose-(inositol-P)₂-ceramide; MRM-MS, multiple reaction-monitoring mass spectrometry; PC, phosphatidylcholine; PE, phosphatidylethanolamine; PI, phosphatidylinositol; PS, phosphatidylserine.

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availability (Alvarez-Vasquez et al., 2007; Zaman et al., 2008; Ejsing et al., 2009; Guan et al., 2009; Young et al., 2010; Gaspar et al., 2011; Klose et al., 2012), but also to sense the levels of the different lipids and adjust their lipid composition to preserve cellular functions (Tuller et al., 1999; Gaspar, 2006; Guan et al., 2009; Young et al., 2010; De Smet et al., 2012). Punctual perturbations in steps of lipid metabolic pathways can be compensated by the interlinked pathways, preserving cell viability with no obvious physiological consequences. Nevertheless, many important diseases have a lipid component in their epidemiology, highlighting the physiological consequences of an altered lipid homeostasis. Despite the obvious importance, relatively little is known about the regulatory mechanisms controlling lipid homeostasis (Holland and Summers, 2008; Petranovic et al., 2010; Roelants et al., 2010; Summers, 2010; Fu et al., 2011).

With a few hundred lipid species and conserved lipid metabolic pathways with mammals, the yeast *Saccharomyces cerevisiae* represents a useful model organism for studying lipid homeostasis (Daum *et al.*, 1998; Ejsing *et al.*, 2009; Nielsen, 2009; Breslow and Weissman, 2010; Carman and Han, 2011; Santos and Riezman, 2012).

Protein phosphorylation is a major regulatory mechanism that controls many basic cellular processes in cells (Manning *et al.*, 2002; Tan *et al.*, 2009; Tan, 2011). A number of large-scale studies have been performed in *S. cerevisiae* to gather data and insights into phosphorylation-based signaling (Ptacek *et al.*, 2005; Fiedler *et al.*, 2009; Bodenmiller *et al.*, 2010; Breitkreutz *et al.*, 2010). Some key enzymes of lipid metabolism, including CTP synthase, PS synthase, choline kinase, and ORM proteins, have been already described as being regulated by phosphorylation (Kobayashi and Nagiec, 2003; Carman and Kersting, 2004; Choi *et al.*, 2010; Roelants *et al.*, 2010). However, until now, a systematic analysis of the effect of kinases and phosphatases on the lipid composition of a cell has not been done.

In this work, we analyzed the lipid composition of 129 yeast strains with gene deletions of nonessential kinases or phosphatases in a systematic approach to uncover new players in the regulation of lipid homeostasis.

RESULTS AND DISCUSSION

The large-scale lipidomic strategy

To assess the effect of a missing kinase or phosphatase on the lipid profile of S. cerevisiae, we systematically analyzed the lipidome of knockout strains of nonessential kinases and phosphatases (Supplemental Table S1). Strains were grown in rich media and harvested at early exponential growth phase. Using class-specific lipid extractions followed by mass spectrometry, our lipidomic approach covered most of the major lipid classes in yeast (Figure 1; Ejsing et al., 2009; Guan et al., 2010). For phospholipid and sphingolipid analysis, we used multiple-reaction monitoring mass spectrometry (MRM-MS), which allows a robust analysis of lipids of interest with high selectivity and sensitivity (Guan et al., 2010). We monitored the signals of hundreds of lipid species (Supplemental Table S2), whose relative quantification was achieved using appropriate internal standards that were spiked into the sample before lipid extraction. For sterols, we used gas chromatography coupled to mass spectrometry (GC-MS). Ergosterol was identified by its pertinent fragment ions and retention time (Guan et al., 2010).

We analyzed the lipid profile of 129 yeast knockout strains and wild type in biological duplicates with up to six technical replicates per biological replicate. To ensure consistent data quality for global comparison between the strains (i.e., to avoid biases arising from interplate variability), data were adjusted and normalized according to the batch of lipid extraction and analysis. We also applied filters



FIGURE 1: Workflow of lipid analysis. The lipid profile of yeast knockouts of protein kinase or phosphatase gene was systematically generated. Each strain was grown in standard conditions and processed in independent biological duplicates. Lipids were extracted according to different protocols and subjected to mass spectrometry analysis. Glycerophospholipids (GPLs) and sphingolipids (SLs) were analyzed by electrospray ionization mass spectrometry (ESI-MS) using multiple reaction monitoring. Sterols were analyzed using gas chromatography coupled to mass spectrometry (GC-MS). MS signal intensities were converted to relative concentrations based on standard curves of internal standards spiked in the samples before lipid extraction. Data were normalized and analyzed as described in *Materials and Methods* and the Supplemental Information.

based on 1) frequency of lipid detection along the screen and 2) average coefficient of variation of lipid detection between the biological replicates as a measure of quality control for lipid detection (Supplemental Information and Supplemental Figure S1). The final list of lipids contained 147 lipids whose acquisition was considered robust. Reproducibility of biological replicates was determined by coefficient of correlation, and highly disparate samples were removed from analysis. For lipid hit selection, we set fold-change thresholds combined with a moderate effect of strictly standardized mean difference (SSMD; Zhang, 2007; Zhang *et al.*, 2007; Supplemental Information and Supplemental Table S3).

We generated a comprehensive large-scale data set of lipid profiles with detailed features such as lipid class, chain length of the fatty acid moieties, unsaturation index, and number of hydroxylations. Our results provide data for lipids covering most of the major lipid classes in yeast in 127 mutant strains and wild types (Supplemental Table S4 and Supplemental Figure S3A). To ensure the specificity of our measurements, we selected representative samples from the screening for validation by high-resolution mass spectrometry using a Thermo Q Exactive mass spectrometer. The masses of the major lipids were detected with an average offset of <2 ppm, and the relative signal intensities of different lipids confirmed the results from the MRM screening (Supplemental Figure S2).

Our lipidomic approach is validated by comparison with data from the literature (described later). On the basis of the high-content data of this screening, we were able to perform multiple queries about patterns of lipid alterations that link kinases and phosphatases to the control of lipid homeostasis. Here we inspect the data for biological connections in the context of lipid homeostasis. In particular,





we show that deletion of distinct members of signaling pathways involved in nutrient sensing have a large effect on the lipid profile. Through an unbiased approach, we found novel connections between nutrient-sensing pathways and the regulation of lipid metabolism (Kobayashi and Nagiec, 2003; Roelants *et al.*, 2011) and also uncovered new, unsuspected players in the regulation of lipid metabolism.

