INSTITUTIONAL ADVISORY & SOLUTIONS

THE PROBABILITY OF RECESSION

A Critique of a New Forecasting Technique

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A recent research publication develops a new business cycle forecasting technique using a metric called "Mahalanobis distance." This measure is intuitive, is based on a straightforward set of computations, is able to identify post-war US recessions with few false positives, and, as claimed by the authors, has a reasonable forward hit rate.

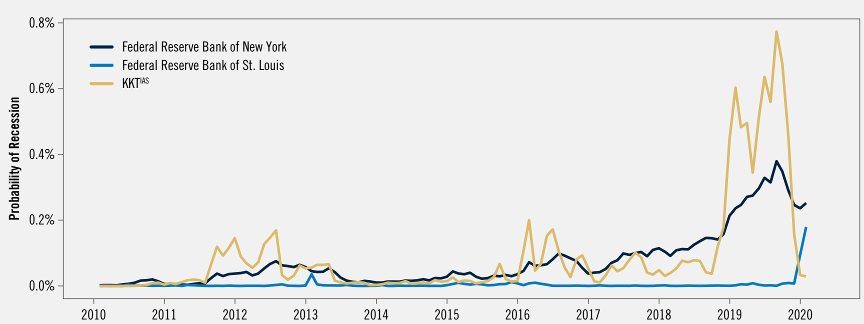
In late 2019, according to this new measure, the estimated probability that the US was in a recession had climbed to about 75%, a prediction that was at odds with many other models. However, by early 2020 and still prior to the pandemic, the measure's probability of recession had retreated, falling below 3%, and remaining subdued through March.

The measure's volatility prompted a closer technical look into its strengths and weaknesses and its potential as a market timing tool.

A recent working paper by Kinlaw, Kritzman and Turkington (hereafter, "KKT")[1] develops a new business cycle forecasting technique using a metric called **"Mahalanobis distance."** This technique measures the statistical similarity between economic conditions at a point in time and conditions during periods of either unusually weak economic growth – "recessions" – or of unusually strong economic growth – "robust growth." The measure, in turn, is used to evaluate the probability that the economy is in recession.

KKT concluded that in late-2019 the probability of recession had climbed above 75%, much higher than many off-the-shelf probability models (see Figure 1) and startling to

Figure 1: Probability of US Recession
KKT^{IAS}, FRB St. Louis, and FRB New York Models



Note: KKT^{IAS} refers to our replication of the KKT methodology (details below).
Source: Federal Reserve Bank of New York, Federal Reserve Bank of St. Louis, Haver Analytics, and PGIM IAS.

1 See Kinlaw et al. (2020).

many practitioners. However, by early 2020 (shortly *after* publication) the probability of recession (per our replication) had declined to less than 3%. The volatility of the KKT measure prompted a need to learn more about the strengths and weaknesses of this new methodology.

In our analysis of the KKT recession probability measure, we find: (1) all four candidate explanatory variables (industrial production growth, employment growth, trailing-twelve month (TTM) equity returns and the yield curve) matter historically; (2) however, the 2019/2020 sharp rise and subsequent decline in the probability of recession were due, in large part, to asset-market variables; (3) as a market timing tool, elevated KKT probability readings are preceded by equity market declines and are followed by equity market appreciation of about 6%; and (4) the probability of recession is sensitive to several technical issues in parameter estimation, particularly with respect to the variance-covariance matrix (VCV) used to weight the data. Our analysis of the KKT measure proceeds as follows:

