Abstract—The postgenomic shift in paradigm from reductionism to systems-wide network inference has increased recognition that cardiovascular diseases are not simply determined by the genome but arise from an interaction and dynamic dysregulation of gene regulatory networks, proteins, and metabolic alterations. The advent of postgenomic technologies promises to interrogate these complex pathophysiological perturbations by applying concepts of systemic relationships to biomarker discovery. A multibiomarker panel consisting of biomarkers capturing different levels of information (eg, microRNAs to assess endothelial and platelet activation, molecular lipid species to profile metabolic status, and proteolytic degradation products to assess vascular integrity) could outperform inflammatory biomarkers without vascular specificity in their ability of predicting cardiovascular risk. As atherosclerosis develops over decades, different biomarkers may be required for different stages of disease. Thus far, there is no simple blood test to directly assess the health of blood vessels or identify vulnerable patients. We discuss strategies for biomarker discovery using post genomics technologies, with a particular focus on circulating microRNAs. The aim is to reveal distinctive cardiovascular phenotypes and identify biomarker signatures that complement the Framingham risk scores in clinical decision-making and in a stratified medicine approach for early preventive treatment of disease. (Arterioscler Thromb Vasc Biol. 2013;33:206-214.)

Key Words: biomarker ■ lipids ■ metabolomics ■ microRNAs ■ proteomics

Is There a Need for New Cardiovascular Biomarkers?
Discovery of novel biomarkers and improvement of risk prediction algorithms will be a key to fulfill the promise of personalized medicine. Although genuine personalized treatment is probably an unrealistic expectation within the budget constraints of current health systems, a stratified medicine approach to identify individuals at high risk may help to allocate available resources most efficiently in a setting with a rising epidemic of cardiovascular disease (CVD) fueled by obesity, hypertension, and diabetes mellitus and by an aging population. Besides, biomarkers may improve patient motivation; by facilitating risk communication and compliance to lifestyle changes and therapies.

The search for cardiovascular biomarkers dates back to the mid 1960s when creatine kinase and its cardiосpecific isoform creatine kinase-MB were established as indicators of acute myocardial damage. About a decade later, the Framingham Study pioneered the quest for long-term cardiovascular risk prediction. Framingham risk scores, as well as others, such as Prospective Cardiovascular Münster (PROCAM) study, Systemic Coronary Risk Evaluation (SCORE), and Reynolds, are widely accepted and implemented tools in clinical decision-making. These scores inform treatment decisions, but they leave ample room for improvement. Currently, the majority of cardiovascular risk is not explained by traditional risk factors. In fact, most events occur in patients with an average risk score who are erroneously deemed to be at intermediate or low risk because they have no or only 1 of the cardiovascular risk factors. In contrast, many high-risk individuals do not experience a cardiovascular event even in the long term. Thus, the renewed interest in biomarkers is warranted, and the recent advances in postgenomic technologies offer unprecedented opportunities for biomarker discovery.

How Well Do Current Cardiovascular Risk Factors Predict Risk?
Up to now, biomarkers linked to systemic and vascular inflammation, oxidative stress, or vascular calcification received most of the attention. In the latest (2010) release of the American College of Cardiology Foundation/American Heart Association guidelines for cardiovascular risk assessment in asymptomatic individuals, a few of these biomarkers (C-reactive protein, hemoglobin A1C, urinary albumin excretion, and lipoprotein-associated phospholipase A2) were given a class Ia or I Ib recommendation for clinical use in particular subgroups. Others like natriuretic peptides or oxidized phospholipids...
apoB-100–containing lipoproteins show promise and are currently being tested to establish their additive predictive value. CVD is inherently so complex that a single biomarker is unlikely to capture the individual predisposition to develop CVD or herald its sequelae. Also, it is challenging to improve the established cardiovascular risk scores by measuring new biomarkers and achieve meaningful incremental values over and above traditional risk factors. For example, C-reactive protein improves cardiovascular risk prediction in the general population, but its incremental predictive value is somehow limited because of its strong correlation with other risk factors, such as body mass index and smoking. Conventional risk scores already combine different levels of information (age, sex, family history, smoking status, hypercholesterolemia, hypertension, and diabetes mellitus) by relatively inexpensive measurements that can be readily performed in the clinic. To recapitulate this multi-risk factor strategy, advanced statistical and bioinformatics methods should be used to identify biomarker signatures that provide complementary information (ie, by determining the response of an individual to a given burden of cardiovascular risk factors).

Clinical Use of Genetic Testing for Cardiovascular Risk Prediction?