General aspects of lipid homeostasis revealed by large-scale screening

As a first unbiased attempt to find the similarities between lipid profiles of different mutants, we generated a correlation matrix of the mutants (Figure 2A). Two prominent clusters emerged, enriched in components of amino acid– and glucose-sensing pathways. By this exploratory approach, when one plots the quantities of all lipids relative to wild type for the 127 strains, high complexity is seen (Supplemental Figure S3A), suggesting that diverse signaling pathways control different aspects of lipid homeostasis. Of importance, using an unbiased clustering analysis, the vps15 and vps34 mutants clustered adjacent to each other. The two corresponding proteins are members of the same functional complex involved in autophagy and protein sorting (Obara *et al.*, 2008). This shows that our method of lipid profiling can give valuable information about biological function. This has important consequences because it suggests that determination of lipid profile is a useful tool to identify potential defects in cellular signaling pathways. Lipid alterations associated with disease could therefore be useful biomarkers to pinpoint disease mechanisms.

To simplify data analysis and uncover gene associations and regulatory pathways, we split the lipid data into major categories of interest. Lipids were classified according to their structural features into different lipid classes and subclasses based on their backbone, head group, fatty acid chain length, unsaturation index of the glycerophospholipids, and hydroxylation state of sphingolipids (Supplemental Table S2).

Concentrating on particular lipid classes, we were able to extract general information on the ability of yeast cells to remodel their lipid profile. Overall we noticed an interesting pattern in the magnitude of perturbations of each lipid class: the extent of changes (expressed as variance) of sphingolipids oscillated between 0.2 and 0.8, whereas that for total glycerophospholipids was between 0.05 and 0.08 (Supplemental Table S3 and Supplemental Figure S3B). These data suggest that the ceramidesphingolipid pathway is more easily affected by disturbances in the kinase-phosphatase network compared with the glycerophospholipid pathway because they show a broader distribution in the magnitude of lipid amounts. Part of the explanation for this distinction could be the architecture of the biosynthesis and degradation pathways of these major groups: 1) ceramides and complex sphingolipids are synthesized in a linear manner with a single point of entry in

the pathway through serine palmitoyltransferase with either conversion to complex sphingolipids or exit through a single portal (via the lyase, Dpl1p), whereas 2) phosphatidylcholine (PC), phosphatidylethanolamine (PE), phosphatidylinositol (PI), and phosphatidylserine (PS) have multiple paths of synthesis (de novo, Kennedy, and/or the reacylation of lysophospholipids; Supplemental Figure S4).

When comparing regulation of different lipid classes, we observed that PC and PE levels are highly correlated (r = 0.71; Supplemental Figure S5A). This suggests that the control of homeostasis of these two lipid classes is closely related and probably employs similar regulatory mechanisms. The ratio PE:PC in the plasma membrane has been proposed to be critical for plasma membrane stability, and mechanisms of control have been recently suggested (Roelants *et al.*, 2010; Tavassoli *et al.*, 2013). Pis1p and Cho1p compete for CDP-DAG for the synthesis of PI and PS, respectively, making this branch an important point of regulation (Henry *et al.*, 2012). Investigation of the mutants with unbalanced PI/PS ratio (Supplemental Figure S5B) reveals novel candidates for the regulation of this switch.

Sterols were the least affected of the lipid classes, with hits in <10% of the mutants (Supplemental Table S4 and Supplemental Figure S3B). Ergosterol is a main component of the yeast plasma membrane (Zinser *et al.*, 1993), and, not surprisingly, most genes of its synthesis are essential for cell viability; nonessential gene

		В			
relative impact	0.7		High	High impact	
	0.6 - 8	CKAZ	CNA1	DPEZO	
	0.5 - 🔗	CALOS	CNAI	DBF20	FFKI
	04 -	GAL83	GCNZ	IIVIEZ	KCC4
	0.4	MIH1	MRK1	NNK1	OCA1
	0.3 -	PBS2	PHO85	PPH21	PSK2
	0.2	PSR1	PTC1	PTC5	PTK2
	0.1	PTP2	RIM15	RTK1	SNF1
	and the second	STE11	TOR1	ТРКЗ	VPS15
		VPS34	YPK1	УРК2	YPI 150V
	veast strains	VV/111			
	•	TVHI			

FIGURE 3: Nutrient-sensing pathways have a strong effect on the lipid profile. (A) The relative impact (RI) of a given knockout gene on the lipidome is a global measurement of disturbance in the lipid profile, calculated by the relative number of lipids that scored as a hit from all lipids analyzed (details in the text). High impact, RI > 0.22. (B) High-impact mutants implicated in nutrient-sensing pathways are highlighted in blue.

deletions cause many abnormalities (Munn et al., 1999; Umebayashi and Nakano, 2003; Guan et al., 2009; Aguilar et al., 2010). Although regulation through gene expression is well described for ergosterol synthesis, enzymatic regulation of ergosterol biosynthesis steps is largely unknown, with no reference of phosphoregulation, suggesting that there might be minimal direct regulation (Sturley, 2000) by protein phosphorylation. Nevertheless, changes in sterol levels might arise by a secondary effect of changes in other lipid classes.

Global analysis reveals the effect of nutrient-sensing pathway on the lipidome

Α

Given that kinases and phosphatases belong to highly interconnected networks (Sharifpoor et al., 2012) with multiple compensatory effects, we anticipated that most of single-gene knockouts would have minimal consequences on the lipid profile. We decided to estimate the effect of a specific gene deletion on the lipidome as a function of the relative number of lipids that scored as a hit (Supplemental Information and Supplemental Table S6). Indeed, the majority of gene deletions had a minor effect on the lipidome (Figure 3A), and these small changes might simply reflect secondary effects. On the other hand, the high-impact group was enriched for members of central signaling pathways controlling metabolism. Kinases and phosphatases related to glucose metabolism (SNF1, GAL83, PPH21), nitrogen metabolism (TOR1, GCN2), phosphate metabolism (PHO85), and stress pathways (PBS2) were identified, suggesting that broad-spectrum signaling pathways might be important regulatory hubs of lipid homeostasis (Figure 3B).