1. **Overview: A Bayesian path from Mahalanobis distance to recession probability.** We review the details of calculating the Mahalanobis distance and the *pseudo* Bayesian method to convert the Mahalanobis metric into an estimate of the probability that economy is in a recession given a draw of current economic and market data. To analyze the KKT measure (available through October 2019) we first replicate it using the same methodology and inputs. We label our replicated version of KKT as KKT^{IAS}. Not only does KKT^{IAS} line up closely with (the original) KKT but also with NBER-dated recessions. Both KKT^{IAS} and KKT spiked up sharply in late 2019, with KKT^{IAS} receding quickly by year-end.
2. **KKT^{IAS} inputs: Macroeconomic and market variables matter.** Historically, all four input variables – industrial production growth, employment growth, TTM equity returns, and the yield curve – play an important role in the KKT^{IAS} recession probability indicator. However, market-based variables played an outsized role in driving up the probability of recession in late-2019 and in the subsequent decline.
3. **Can portfolio managers use KKT?** In short, a rising probability of recession may be a *risk-on* signal for markets. We find that S&P 500 returns are negative, on average, in the 12-months *before* the probability of recession climbs above 80%. Once the probability of recession climbs above 80%, cumulative S&P 500 returns subsequently rise by an average of about 6% over 12m.
4. **Technical details: Estimating the variance covariance matrix.** The KKT measure is sensitive to how the data are processed and how some of the key parameters are estimated. In particular, we investigate the role of the variance covariance matrix in calculating the probability of recession.
5. **Upward bias?** Compared to other probability models, the KKT^{IAS} measure seems to be biased upward. For example, a 75% KKT^{IAS} reading is consistent with a 25% recession probability when using a logit specification. This observation requires further analysis.

A Bayesian Path from Mahalanobis Distance to Recession Probability

KKT employs a statistic, the "Mahalanobis distance," to the problem of business cycle forecasting (though similar metrics are used in risk modeling, etc.). The idea underlying the Mahalanobis distance is that, at a point in time, a set of economic data, say y, can be described in terms of its "proximity" to, or "distance away" from, economic data that are typically observed during "recessionary" (or "robust growth") periods. In other words, the Mahalanobis measure is like a similarity score.

This distance measure is:

$$\sqrt{(y-\mu_r)'\Sigma_r^{-1}(y-\mu_r)}\,, \tag{1}$$

where μ_r and Σ_r represent, respectively, the mean vector and VCV matrix of the economic data series during recessions. Without the VCV, this would just be the usual Euclidian distance between the currently observed data and the average values of these data during recessions. Mahalanobis distance is a more general measure because it weights each Euclidian distance by the variability and co-variability of the underlying macroeconomic data set. For example, if a given piece of economic datum (say, housing starts) during recessions exhibited a lot of variability, then the distance of currently observed housing starts from the average level during recessions would have its weight reduced in the overall distance measure calculation. **The formula above summarizes, in a single number, how similar a given set of economic data is to those data observed during recessions.**

There is a Bayesian path to transform the Mahalanobis distance measure into a "probability of recession." In effect, the idea is to transition from the probability of observing a set of economic data given a recession, to an assessment of the **probability of a recession given the observed set of data.** It is this latter probability that is of critical investor interest.

The KKT method first sorts economic environments into two distinct states: recession and robust growth. Recessions are defined (announced with a lag) per the NBER; robust growth periods are defined as periods where industrial production growth is in its top quartile. Naturally, the economy behaves differently depending on the economic state. The critical underlying assumption is that during periods of robust growth macroeconomic variables (y) are drawn from a multivariate Normal distribution with mean μ_g and variance Σ_g, and during recessions the same set of macroeconomic variables are drawn from a *different* (but still) Normal distribution with a recessionary mean μ_r and variance Σ_r. The means and VCV matrices are the parameters that need to be estimated.

Now, suppose we observe a current set of economic data, y. The KKT measure simply asks: Are these data more likely to have come from the robust growth distribution or the recession distribution? In other words, given an observation of y, which set of parameters (μ_r and Σ_r) or (μ_g and Σ_g) is more likely to have produced the observed y. The two likelihoods are:

$$L(y \mid \text{Robust Growth}) = \frac{1}{\sqrt{\det(2\pi\Sigma_g)}} \exp\left(-\frac{(y-\mu_g)'\Sigma_g^{-1}(y-\mu_g)}{2}\right)$$

$$L(y \mid \text{Recession}) = \frac{1}{\sqrt{\det(2\pi\Sigma_r)}} \exp\left(-\frac{(y-\mu_r)'\Sigma_r^{-1}(y-\mu_r)}{2}\right) \tag{2}$$

Given these two likelihoods, a *pseudo*-Bayes' formula[2] can be used to compute what the investor wants to know: Given that we observe the economic data y, what is the probability we are in a recession? The answer is as follows:

$$\Pr(\text{Recession} \mid y) = \frac{L(y \mid \text{Recession})}{L(y \mid \text{Recession}) + L(y \mid \text{Robust Growth})} \tag{3}$$