Although heredity encompasses an important aspect in the development of CVD and genome-wide association studies have unraveled intriguing susceptibility loci, the advance in cardiovascular risk prediction offered by genetic markers is modest at best. As a trait with complex genetic causes, CVD does not follow readily predictable patterns of inheritance but results from variation within multiple genes and their interaction with behavioral and environmental factors. Genome-wide association studies have identified single nucleotide polymorphisms (SNPs) for cardiovascular risk, but the risk alleles are common and have small effects (odds ratios of 1.1–1.3). Combining modest-risk genotypes, genes involved in lipid metabolism, endothelial function, and clotting did result in a significant 12% net reclassification improvement compared with Framingham risk score, by using 13 meta-analysis proven candidate gene SNPs and adding 7 genome-wide association SNPs. Nonetheless, the American College of Cardiology Foundation/American Heart Association guidelines opt for a thorough assessment of CVD family history but recommend against genetic testing for SNPs in CVD susceptibility genes. At present, it seems unlikely that genetic testing for cardiovascular risk will have a wider clinical use. The genotype may influence cardiovascular risk, but this risk is mediated through its impact on trait. Most genotypes will not predict risk over and above measures of cognate trait. Also, there is an urgent need to translate the results from genome-wide association studies into mechanistic insights. What is missing are those carved paths of linking SNPs to cell signal transduction and metabolism to promote our understanding of pathogenetic mechanisms.

Post Genomics Technologies: Beyond Individual Biomarkers

The assessment of individual biomarkers has provided much insight, but complimentary approaches are being pursued to advance CVD risk prediction:

1. The development of multistage risk scores or targeted scores for patient subgroups diverging from the current strategy of “one prediction tool fits all.”
2. The consideration of measures of preclinical disease status similar to cancer medicine. Coronary artery calcium, carotid artery intima-media thickness, and plaques are assumed to reflect life-time exposure to known and unknown risk factors and their interaction with an individual’s genetic background.
3. To go beyond genomics and interrogate the transcriptome, proteome, metabolome, and lipidome and move from solitary serum biomarkers, most of which are not specific to the vasculature, to biomarker signatures, and to biomarker networks.

The genetic specification of a human being, once assumed to be of almost limitless complexity, consists of just 20 000 protein-coding genes. Yet, >80% of the human genome is actively transcribed. These noncoding regions of the human genome have previously been termed junk DNA. It is now clear that biological complexity is determined not by the number of protein-coding genes (C. elegans has a similar number of protein-coding genes as humans, rice plants have twice as many), but by the regulation of these gene products. This shift in perspective quickly led to the creation of postgenomic sciences: transcriptomics for RNAs, proteomics for proteins, and metabolomics for small molecules. The genetic make-up of an individual may predispose to CVD but neither can it predict its onset nor progression. Biomarkers originating from postgenomic technologies are closer to the CVD phenotype than SNPs and provide information on epigenetic regulation, cell activation, tissue repair, and metabolic processes within the vasculature that may not be captured by standard risk factors. Given the recent advances in assessment methods (postgenomics technologies) and bio-statistics (methods capable of handling extensive amounts of data with high dimensionality and collinearity, network inference algorithms), this new phase in biomarker discovery and vascular risk prediction offers the realistic hope for improving patient stratification and clinical management.

Circulating MicroRNAs

MicroRNAs (miRNA) are short segments of RNA that are not translated into proteins, but function as posttranscriptional regulators of gene expression and have been implicated in CVD. Seminal studies by Mitchell et al have revealed the presence of endogenous miRNAs in the circulation that are not cell-associated. Unlike messenger RNAs, miRNAs are stable in blood. In the circulation, miRNAs are protected from RNAse activity by microvesicles (exosomes, microparticles, and apoptotic bodies), RNA-binding proteins (eg, Ago2 complexes), or lipoproteins (low-density lipoproteins and high-density lipoprotein). Thus, besides their classical role as a delivery vehicle for cholesterol, lipoproteins may also act as a carrier or depot for endogenous miRNAs and facilitate their transport and delivery to recipient cells. The existence of a miRNA pool within the circulation is an exciting new aspect of current biology and attracting considerable attention. miRNAs may offer distinct advantages over other biomarkers:
Unlike messenger RNAs, miRNAs are stable in blood. Circulating cells are probably the major contributor to the extracellular miRNA pool. Acute organ damage can lead to an increase of tissue-specific miRNAs (eg, cardiac miR-1 becomes detectable in the circulation after acute myocardial infarction [AMI]), but it is not a foregone conclusion that changes in tissue miRNAs will give rise to a corresponding change in circulating levels.