The ability to adapt the membrane lipid profile to different environmental conditions seems to be an important adaptive feature of yeast. It was shown that the carbon source influences the glycerophospholipid and sphingolipid profile of yeast (Tuller *et al.*, 1999; Klose *et al.*, 2012). Nutrient-sensing mechanisms trigger multiple signaling pathways, which are finely orchestrated (Zaman *et al.*, 2008), but the functional wiring that connects nutrient sensing to lipid homeostasis is largely unknown. Our data reveal important candidates for these regulatory networks.

Glycerophospholipid homeostasis is linked to nutrient-sensing pathways

In *S. cerevisiae*, the major glycerophospholipids are PC, PE, PI, PS, phosphatidylglycerol, and cardiolipins. The control of glycerophospholipid homeostasis is fairly complex, with routes of synthesis,

degradation, and recycling contributing to the overall lipid profile of a cell. The regulatory modes involve genetic and biochemical mechanisms (Henry *et al.*, 2012) in order to maintain a proper membrane lipid composition in response to changes in growth conditions.

Two important features of the lipidome with implications for membrane properties are the chain length and unsaturation index of fatty acids of glycerophospholipids. In *S. cerevisiae*, chain length is determined by the elongases Elo1p, Elo2p, and Elo3p, whereas desaturation is performed by Ole1p. Oleic acid (C18:1) and palmitoleic acid (C16:1) together with palmitic acid (C16:0) and stearic acid (C18:0), are the most abundant fatty acids in *S. cerevisiae* (Stukey *et al.*, 1989; Tehlivets *et al.*, 2007). The combination of fatty acids in the *sn-1* and *sn-2* positions of the glycerophosphate backbone differs in each lipid class (the major PC is PC32:2 and the major PE is 34:1; Supplemental Table S4), and the mechanism by which cells coordinate the different compositions is largely unknown (Boumann *et al.*, 2004b).

To address the mechanisms of control of these features through protein phosphorylation, we performed an unbiased comparison of lipidomics data from all the mutants. By hierarchical clustering based on the glycerophospholipid profiles, we observed two groups affecting the chain length of fatty acids with opposite effects. Among these, there were mutants in components of common signaling pathways—for example, in the glucose-sensing pathway, such as *SNF1*, *GAL83*, *ELM1*, *TOS3*, and *PPH21*—that caused an increase in the amounts of long-chain species of glycerophospholipids. In contrast, knockouts of *TOR1* and *GCN2* (among others) increased the amounts of short-chain-length species and decreased the levels of the longer ones (Supplemental Figure S6).

SNF1 and TOR1 are major regulators of energy homeostasis in yeast. They are central players in glucose- and nitrogen-sensing pathways, respectively, as well as regulators of the switch between catabolism and anabolism. The signals triggered by Snf1p and Tor1p induce opposite responses (activation/repression) of similar processes (Usaite *et al.*, 2009; Zhang *et al.*, 2011). By comparing the changes in glycerophospholipid (GPL) profile in the two mutant strains (Figure 4A), we observed that the lipid composition also reflects this functional anticorrelation. The major differences between $snf1\Delta$ and $tor1\Delta$ mutants are in the fatty acid chain length of GPLs (Figure 2B and Supplemental Table S5).

Despite the clear lipid alterations promoted by the absence of nutrient-sensing pathway components, the mechanisms



FIGURE 4: Nutrient-sensing pathways revealed by lipidomic screening. Global analysis of lipid changes revealed a strong effect of major nutrient-sensing pathways in the lipid profile of a cell. (A) Changes in glycerophospholipid profiles of $snf1\Delta$ and $tor1\Delta$ mutants are anticorrelated and reflect their opposite biological roles in cellular metabolism. (B, C) The $snf1\Delta$ mutant was complemented by SNF1, which also reversed its lipid profile back to wild-type cells. EV, empty vector. Data are median and SD of biological triplicates. *p < 0.05, t test.

behind this are not understood (Klose *et al.*, 2012). *SNF1* was first described as regulator of glucose repression (Celenza and Carlson, 1984), but its roles span the whole spectrum of cellular metabolism (Polge and Thomas, 2007; Usaite *et al.*, 2009). A defined linkage between *SNF1* and lipid metabolism occurs through the negative regulation of *ACC1* (acetyl-CoA carboxylase) upon glucose deprivation (Woods *et al.*, 1994). More recently, a lipid-related epistasis miniarray profile uncovered a negative genetic interaction of *SNF4* (a subunit of Snf1 kinase complex) with genes from the de novo biosynthesis of glycerophospholipids, suggesting that Snf1 signaling might coordinate the Kennedy pathway (Surma *et al.*, 2013).

We first confirmed the role of Snf1p in controlling the lipid profile by complementation of the *snf1* Δ strain with a plasmid carrying the *SNF1* gene (Figure 4B). The changes observed in the chain length of GPL in *snf1* Δ were reverted to wild-type levels by gene complementation (Figure 4C).

To obtain mechanistic insights, we then examined whether the changes in the lipid profile are related to preferential use of one of the two different biosynthetic routes for PC and PE (Henry *et al.*, 2012). GPLs of a mutant strain for the CDP-DAG pathway were reported to contain higher amounts of C18 than C16 fatty acyl chains (Schuiki *et al.*, 2010), which suggests that the glucose-sensing-related mutants might be using it preferentially, which would be consistent with negative regulation of the Kennedy pathway by Snf1p.

To test this hypothesis, we determined the lipid profile of $snf1\Delta$ cells in strains that possess only one functional biosynthetic route for PE and PC: either the CDP-DAG pathway (de novo; $cki1\Delta$, $eki1\Delta$, $dp/1\Delta$, referred to as CED Δ) or the Kennedy pathway ($psd1\Delta$, $psd2\Delta$, $ale1\Delta$, referred to as PPA Δ ; Figure 5A).