The quality of a business cycle forecasting tool depends on the accuracy of its signal from equation (3). A crucial input is selecting the most informative set (y) of macroeconomic variables. For KKT, the set y consists of two economic variables – TTM percentage change for both industrial production and nonfarm payrolls, which are part of the data set used by the NBER business cycle dating committee, and two financial market variables – TTM S&P 500 returns and the TTM average slope of the US yield curve, defined as the 10y yield less the federal funds rate. KKT uses more than 100y of data – revised data from 1916 to 1956 and unrevised (*i.e.*, "as-of" or contemporaneous) data from 1956 onward.

Mahalanobis-Based Recession Probability: Replicating the KKT Measure

To study the properties of the KKT recession probability measure, we replicate it. An important caveat is that we use fully-revised data from 1954 onward[3], not "as of data." Nor do we use as long a "start-up" period. That said, Figure 2 shows our KKT$^{\text{IAS}}$ *out-of-sample* recession probability measure, using an expanding window of historical data, with a 12m-long startup data set. Said differently, we estimate the first set of parameters – means and VCV – once 12m of recession and robust growth data are observed. After that, the data window expands. In the VCV estimation, historical observations are equally weighted. The month for which the prediction is made is not included in the data window. As Figure 2 shows, KKT$^{\text{IAS}}$ captures most post-war recessions. And, in terms of recent performance, KKT$^{\text{IAS}}$ peaked at 77% in August 2019 and subsequently fell to less than 3% by January 2020.

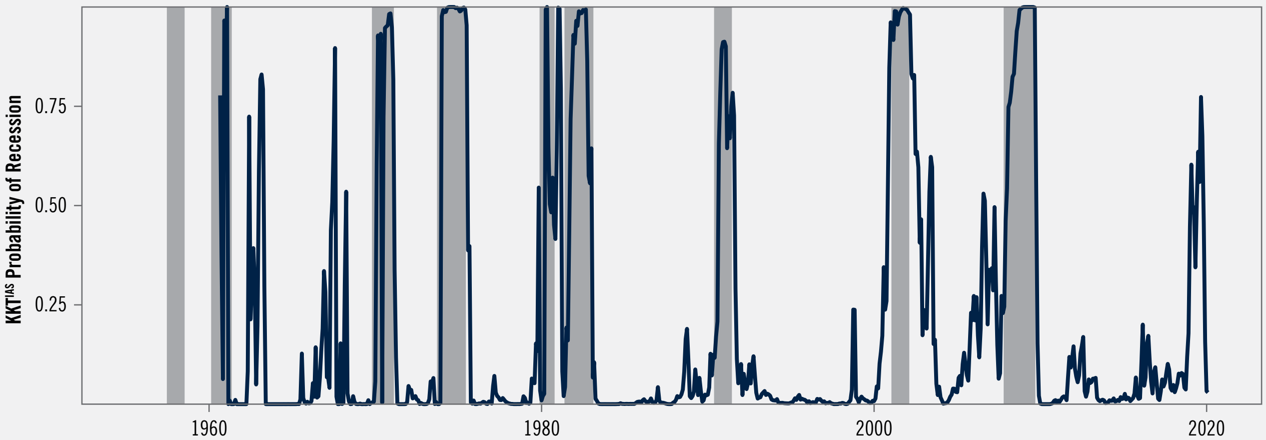
Equation (3) shows there are several critical inputs into the recession probability measure. First is the choice of the macroeconomic and market variables used to estimate the model (what is in, or not in, the model and why;).[4] Second is the estimation of the means and VCVs that govern the data generating process during recessionary and robust growth periods, respectively.

2 The formula uses likelihoods, not probabilities.

3 For expediency, we did not use vintage data. It is worth noting that industrial production revisions tend to be modest and market data are not revised. That said, to fully assess the out of sample predictive ability of this type of model, vintage data is preferred.

4 In their paper, the authors are silent on the choices they made on both counts: there is no discussion of other potential macro economic and market inputs beyond the four variables; there is little detail provided on how they estimate the VCV matrix; and there is no sensitivity analysis on how some of their choices effect the measured probability of recession. Here, we focus on our main conclusions, having previously provided KKT with an extensive and technical discussion of these issues.