This study stands out with its prospective design and a population cohort of 820 individuals. Most studies published on miRNAs to date are small case-control studies comparing patients with manifest disease and healthy controls (Table). Evidence based on case-control comparisons has to be interpreted with caution because miRNAs are measured after disease onset and a temporal relationship cannot be established (reverse causality). Also, there is a need to standardize normalization procedures and introduce minimum requirements for statistical analysis. Prospective population-based studies comprise a wide range of individuals representative of the general community, and samples are taken before the onset of disease offering a better opportunity to identify miRNA signatures with specificity for CVD. Because it is currently unclear how cardiovascular risk factors impact on RNA biomarkers, our aim was to first assess the response of miRNAs to cardiovascular risk factors before identifying miRNA signatures of risk of AMI. The principal findings of these studies are as follows:

1. Among all cardiovascular risk factors tested (hypercholesterolemia, type II diabetes mellitus, smoking, and hypertension), type II diabetes mellitus had the most pronounced effect on circulating miRNA profiles.
2. A miRNA-based biomarker signature comprising just 3 miRNAs (miR-126, miR-223, and miR-197) of 19 miRNAs (Figure 1A) added information to an established standard, the Framingham Risk Score for Hard Coronary Heart Disease.
3. The integrated discrimination improvement, Akaike information criterion, and net reclassification index were used to assess to what extent adding information on miRNAs stratifies patients to risk categories that better reflected their disease outcome (Figure 1B).
4. The population study was accompanied by an intervention study in healthy individuals to determine their cellular origin. On the basis of expression profiles after limb ischemia-reperfusion injury, miR-126, miR-197, and miR-223 were part of 1 cluster that also included miR-21 and miR-24. All these miRNAs are highly expressed in platelets and platelet microparticles. This is, to our knowledge, the first time that the contribution of a specific cell type to circulating miRNAs has been defined by a controlled intervention.

The diagnostic and prognostic potential of circulating miRNAs requires confirmation and cross-validation in follow-up studies as well as independent cohorts. miRNA measurements before and after cardiovascular events during observation will be the ideal setting to define which miRNA pattern antedate the event and which develop as a response of disease manifestation (reverse causality). In addition, measurements are currently performed in plasma and serum. No study has as yet addressed the compartmentalization of circulating miRNAs in the context of cardiovascular risk prediction.

**miRNAs as Novel Biomarkers for Cardiovascular Risk Prediction**

To identify changes in circulating miRNAs that might precede subsequent cardiovascular events, we measured miRNAs in the Bruneck study. This study stands out with its prospective design and a population cohort of 820 individuals. Most studies published on miRNAs to date are small case-control studies comparing patients with manifest disease and healthy controls (Table). Evidence based on case-control comparisons has to be interpreted with caution because miRNAs are measured after disease onset and a temporal relationship cannot be established (reverse causality). Also, there is a need to standardize normalization procedures and introduce minimum requirements for statistical analysis. Prospective population-based studies comprise a wide range of individuals representative of the general community, and samples are taken before the onset of disease offering a better opportunity to identify miRNA signatures with specificity for CVD. Because it is currently unclear how cardiovascular risk factors impact on RNA biomarkers, our aim was to first assess the response of miRNAs to cardiovascular risk factors before identifying miRNA signatures of risk of AMI. The principal findings of these studies are as follows:

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### Table. Summary of Clinical Studies on miRNA Biomarkers