Analysis of the relative levels of GPL-containing short-chain (C28-C32) and long-chain (C34-C40) fatty acids showed that, in wild type (WT), there is a prevalence of long-chain fatty acids in PI, PS, and PE (and short chain in PC; Figure 5B, blue bars). This steadystate composition is a result of the contributions of both synthesis and turnover pathways. The lipid profile is altered when cells can use only the CDP-DAG pathway (CED Δ), with the relative amount of short-chain fatty acids being higher (Figure 5B, red bars). In cells in which the CDP-DAG pathway was compromised and the GPLs were synthesized by the Kennedy pathway, the strain contained higher amounts of long-chain fatty acids, similar to the wild-type strain (Figure 5B, green bars). These results are consistent with previous reports of prevalence of C18 fatty acids via the Kennedy pathway (Schuiki et al., 2010). At first surprising, the ratio between long and short PC species is somewhat less affected by the availability of a given biosynthetic route, as seen by the similar values for WT and mutant strains. However, the robustness of the PC profile is most likely due to both the use of the methylation pathway from PE to PC, which preferentially uses the short species PE32:2 as a substrate (Boumann et al., 2004a), and the constant remodeling of newly



FIGURE 5: *SNF1* regulates the homeostasis of fatty acid chain length in glycerophospholipids. (A) Scheme of GPL biosynthesis in *S. cerevisiae*. Under normal conditions, the CDP-DAG pathway (red box) is the major route for synthesis of GPLs with a contribution of the Kennedy pathway (green box). (B) Ratio of long-chain fatty acids (FAs; >C18) over short-chain FAs (<C16) in GPL. WT strain (blue bars) and a strain containing only the Kennedy pathway (*PPA* Δ , green bars) have a prevalence of long-chain FAs in PI, PS, and PE but not in PC. The strain containing only CDP-DAG pathway (*CED* Δ , red bars) has similar amounts of long- and short- chain FAs in PI, PS, and PE and a prevalence of short-chain FAs in PC. *SNF1* deletion caused a general increase in the amount of long-chain FAs in all GPLs. No selective effect of *SNF1* deletion on the CDP-DAG or Kennedy pathway was observed. Data are represented as ratio of long/short GPLs. Mean and SD of three independent biological replicates are shown. Data given in Supplemental Table S11.

synthesized PC species (Boumann *et al.*, 2003). Moreover, a functional Kennedy pathway has been described as required for maintenance of the steady-state PC profile, specifically for the incorporation of C16:0 acyl chains (de Kroon, 2007; De Smet *et al.*, 2012), which is in agreement with the observed decrease in PC32:1 but not PC32:2 in CED cells (Supplemental Table S11).

When *SNF1* was disrupted, we observed a general increase in the levels of GPLs with long-chain fatty acids in all lipid classes. Of importance, this effect was not pathway dependent. On *SNF1* deletion, both mutant strains showed a substantial increase of long-chain-containing GPL as compared with the reference strains (Figure 5).

Therefore this experiment confirmed that the CDP-DAG and Kennedy pathways generate different lipid species of PE and PC, which reflects the previously suggested different fatty acid selectivity between the two pathways. It also showed that the effect of *SNF1* deletion on length of fatty acyl chains and the steady-state levels of GPL is independent of the synthetic pathway being used (CDP-DAG or Kennedy pathway). Instead of pathway substrate selectivity, our data suggest that deletion of *SNF1* causes an increase in the availability of long-chain fatty acids, which would be incorporated by both synthesizing pathways. Given that Snf1p is a negative regulator of Acc1p, one can envisage a scenario in which, upon *SNF1* deletion, Acc1p activity is higher, increasing the levels of malonyl CoA (Shirra *et al.*, 2001; Shin *et al.*, 2012), a substrate for fatty acid elongation by the elongases Elo1 and Elo2p (Tehlivets *et al.*, 2007). The greater abundance of long-chain fatty acids would then be reflected in an unbalanced ratio of long- and short-chain fatty acids.

Our data not only imply that the glucose signaling pathway is linked to the GPL profile via regulation of fatty acid metabolism, they also suggest that Snf1p plays a biological role under nutrientrich conditions (>1.5% glucose), in which it is allegedly inactive (Momcilovic and Carlson, 2011).

Curiously, data from a phosphoproteomic study (Bodenmiller et al., 2010) revealed that the Pct1p phosphorylation (cholinephosphate cytidyltransferase, a rate-determining enzyme of the



FIGURE 6: Novel candidates for regulation of sphingolipid homeostasis. (A) Relative changes (log₂[normalized data]) in total amounts of ceramides (CER) and the major complex sphingolipid (IPC). Strains that scored as a hit for low levels (blue) or high levels (red) are listed. Details are in the text.

CDP-choline branch of the Kennedy pathway) is strongly reduced in $snf1\Delta$, which suggests a certain level of regulation of the pathway (which might be masked by the overall effect of high levels of long-chain fatty acids in our measurements).

Among the mutants with a large effect on GPL, $vps15\Delta$ and $vps34\Delta$ mutants shared some of the lipid phenotypes with $snf1\Delta$. *VPS15* and *VPS34* are genes that code for the protein complex responsible for phosphatidylinositol 3-phosphate synthesis (Strahl and Thorner, 2007). Although initially puzzling, a biological connection has recently been described showing that that the mammalian homologue of Snf1p, AMP kinase, controls the activity of Vps34p complexes in mammalian cells during nutrient stress and autophagy (Kim *et al.*, 2013). Our data suggest that this new biological connection might be conserved from yeast to mammals, opening up the possibility of using yeast genetics to understand the mechanism. Consistent with a fairly direct connection of nutrient sensing and lipid homeostasis, $vps15\Delta$ and $vps34\Delta$ mutants also affect the phosphorylation of the same Pct1p phosphopeptide (Bodenmiller *et al.*, 2010).

Revealing new candidates of sphingolipid homeostasis

Despite the significance of sphingolipid intermediates as bioactive molecules involved in key physiological and pathological processes, we are just starting to understand the control of their homeostasis (Cowart and Hannun, 2007; Brice et al., 2009; Roelants et al., 2011; Liu et al., 2012). In our search for novel regulators of the sphingolipid pathway, we sought concurrent changes in the levels of ceramides and complex sphingolipids as a indicator of the pathway activity. Ceramides and inositolphosphorylceramide (IPC), which is a major subclass of complex sphingolipids, were quantified. We found a number of candidates with alterations in these lipid classes, and, as expected, our lipidomic analysis revealed $cka2\Delta$ and $ypk1\Delta$ as strong positive regulators of sphingolipid amounts (Figure 6). Indeed, they regulate ceramide synthase (Kobayashi and Nagiec, 2003) and Orm proteins (Roelants et al., 2011; Sun et al., 2012), respectively. We also found increased amounts of sphingolipids in $tor1\Delta$, which is in agreement with the recent finding of its role in the negative regulation of Orm proteins (Shimobayashi et al., 2013).