Figure 2: KKT^{IAS} Probability of US Recession
(Out-of-sample estimate, 12m start-up data set, expanding window)



Note: Gray bars represent periods of NBER recessions.
Source: BLS, Federal Reserve Board, Haver Analytics, NBER, Standard and Poor's, and PGIM IAS. For illustrative purposes only.

Choosing Inputs: Both Macroeconomic and Market Variables Matter

A critical choice for KKT is the selection of input variables (industrial production growth, employment growth, equity returns and the yield curve). However, the authors offer little discussion of how they made this choice. This omission is compounded by the fact that the KKT methodology does not easily lend itself to an assessment of the significance (statistical or economic) of each input variable.

We dig into this issue in several ways: a direct assessment of the role that each of the underlying macro economic series plays in the KKT^{IAS} model, a regression-based analysis of KKT^{IAS}, and an alternative, logistic regression model.

We assess the role of each input variable in KKT^{IAS} by replicating the measure several times, each time leaving out one of the inputs (see Figure 3). Our expectation was that the financial variables would prove to be of outsized importance, both historically and in late-2019. However, it seems that no single variable has a dominant influence on the recession probability measure. (We discussthe 2019 experience in the next section where the market variables have more importance.)

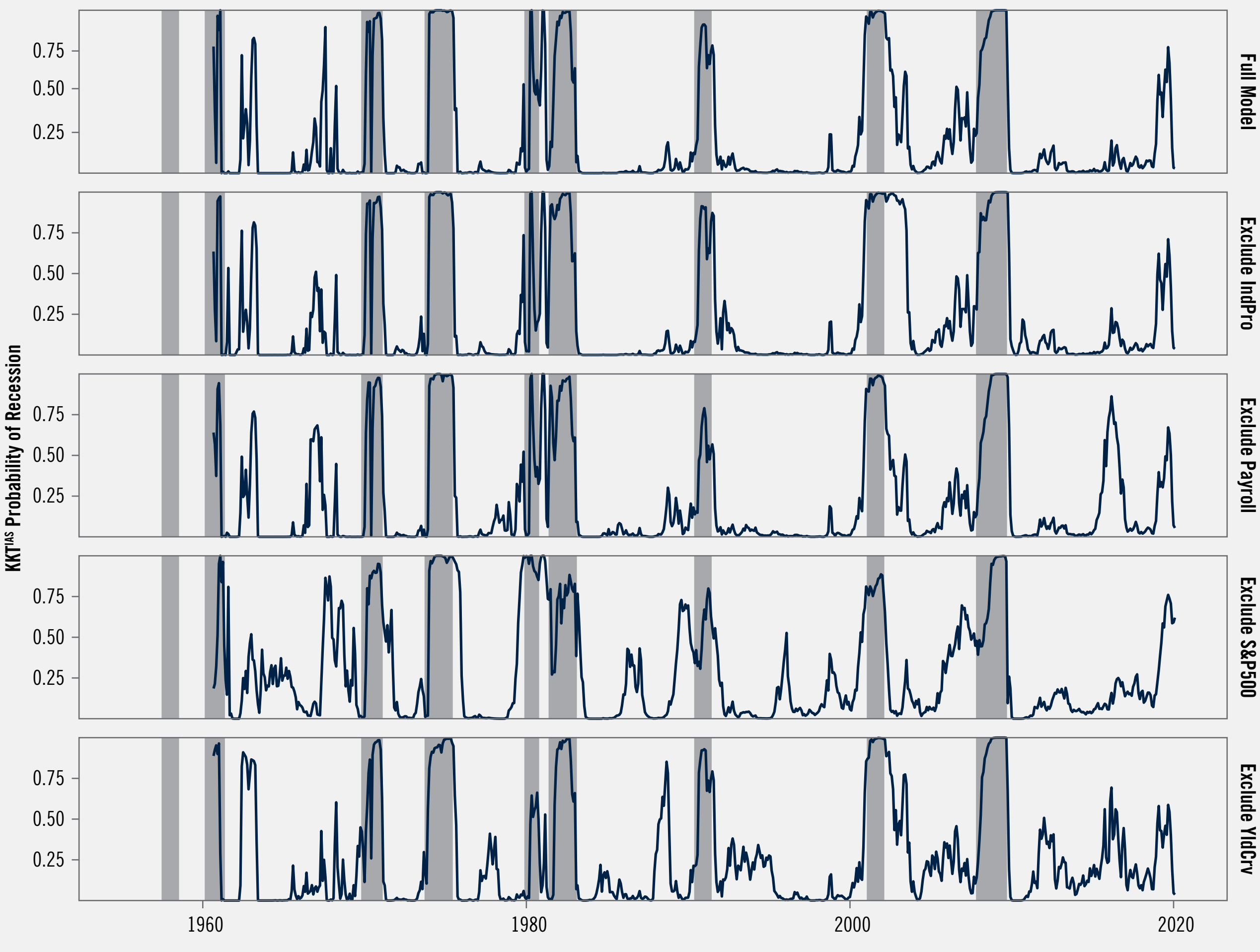
A linear regression of the KKT^{IAS} probability measure on its four underlying inputs confirms that all four dependent variables are statistically significant (see Figure 4). Although KKT^{IAS} is, by construction, a *non-linear* function of the four regressors, a linear regression model[5] serves as a "quick and dirty" confirmation that all four input variables play a role in driving KKT^{IAS}.