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<th>Description of Study Population</th>
<th>Study Size</th>
<th>No. of miRNAs Measured</th>
<th>Normalization</th>
<th>Statistical Adjustment*</th>
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<tr>
<td>Zampetaki et al24</td>
<td>General population → DM2 over 10 years</td>
<td>80 vs 80, 19† vs 19†</td>
<td>13</td>
<td>RNU6B, miR-454</td>
<td>++</td>
<td>Network analysis</td>
<td>…</td>
<td>Impaired glucose tolerance</td>
</tr>
<tr>
<td>Zampetaki et al25</td>
<td>General population → AMI over 10 years</td>
<td>820 vs 80, 19† vs 19†</td>
<td>19</td>
<td>U6, Ct average</td>
<td>++</td>
<td>Network analysis, L1 penalization, best subset (AIC)</td>
<td>C-index, NRI, IDI</td>
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<td><strong>Prospective studies/patients with preexisting CVD</strong></td>
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<tr>
<td>Widera et al26</td>
<td>ACS patients → all-cause mortality over 6 months</td>
<td>444 vs 444</td>
<td>6</td>
<td>Cel-miR-54</td>
<td>++</td>
<td>Network analysis</td>
<td>AUC</td>
<td>hs-cTnT</td>
</tr>
<tr>
<td>Eitel et al27</td>
<td>ACS patients → MACE over 6 months</td>
<td>216 vs 216</td>
<td>1</td>
<td>Cel-miR-39</td>
<td>++</td>
<td>Only 1 miRNA tested</td>
<td>…</td>
<td>Cardiac MRI</td>
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<td><strong>Case-control studies/acute coronary syndromes (ACS)</strong></td>
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<tr>
<td>Ai et al28</td>
<td>AMI patients vs hospital controls</td>
<td>93 vs 66</td>
<td>2</td>
<td>U6, Ct average</td>
<td>0</td>
<td>…</td>
<td>AUC</td>
<td>cTnI, CK-MB</td>
</tr>
<tr>
<td>Wang et al29</td>
<td>AMI patients vs non-AMI patients vs healthy controls</td>
<td>33 vs 33 vs 30</td>
<td>6</td>
<td>Cel-miR-39</td>
<td>0</td>
<td>…</td>
<td>AUC</td>
<td>cTnI</td>
</tr>
<tr>
<td>D’Alessandra et al30</td>
<td>STEMI patients vs healthy controls</td>
<td>33 vs 17</td>
<td>6</td>
<td>miR-17-5p</td>
<td>0</td>
<td>…</td>
<td>…</td>
<td>…</td>
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<tr>
<td>Adachi et al31</td>
<td>ACS vs HF vs controls</td>
<td>14 vs 15 vs 10</td>
<td>1</td>
<td>Internal reference small RNA</td>
<td>0</td>
<td>Only 1 miRNA tested</td>
<td>…</td>
<td>…</td>
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<tr>
<td>Cheng et al32</td>
<td>AMI vs controls</td>
<td>31 vs 20</td>
<td>1</td>
<td>?</td>
<td>+</td>
<td>Only 1 miRNA tested</td>
<td>…</td>
<td>CK-MB</td>
</tr>
<tr>
<td>Kuwabara et al33</td>
<td>ACS vs non-ACS patients</td>
<td>29 vs 42</td>
<td>2</td>
<td>?</td>
<td>0</td>
<td>…</td>
<td>AUC</td>
<td>cTnI</td>
</tr>
<tr>
<td>Oerlemans et al34</td>
<td>ACS vs non-ACS patients</td>
<td>106 vs 226</td>
<td>5</td>
<td>RNU6</td>
<td>++</td>
<td>…</td>
<td>AUC</td>
<td>hs-cTnT</td>
</tr>
<tr>
<td>Long et al35</td>
<td>AMI vs healthy controls</td>
<td>17 vs 25</td>
<td>2</td>
<td>RNU6</td>
<td>0</td>
<td>…</td>
<td>AUC</td>
<td>cTnI</td>
</tr>
<tr>
<td>Devaux et al36</td>
<td>NSTEMI vs STEMI vs healthy controls</td>
<td>113 vs 397 vs 87</td>
<td>2</td>
<td>3 Cel-miRNAs</td>
<td>0</td>
<td>…</td>
<td>AUC, NRI</td>
<td>CK-MB, cTnT, hs-cTnT</td>
</tr>
<tr>
<td><strong>Case-control studies/coronary artery disease (CAD)</strong></td>
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<tr>
<td>Fichtlscherer et al37</td>
<td>CAD patients vs healthy controls</td>
<td>67 vs 31</td>
<td>8</td>
<td>Cel-miR-39</td>
<td>0</td>
<td>…</td>
<td>…</td>
<td>Baseline characteristics</td>
</tr>
<tr>
<td>Gao et al38</td>
<td>Hyperlipidemic patients with and without CAD vs normolipidemic controls</td>
<td>255 vs 100</td>
<td>4</td>
<td>Cel-miR-39</td>
<td>++</td>
<td>…</td>
<td>…</td>
<td>Total cholesterol, triglycerides, LDL, HDL</td>
</tr>
<tr>
<td>Sun et al39</td>
<td>CAD vs non-CAD patients</td>
<td>31 vs 36</td>
<td>1</td>
<td>miR-16</td>
<td>0</td>
<td>Only 1 miRNA tested</td>
<td>…</td>
<td>LDL</td>
</tr>
<tr>
<td><strong>Case-control studies/heart failure</strong></td>
<td></td>
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<tr>
<td>Tijsen AJ et al40</td>
<td>HF vs non HF vs healthy controls</td>
<td>30 vs 20 vs 39</td>
<td>16</td>
<td>miR-1249</td>
<td>+</td>
<td>…</td>
<td>AUC</td>
<td>BNP and ejection fraction</td>
</tr>
<tr>
<td>Goren et al41</td>
<td>HF patients vs controls</td>
<td>30 vs 30</td>
<td>186;4 Ct average</td>
<td>0</td>
<td>…</td>
<td>AUC</td>
<td>BNP</td>
<td></td>
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</tbody>
</table>