Among the other strains with low levels of ceramides and IPC, one unsuspected mutant is $ctk1\Delta$. CTK1 is a subunit of C-terminal domain kinase (CTDK-1) that is involved in transcriptional regulation and translational events (Hampsey and Kinzy, 2007). Of interest, data from a phosphoproteomic study (Bodenmiller et al., 2010) showed that Ypk1p phosphorylation is strongly reduced in $ctk1\Delta$, which was confirmed here (Supplemental Figure S7A). Analysis of the same phosphoproteomic data also showed that YPK1 and CTK1 share multiple coregulated phosphopeptides, reinforcing the idea that they work on similar pathways (Supplemental Figure S7B). This scenario suggests that CTK1 is a novel regulator of sphingolipid homeostasis, but the mechanisms remain to be elucidated.

In the groups of mutants with increased amounts of ceramides and sphingolipids, we noticed the presence of mutants involved in the osmotic response pathway, such as $hog1\Delta$, $slt2\Delta$, and $pbs2\Delta$ (Figure 6). Alterations in the availability of free water and osmotic pressure regulation are two of the most basic challenges of living cells, and, not surprisingly, osmoadaptation mechanisms are essential and well-conserved cellular features (Hohmann, 2002). A highosmolarity shock triggers the high-osmolarity (HOG) pathway, whereas a low-osmolarity shock activates a cell wall integrity pathway (Supplemental Figure S8), both of which ultimately orient cells to adjust their metabolism and surface properties (Hohmann, 2002). Several mutants of the high-osmolarity and cell wall integrity pathways were found to be sensitive to inhibitors of sphingolipid synthesis, aureobasidin and/or myriocin (Hillenmeyer et al., 2008). Inhibition of sphingolipid synthesis has also been reported to activate protein kinase C signaling (Jesch et al., 2010).

It was reported that inhibition of sphingolipid synthesis results in activation of the HOG pathway (Barbosa *et al.*, 2011; Tanigawa *et al.*, 2012). Our results suggest a feedback between osmotic stress signals and sphingolipid homeostasis. Previous work showed a link between membrane tension and control of sphingolipid metabolism through relocalization of SIm1p to activate TOR complex 2 (Berchtold *et al.*, 2012). In this model, membrane stretching activates SIm1 protein relocalization, and reducing the osmolarity of the medium induces SIm protein relocalization through changes in membrane tension (Berchtold *et al.*, 2012). Our results suggest that an increase in osmolarity, detected through the HOG pathway,

works to oppose sphingolipid biosynthesis. We do not know whether the high-osmolarity response acts through SIm proteins and TOR complex 2.

In yeast, most of the C24-C26 fatty acids are found in sphingolipids, which are located primarily on the plasma membrane. Although sphingolipids are essential for cell viability, a mutant has been described that is able to survive in the absence of sphingolipids by producing compensatory glycerophospholipids containing a very long chain fatty acid (PI44:1 and PI42:1, not normally abundant in the cells; Vionnet *et al.*, 2010). It has been proposed that these unusual glycerophospholipids can partially mimic the structure and function of sphingolipids in the cellular membranes (Schneiter *et al.*, 2004). We observed that mutants with low levels of complex sphingolipids also show increased levels of C24- or C26-based PI (Supplemental Figure S9). One of those, *pho85* Δ , has a negative genetic interaction with *elo3* Δ (Huang *et al.*, 2002), which might arise due to defects in both sphingolipid regulation and compensatory pathways to produce C26-PI.

Our lipid analysis revealed that $pho85\Delta$ cells presented a unique sphingolipid profile (Figure 7A and Supplemental Table S5), leading us to hypothesize a link between sphingolipid metabolism and phosphate-sensing pathways. This mutant showed an accumulation of mannose-inositol-phosphorylceramide (MIPC) and reduced amounts of IPC. Results with mannose-(inositol-P)2-ceramide (M(IP)₂C) in this mutant were not statistically significant and therefore are not discussed here. The Pho80-Pho85 cyclin/cyclin-dependent-kinase (CDK) complex is a key component of the phosphate (PHO) signaling response in yeast. Inositol-pyrophosphates are highly energetic molecules with functions in different cellular processes (Bennett et al., 2006). They are formed by the sequential phosphorylation of inositol-triphosphate (IP₃) to IP₄ and IP₅ by Arg-82 and then to IP₆ by Ipk1p. In yeast, IP₇ can be synthesized by Vip1p (1PP-IP5) or Kcs1p (5PP-IP5), but only the product from Vip1p has been described as a specific inhibitor of the Pho80-Pho85 cyclin/CDK complex in a Pho81-dependent manner (Figure 7B; Lee et al., 2007).

We determined the sphingolipid profiles of vip1 Δ and kcs1 Δ mutants, and results showed that $kcs1\Delta$ mutation produced a perturbation similar to $pho85\Delta$, whereas the $vip1\Delta$ mutant was rather unaffected (Figure 7A and Supplemental Table S7). It has been described that the $kcs1\Delta$ mutant has an activated Pho4 pathway (Lee et al., 2007). The Pho85-Pho80 CDK complex regulates the expression of genes involved in phosphate metabolism by controlling the phosphorylation state and localization of the transcription factor PHO4. Under phosphate-rich conditions, Pho4p is phosphorylated and localizes in the cytosol. However, under phosphate starvation, the CDK inhibitor Pho81p inactivates the complex, which ultimately causes accumulation of nonphosphorylated Pho4p in the nucleus, where it induces transcription of phosphate-responsive genes. The lipidomic results suggest that sphingolipid homeostasis is affected by a perturbed phosphate-sensing pathway. Of interest, it has been recently described that under low-P_i conditions, Pho4p occupancy is highly enriched on the SUR1 gene, which encodes for the catalytic subunit of MIPC synthase (Zhou and O'Shea, 2011). Thus we tested whether SUR1 transcription was affected in the $pho85\Delta$ mutant, in which Pho4p is fully active (O'Neill et al., 1996), and, as expected, SUR1 mRNA expression was increased in pho85 Δ cells (Figure 7C). We also measured the IPC synthase (AUR1) transcript levels and found reduced amounts in $pho85\Delta$. These results are in agreement with the lipid profile of pho85∆ and thus suggest that sphingolipid homeostasis is regulated at the mRNA level by phosphate-sensing signaling pathways.