To further assess the importance of each of the input series and to cross-check the KKT^{IAS} results, we estimate a logit model using the same four inputs (industrial production, payrolls, stock returns, and yield curve) to infer the probability of a recession and to generate test statistics to judge the significance of each of the dependent variables. Using data since 1954, industrial production, stock returns, and the yield curve are all statistically significant – nonfarm payroll variable is insignificant (see Figure 5). We compare the logit and KKT models in more detail below.

5 The purpose of this "linearization" is as a simple cross-check of our conclusions that the four variables are all significant in assessing the probability of recession; this is not an attempt to build a better predictor. Indeed, the value of the KKT methodology is, in part, precisely from the non-linear interactions among the regressors. Simple linear models (like the logit model we estimate below) are not suited to pick up such interactions. However, machine learning techniques are optimized to extract information out of the data and are more "agnostic" as to the parameterization of how that information is extracted. Such models present a potentially fruitful path toward improving upon the current class of recession prediction models.

Figure 3: KKT^{IAS} Probability of US Recession

Full four-variable model and models that exclude a single input variable



Note: Gray bars represent periods of NBER recessions.

Source: BLS, Federal Reserve Board, Haver Analytics, NBER, Standard and Poor's, and PGIM IAS. For illustrative purposes only.

Figure 4: Linear Regression of KKT^{IAS} on Four Input Variables
(Industrial production growth, employment growth, S&P 500 returns, yield curve)

```
Call:
lm(formula = KKT ~ S&P500 + YldCrv + Payroll + IndPro, data = NoneRemoved)

Residuals:
     Min        1Q      Median      3Q       Max
-0.76233   -0.09606  -0.01907  0.08585  0.73895

Coefficients:
              Estimate    Std. Error  t value   Pr(>|t|)
(Intercept)   0.533369    0.012638    42.203    < 2e-16     ***
S&P500        -1.115674   0.046974    -23.751   < 2e-16     ***
YldCrv        -0.061453   0.004593    -13.380   < 2e-16     ***
Payroll       -8.033364   0.661223    -12.149   < 2e-16     ***
IndPro        -0.974839   0.261881    -3.722    0.000213    ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.182 on 709 degrees of freedom
Multiple R-squared: 0.7035,   Adjusted R-squared: 0.7018
F-statistic: 420.5 on 4 and 709 DF,  p-value: < 2.2e-16
```

Source: Federal Reserve Board, Haver Analytics, NBER, Standard and Poor's, and PGIM IAS. For illustrative purposes only.