(Continued)
miR-197, miR-223, miR-24 and miR-21, may reflect abnormal platelet function in diabetic patients. Also, previous comparisons of circulating miRNAs between healthy volunteers and patients with CVD are likely to be confounded by medication, in particular antiplatelet therapy.

**Mechanistic Links Between Circulating miRNAs and Cardiovascular Risk**

To expand mechanistic insights between miRNAs and cardiovascular risk, further downstream analysis will include identifying putative protein targets for these miRNAs. The 3 miRNAs implicated in cardiovascular risk have a mechanistic underpinning in endothelial damage and platelet dysfunction. Currently, most studies rely on bioinformatic algorithms or transcript analysis for the identification of miRNA targets. These algorithms are based on an incomplete understanding of miRNA-mRNA seed pairing and evolutionary conservation of miRNAs. They typically predict hundreds to thousands of target genes for 1 miRNA, but with limited overlap, and even the most sensitive programs fail to identify known targets. Importantly, cell type context is not taken into consideration. A considerable proportion of miRNAs act as translational inhibitors, and many effects can only be observed at the protein level and not at the mRNA level. The use of proteomics methods will be essential for a more comprehensive understanding of miRNA-mediated regulation of gene expression. Similarly, metabolomic techniques should be used to more thoroughly investigate the correlation of miRNAs with clusters of metabolites.

**Lipidomics: Molecular Lipid Profiling for Cardiovascular Risk Prediction**

Our knowledge about lipid biomarkers is mostly related to the classes of lipids rather than to single lipid species within the class. Biomarker studies investigating lipids focused on triglycerides, high-density lipoprotein, low-density lipoproteins, cholesterol, and their derivatives, which have been shown to be involved in the pathophysiology and progression of the disease. With regard to cardiovascular risk prediction, no detailed comparison of individual lipid species across these different classes has been performed till date. Targeting specific lipid species that are most atherogenic could result in a better classification of cardiovascular risk than relying on conventional lipid measurements.

We have recently used a shotgun lipidomics platform to provide a comparative lipidomics analysis of human endarterectomy samples. Shotgun lipidomics as described by Han and Gross uses the different scan options of a triple-quadrupole mass spectrometer to resolve isobaric lipids from different lipid subclasses and to detect even minor components, which would otherwise be masked by the presence of abundant lipid species. First a survey scan in positive and negative mode is acquired. Then, different product ion and neutral loss scans, characteristic for the different lipid classes, are used for the unambiguous identification of certain lipid classes by their product ions. This mass spectrometer-based intrasource separation technique allows the identification and quantification of hundreds of individual lipid species in a complex biological sample. A liquid extraction-based surface sampling device was adapted for the analysis of plaque lipids directly from tissue sections. Both methods, liquid extraction surface analysis from tissue sections and conventional analysis by preparing Folch extracts, showed similar results in terms of detected signals and their intensity. In total, 150 lipid species from 9 different classes were identified, of which 24 were detected in endarterectomy specimens only but not in healthy arteries.
quantitation, authentic standards of the different lipid classes were spiked in Folch extracts. Several lipids were reduced in regions with evidence of rupture, and one could envisage that leakage of these plaque-related lipid products into the circulation may constitute a better marker for plaque burden and vulnerability than total cholesterol levels and plasma lipoproteins. For example, Meikle et al used a target-focused analysis of plasma lipids to highlight the potential importance of measuring distinct lipid species rather than lipid classes in patients with stable and unstable coronary artery disease.