FIGURE 7: A connection between phosphate metabolism and sphingolipids. (A) Sphingolipid profile of $pho85\Delta$, $kcs1\Delta$, and $vip1\Delta$ mutants, showing an imbalance in MIPC/IPC levels in $pho85\Delta$ and $kcs1\Delta$. Data for IPC-C 44:0 and MIPC-C 44:0 (from Supplemental Table S8). (B) The inositol pyrophosphate pathway. The 1PP-IP₅ (IP₇) produced by Vip1 acts as a cofactor of Pho81, an inhibitor of CDK. Inactive CDK results in accumulation of nonphosphorylated Pho4 (not shown) in the nucleus, where it activates gene transcription. (C) Relative amounts of mRNA expression of *AUR1* and *SUR1* genes from the sphingolipid biosynthesis pathway (see Figure 4). Data from three independent biological replicates. Mean and SD. *p < 0.05, t test.

Functional nonredundancy of homologous genes

In all organisms, a single-gene knockout frequently results in no obvious phenotype, which is often a consequence of redundancy between duplicated genes (Li et al., 2010). Genetic redundancy not only provides robustness against deleterious mutations, but it is also a source of biochemical diversity, as the duplicated genes can accumulate mutations and eventually diverge functionally (Gu et al., 2003). Many genes coding for protein kinases and phosphatases in S. cerevisiae have paralogues that arose from whole-genome duplication. One could expect that, due to compensation, single deletion of paralogous genes would have minimal effect on the lipidome and thus would be less frequent in the group of mutants with large effect on the lipidome. Yet we observed that 38% of the high-impact genes had a paralogue counterpart (Supplemental Table S8). Diversification of duplicated genes is commonly asymmetric, that is, one of the duplicates is often more expressed and has more molecular and genetic interactions than the other (Wagner, 2002).

Our results showed that when considering the lipid profile, genes whose deletion had a large effect on the lipidome often had a paralogue with negligible effect (Supplemental Tables S5 and S8).

Between CNA1 and CMP2 (which, together with CNB1, are the subunits of the calcineurin A complex), only deletion of CNA1 had a strong effect, mostly observed as the reduction of lipids with short-chain fatty acids. Cna1p (but not Cmp2p) has been reported to interact with the long-chain fatty acyl-CoA synthetase (Faa4p), which is responsible for activation of exogenous long-chain fatty acids (Breitkreutz *et al.*, 2010), suggesting a distinct role for CNA1 in lipid metabolism.

The glycogen synthase kinase (GSK-3) has four different isoforms in yeast (*MRK1*, *RIM11*, *YGK3*, and *MCK1*). *MRK1* and *RIM11* are paralogous genes with known divergent functions: *RIM11* is involved in meiosis (Bowdish et al., 1994), whereas *MRK1* is important for growth at high temperature (Hirata et al., 2003). Deletion of *MRK1* caused an increase in phospholipids with shorter chain length, suggesting that *MRK1* requirements for growth at high temperature could be related to the increase in chain length observed in cells grown at 37°C (Klose et al., 2012).

FPK1 and its paralogous gene, *KIN82*, have been described as regulators of aminophospholipid flippases (Nakano *et al.*, 2008), which are also involved in sphingolipid (Roelants *et al.*, 2009) and sterol homeostasis (Muthusamy *et al.*, 2009). In both *fpk1* Δ and *kin82* Δ mutants, the levels of ceramides are reduced, whereas ergosterol levels are increased in *fpk1* Δ but reduced in *kin82* Δ .

Our data also showed paralogous genes with a minimal effect on the lipid profile of cells, such as CMK1/CMK2 and SAK1/TOS3. There are no reported connections between the calmodulin-dependent protein kinases Cmk1p and Cmk2p and lipid homeostasis in yeast, whereas the mammalian homologue, CaMKIIp, has been proposed to mediate lipolysis in adipocytes (Rapold et al., 2013). Sak1p and Tos3p are upstream kinases of Snf1p, which are activated by glucose-sensing mechanisms (Hedbacker and Carlson, 2008). We found that Snf1p is a major regulator of lipid homeostasis in yeast, and, of interest, deletion of its third upstream activating kinase, ELM1, gives a similar lipid phenotype as $snf1\Delta$. This suggests that ELM1 is not functionally redundant with SAK1 and TOS3 for lipid homeostasis. The lack of lipid phenotype of SAK1 and TOS3 could be due to a functional redundancy or a lack of involvement in lipid homeostasis, but additional experiments would be required to test these possibilities.

Limitations of the analysis

We show here that systematic lipidomics of yeast mutants is a powerful tool for uncovering new pathways of regulation of lipid homeostasis. This study, however, reveals only a snapshot of all possible cell growth contexts, and we believe many other associations of kinases and phosphatases with control of lipid homeostasis can be revealed under different growth conditions. Our findings should thus serve as starting point for researchers in the field to explore a broader range of biologically relevant contexts, such as different growth phases, nutrient-depleted media, and different osmotic and pH conditions. In addition, our type of analysis does not differentiate between direct and indirect effects of the mutations studied. As with any screen of this type using a deletion mutant collection, care should be taken when interpreting the results. As shown here as an example for the $snf1\Delta$ mutant, it is advisable to perform complementation studies or recreate mutants freshly and retest before making definitive conclusions.

One avenue to differentiate between direct and indirect effects would be to use analogue-sensitive alleles of the kinases (Bishop

et al., 2000) and determine a time course of events in the change of the lipid profile.

Despite having covered many of the major membrane lipids in yeast, our targeted lipidomics analysis was clearly not exhaustive. Other biologically relevant lipid species, such as phosphoinositides, phosphatidic acid, and triacylglycerides, have not been included due to the need of specific extraction and analytical methods that did not fit our large-scale lipidomics pipeline.

Final considerations and perspectives

We present here a new approach to gaining novel insights into the regulation of lipid homeostasis. By approaching the data from an oriented perspective, we can shortlist mutants and/or lipid phenotypes of interest and evaluate their correlation with a specific biological phenomenon, as done here for our search for new regulators of sphingolipid homeostasis. However, one can also approach it from a discovery perspective, in which lipid patterns emerge from global unbiased comparison, revealing unprecedented biological connections, such as between nutrient-sensing pathways and glycerophospholipid homeostasis.

The precise mechanism controlling the functional relationship between nutrient-sensing pathways and lipid homeostasis remains to be studied in detail, but it seems clear that there is a regulation by the glucose-sensing signaling pathway. Of importance, our analysis was performed with cells grown to early log phase in rich media, in which canonical nutrient-sensing signaling, such as the glucoseand phosphate-sensing pathways, are believed to be inactive. Nevertheless, we found significant alterations in the lipid profile, calling into question this assumption and suggesting that Snf1p activity is required for the correct regulation of glycerophospholipid homeostasis under these conditions.

The conditions we used in our work are frequently used in laboratory experiments, and therefore our data should be relevant for data mining when searching for links between lipid composition and mutant phenotypes. In another attempt to find new players in lipid homeostasis, a recent study described a high-throughput lipidomic platform to screen yeast libraries (Tarasov *et al.*, 2014). With an unconventional approach based on cell cultures grown on solid media and collected at stationary phase, the data generated will be difficult to compare with data from standard culture conditions due to the strong effect of growth phase and nutrient availability on the lipid profile of cells (Carman and Han, 2011; Klose *et al.*, 2012; Jewett *et al.*, 2013).

For future data mining and to provide a better link to studies of metabolism in general, we ensured that the lipids we present here are all now entered into the Chemical Entities of Biological Interest database, facilitating future bioinformatics approaches (Supplemental Table S10). We presented a robust strategy to systematically analyze the lipidome of yeast on a relatively large scale, and the data generated here represent a novel, rich set of information to understand lipid homeostasis and provide links between lipid levels and other phenotypes. New technical improvements will be necessary to make this methodology truly high throughput, especially concerning standardizing growth conditions for high throughput and the amount of time spent on MS analysis.

Our systematic lipidomic approach not only shows high agreement with preexisting results in the literature, but it also has predictive power, as it revealed intricate connections between the lipid profile of a cell, nutrient-sensing mechanisms, and environmental conditions. The signaling pathways seen here are fairly well conserved in mammalian cells, and it is likely that they will also be used there, perhaps linked to other nutrient controls, to regulate lipid homeostasis. Results of a similar analysis using small interfering RNAtreated cells for the mammalian kinome will test this hypothesis.

The kinase-phosphatase network of a cell is composed of a multitude of interactions and extensive cross-talk (Breitkreutz *et al.*, 2010). Many homologues in the protein kinase and phosphatase families that have been described to be functionally redundant, primarily for cell viability, showed distinct lipid patterns, suggesting that individual paralogues play distinct roles in lipid metabolism.

The data provided here contains a wealth of information, which will be further inspected for more biological and mechanistic connections in the context of lipid homeostasis. Owing to the close interaction between lipid metabolism and other cellular processes, such as energy homeostasis, gene regulation, membrane trafficking, and protein metabolism, it is clear that data from lipidomics studies are essential to comprehend the system as a whole. Finally, knowing the regulatory networks of lipid homeostasis is critical to tackling how its deregulation contributes to diseases, such as metabolic syndrome, Alzheimer disease, and genetic disorders of lipid catabolism (Outeiro and Muchowski, 2004; Smolenska-Sym *et al.*, 2004; Cookson *et al.*, 2011; Kaur *et al.*, 2013).

MATERIALS AND METHODS

Media, strains, and plasmids

Strains used in this study are presented in Supplemental Table S1. Yeast precultures were grown in rich medium (yeast extract/peptone/dextrose [YPD]: 2% glucose [Merck, Darmstadt, Germany], 1% Bacto Peptone [Difco, Allschwil, Switzerland], 2% Bacto Yeast Extract [Difco], 10 mM 2-(N-morpholino)ethanesulfonic acid [Sigma-Aldrich, Steinheim, Germany], 40 mg/ml L-tryptophan [Fluka, Steinheim, Germany], uracil [Sigma-Aldrich], and adenine ([Sigma-Aldrich]) to saturation and diluted to 0.003 OD₆₀₀ unit/ml, and cultures were grown to early exponential phase $(1-2 OD_{600})$ units/ml) in YPD at 30°C. Preliminary experiments using wild-type cell cultures showed that glucose levels remained well above 1% under these growth conditions. Metabolism was quenched by addition of trichloroacetic acid (TCA) to a final concentration of 5% (vol/vol) and cooling on ice. Pellets equivalent to 25 \mbox{OD}_{600} units were washed with cold 5% TCA and rinsed with distilled water. Cell pellets were frozen and kept at -80°C until lipid extraction. SNF1 constructs were expressed from its native promoter on a centromeric plasmid, pCE108 (Momcilovic and Carlson, 2011). Plasmid SNF1-WT was obtained from the lab of Marian Carlson (Columbia University Medical School, New York, NY). The snf1 Δ strain was constructed by one-step gene replacement using standard protocols.

Chemicals and lipid standards

We used 17:0/14:1 PC (LM1004), 17:0/14:1 PE (LM-1104), 17:0/14:1 PI (LM-1504), 17:0/14:1 PS (LM-1304), C17 ceramide (860517), and C8-glucosyl(β) ceramide (860540) as internal lipid standards, which were purchased from Avanti Polar Lipids (Alabaster, AL). Cholesterol was used as sterol standard and was purchased from Fluka. Pyridine (ReagentPlus) and methylamine solution (33% in absolute ethanol) were from Sigma-Aldrich. HPLC-grade chloroform was purchased from Acros (Geel, Belgium), and LC-MS–grade methanol and LC-MS–grade ammonium acetate were from Fluka. LC-MS–grade water was purchased from Fisher Scientific (Loughborough, United Kingdom).

Lipid extraction and analysis

Glycerophospholipids and sphingolipids. Lipids were extracted as previously described (Guan *et al.*, 2010) with minor modifications. Briefly, cells (25 OD_{600} units) were resuspended in 1.5 ml of extraction