Proteomics: Assessing Vascular Integrity by Monitoring Proteolysis

With regard to biomarker discovery, proteomics has overpromised but underdelivered. The cardiovascular field is no exception. The plasma proteome is the most complex proteome of the human body. Current mass spectrometry techniques offer 4 to 5 orders of magnitude of linear dynamic range. Yet, the dynamic range of biomarkers routinely measured in the clinics spans 10 orders of magnitude. Under sampling results in an underrepresentation of classical plasma proteins in proteomic data sets. Unlike tissue leakage products, such as cardiac troponins, changes in abundant plasma proteins frequently lack specificity for disease. An alternative strategy is the application of proteomics directly to the diseased tissue, where the potential biomarkers are less dilute.

Although others have focused on circulating cells to identify cardiovascular biomarkers, we have developed a proteomics method to analyze the composition of the
cardiovascular extracellular matrix.56,57 By using a decellularization step, we overcome differences in cellular heterogeneity. Tissue heterogeneity is a major concern for any omics technology. Most clinical samples represent an endstage of human disease. In whole tissue, changes between controls and disease may reflect changes in the proportion of cell populations (ie, in inflammatory infiltration) rather than differential expression within a resident cell type. This problem is exaggerated with ever more sensitive techniques, such as next generation sequencing. Without information on cell composition, omics experiments may become an expensive substitution for histology. Besides, transcriptomics provides only a snapshot of gene expression at 1 time point; mRNAs are not informative about the events that occurred during the disease process or proteolytic activity. Instead, the extracellular matrix provides a read-out of vascular integrity and the inflicted damage during disease progression. These tissue-based experiments can be combined with an activity-based proteomics approach to identify novel protease targets and relate proteolytic activity ex vivo to the observed degradation products of extracellular matrix in vascular disease.58 Proteolytic activity is the key for plaque destabilization and aneurysm rupture. Numerous proteases, in particular matrix metalloproteinases, have been implicated. Yet, their targets in the vasculature are incompletely understood. By identifying proteolytic cleavage products in vascular disease, proteomics could provide a valuable resource that may reveal novel biomarkers.59 These biomarkers can then either be detected in the circulation or in urine, where proteolytic degradation products tend to accumulate.60

**Biomarker Validation**

Independent of the molecular entity of the biomarker, validation should adhere with rigor to the respective scientific statement by Hlatky et al61 endorsed by the American Heart Association. This includes the proof of an independent and robust association in adequately sized prospective population studies, stringent replication, testing of an incremental predictive value and of clinical use involving analyses on model calibration, risk discrimination, and risk reclassification. Tests commonly applied in this context are the c-statistics/index, the net reclassification index based on clinically relevant categories of risk,62 continuous net reclassification index,63 prospective net reclassification index,63 and integrated discrimination improvement.62 On top of biomarker discovery and validation, optimal timing and frequency of risk assessment as well as the best-fitting prediction period deserve adequate attention. Ascertainment of short-term CVD risk and of an unstable plaque phenotype, using imaging, blood, and urine biomarkers, is as yet an unmet goal with high clinical priority. Finally, the best new biomarkers and respective risk score extensions should be directly compared in randomized trials for cost-effectiveness and efficacy beyond current practice.61

A major drawback for biomarker studies using postgenomic technologies is the lack of standardization (ie, different RNAs are used for normalization of circulating miRNAs), and there are no search algorithms for unambiguous metabolite identification by mass spectrometry. Also, conventional statistical tests are not suitable for highly correlated variables such as miRNAs or metabolites. As postgenomic technologies advance, it is paramount to establish minimum standards for data analysis. Much can be learned from the tools and methods applied to genetics and genomics, but there is also a need for the development and application of new methods and tools specific to postgenomic technologies.

**Conclusions**

Over the last decade, innovative methods opened new possibilities for harnessing the potential of postgenomic technologies to study CVD processes in clinical samples. Postgenomic technologies have the distinct advantage that read-outs at the transcriptome, proteome, and metabolome level and are closer to the phenotype of complex traits such as CVD, with contributing factors ranging from genes to environment. The aim is the integration of different levels of information to better characterize the complexity underlying cardiovascular and metabolic diseases with the goal of illuminating biology and discovering
clinical biomarkers that may help to stratify patients. For example, changes in circulating miRNAs could be related to lipi-
domic as well as proteomic signatures to find new regulatory mechan-
isms of CVD. If successful, postgenomic technologies may propel multimarker strategies in the clinics. A comprehen-
sive noninvasive biosignature, comprising a panel of biomark-
ers, may serve as a potential tool in the early diagnosis and
prognostication of cardiovascular risk and prioritize individuals
at risk for therapeutic interventions. Nonetheless, “prediction is
very difficult, especially about the future” (Nils Bohr).

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as cardiovascular biomarkers.

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