solvent (ethanol, water, diethyl ether, pyridine, and 4.2 N ammonium hydroxide [15:15:5:1:0.018, vol/vol]). A mixture of internal standards (7.5 nmol of 17:0/14:1 PC, 7.5 nmol of 17:0/14:1 PE, 6.0 nmol of 17:0/14:1 PI, 4.0 nmol of 17:0/14:1 PS, 1.2 nmol of C17:0-ceramide, and 2.0 nmol of C8-glucosylceramide) and 250 µl of glass beads was added, the sample was vortexed vigorously (multitube vortexer; Labtek International, Christchurch, New Zealand) at maximum speed for 5 min and incubated at 60°C for 20 min. Cell debris was pelleted by centrifugation at $1800 \times g$ for 5 min, and the supernatant was collected. The extraction was repeated once, and the supernatants were combined and dried under a stream of nitrogen or under vacuum in a Centrivap (Labconco, Kansas City, MO). The sample was divided into two equal aliquots. One half was used for ceramide and sphingolipid analysis, in which we performed an extra step to deacylate glycerophospholipids using monomethylamine reagent (methanol, water, n-butanol, methylamine solution [4:3:1:5, vol/vol]; Cheng et al., 2001) to reduce ion suppression due to glycerophospholipids in sphingolipid detection. For desalting, both lipid extracts were resuspended in 300 µl of water-saturated butanol and sonicated for 5 min. We added 150 µl of LC-MS-grade water, and samples were vortexed and centrifuged at $3200 \times g$ for 10 min to induce phase separation. The upper phase was collected. Another 300 µl of water-saturated butanol was added to the lower phase, and the process was repeated twice. The combined upper phases were dried and kept at -80°C until analysis. For glycerophospholipid and sphingolipid analysis by electrospray ionization-MS/MS, lipid extracts were resuspended in 500 µl of chloroform:methanol (1:1, vol/ vol) and diluted in chloroform:methanol:water (2:7:1, vol/vol/vol) and chloroform:methanol (1:2, vol/vol) containing 5 mM ammonium acetate for positive and negative mode, respectively. A Triversa Nanomate (Advion, Ithaca, NY) was used to infuse samples with a gas pressure of 30 psi and a spray voltage of 1.2 kV on a TSQ Vantage (ThermoFisher Scientific, Waltham, MA). The mass spectrometer was operated with a spray voltage of 3.5 kV in positive mode and 3 kV in negative mode. The capillary temperature was set to 190°C. MRM-MS was used to identify and quantify lipid species as previously described (Guan et al., 2010). Data were converted and quantified relative to standard curves of internal standards that had been spiked in before extraction. Two independent biological replicates were analyzed, each of which comprised up to six technical replicates.

For glycerophospholipid and sphingolipid analysis by highresolution mass spectrometry, we used a Q Exactive Hybrid Quadrupole-Orbitrap Mass Spectrometer (Thermo Scientific). Lipid extracts were dissolved in 500 µl of chloroform:methanol (1:1, vol/ vol) and diluted two times in 5 mM ammonium acetate in chloroform:methanol:water (2:7:1, vol/vol/vol) for both positiveand negative-ion-mode mass analysis. Samples were analyzed by direct infusion. Positive-ion-mode analysis was performed using scan range m/z = 650-800 (for monitoring PC and PE) and 540-750, using lock mass 588.4471 (for ceramides). Negative-ion-mode analysis was performed using scan range m/z = 700-850 (for monitoring PI and PS) and 550-1150 (for complex sphingolipids). The acquisition was set to 100 scans. Spectra were acquired using mass resolution of 280,000 and automatic gain control at 3e⁶. Lipid species were identified according to their m/z, and their abundance was calculated by their signal intensities relative to internal standards (17:0/14:1 PC for PC and PE, 17:0/14:1 PI for PI, 17:0/14:1 for PS, C8-glucosylceramide for complex sphingolipids, and C17 ceramide for ceramides).

Sterols. Briefly, cells (25 OD_{600} units) were resuspended in 600 µl of water and 1500 µl of methanol. Cells were vigorously vortexed for

5 min, and 750 µl of chloroform was added. Samples were vortexed and centrifuged for 1 min at $100 \times q$ to pellet the beads and cell debris. The supernatant was transferred to a clean tube. The beads were washed once with 600 µl of chloroform:methanol [1:2, vol/vol]), the supernatant was combined with the first one, and 400 µl of water was added to induce phase separation. Samples were centrifuged for 10 min at $3200 \times q$, the aqueous upper phase was discarded, and the lower, organic phase was transferred to a new tube and dried. Samples were then fractionated on a solidphase extraction column. Briefly, a silica column (SiOH, 100 mg/1 ml, Chromabond; Macherey-Nagel, Switzerland) was preequilibrated with 2×1 ml of chloroform. Sample was resuspended in 250 µl of chloroform, vortexed well, sonicated for 5 min, and loaded on the column. The sample was eluted by addition of 2× 650 μl of chloroform. The eluent, containing the sterols, was dried and flushed with a steam of nitrogen before storage to avoid oxidation. Extracts were analyzed by GC-MS as previously described (Guan et al., 2010).

Phosphate measurement. The total lipid extract was resuspended in 500 µl of chloroform:methanol (1:1, vol/vol), and 50 µl was placed in 13-mm disposable Pyrex tubes. After solvent evaporation, 20 µl of water and 140 µl of perchloric acid (70%) were added to the tubes. Samples were heated for 1 h at 100°C in a fume hood. Tubes were allowed to cool for 5 min at room temperature. Next 800 µl of freshly prepared water:1.25% NH₄ molybdate:1.67% ascorbic acid (5:2:1, vol/vol) was added to the tubes, followed by 5 min of heating at 180°C. Tubes were cooled at room temperature, and 100 µl was used for measurement of absorbance at 820 nm. A standard curve was generated with 0–20 µl of 3 mM KH₂PO₄ standard solution and processed identically.

Real-time PCR analysis. Total RNA was extracted using the RNeasy Mini Kit (Qiagen, Hilden, Germany). cDNA was synthesized by reverse transcription using Superscript II (Invitrogen, Zug, Switzerland) in a reaction of 1 µg of RNA, 1 µl of dNTPs (10 mM each; Invitrogen), 2 µl of hexamer (120 ng/µl), 4 µl of reverse transcriptase buffer, 2 µl of dithiothreitol (0.1 M), 0.5 µl of RNasin (40 U/µl; Promega, Dübendorf, Switzerland), and 1 µl of Superscript II. The reaction was composed of cycles of 10 min at 25°C, 50 min at 42°C, and 15 min at 70°C. Quantitative real-time PCR was done on an iCycler (Bio-Rad, Hercules, CA) with PCR System iQ SybrGreen Supermix (Bio-Rad). The list of primers is given in Supplemental Table S9. The reaction was composed of an initial incubation of 94°C for 1 min, followed by 40 cycles of 10 s at 95°C and 30 s at 60°C. All results were analyzed by the $2^{-\Delta\Delta CT}$ method (Livak and Schmittgen, 2001), using *ACT1* as a housekeeping gene.

Statistical methods

A detailed description of the lipidomic data analysis is given in the Supplemental Information. Unless otherwise noted, pairwise statistical analysis was based Student's *t* test, with $\alpha = 0.05$.

Information about lipid compounds annotated in this study is available on www.lipidomes.org.

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