Figure 5: Logistic Regression of US Recession (= 1) on Four Input Variables
(Industrial production growth, employment growth, S&P 500 returns, yield curve)

```
Call:
glm(formula = isRecession2 ~ S&P500 + YldCrv + Payroll + IndPro, family = binomial(link = "logit"), data = macroData)

Deviance Residuals:
     Min        1Q        Median      3Q         Max
-2.97561   -0.25014   -0.09978   -0.04100   2.54520

Coefficients:
              Estimate    Std. Error  z value   Pr(>|z|)
(Intercept)   -0.9307     0.2260      -4.118    3.82e-05   ***
S&P500        -12.6950    1.4676      -8.650    < 2e-16    ***
YldCrv        -0.7378     0.1050      -7.026    2.12e-12   ***
Payroll       -16.5059    14.4291     -1.144    0.253
IndPro        -27.1058    6.0688      -4.466    7.95e-06   ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

    Null deviance: 636.76   on 786   degrees of freedom
Residual deviance: 266.13   on 782   degrees of freedom
AIC: 276.13
```

Source: Federal Reserve Board, Haver Analytics, NBER, Standard and Poor's, and PGIM IAS. For illustrative purposes only.

A Detailed Look at the 2019-2020 Movements in KKT^{IAS} Recession Probability

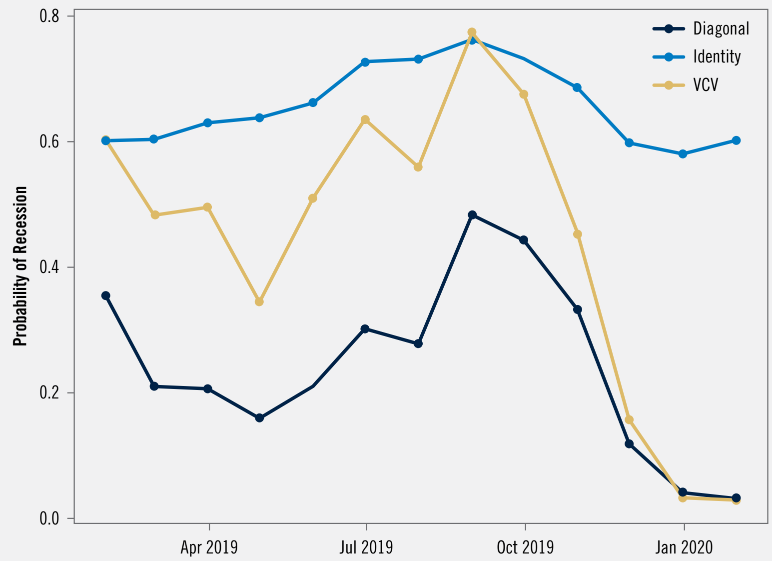
The KKT^{IAS} probability of recession climbed sharply in late 2019, reaching 77% in August (almost exactly matching KKT), and then subsequently declined sharply, falling to 2.9% by January 2020 (see Figure 6). The rapid spike and subsequent sharp retreat suggest a significant role for the market input variables as economic data seem too slow moving to produce such sharp swings in the cyclical assessment.

The non-linearities in KKT^{IAS} make an exact arithmetic decomposition intractable. Moreover, the role of the VCV is to capture potentially important interaction effects (deviations of current data from their recessionary means are weighted by the *inverse* of the VCV matrix – see equation (3)). Instead, we took a brute force approach and ran all possible KKT^{IAS} models, given four potential explanatory variables (see Figures 7a and 7b). What emerged is that the quick change in recession probability from the lows in April 2019 to the highs in August 2019 was driven in large part by the two market input variables. Economic variables *on their own*, did very little, but the interaction of market and economic variables led to an even greater shift higher.

Relative to the 43ppt increase in recession probability in the full model, nonfarm payrolls alone caused a 2ppt increase in recession probability from April to August; a model with just the yield curve saw an 8ppt increase; a model with just the equity market saw a 23ppt increase (see Figure 7a). Market variables do seem to play a dominant role. And, together they explain 33ppt of the 43ppt increase. Interestingly, the importance of economic data becomes manifest through the interaction with market data. For example, employment growth alone leads to a negligible change in probability, but when combined with market variables, leads to a 43ppt increase in recession probability compared to the 33ppt increase using the market variables alone.

Similarly, from August 2019 to January 2020, as the probability of recession fell by 74ppt, the yield curve and equity market together led to a 52ppt decline, as stocks rallied, and the curve steepened (see Figure 7b). While employment growth *alone* barely lowered the probability of recession. When combined with payroll data the decline was 67ppt.

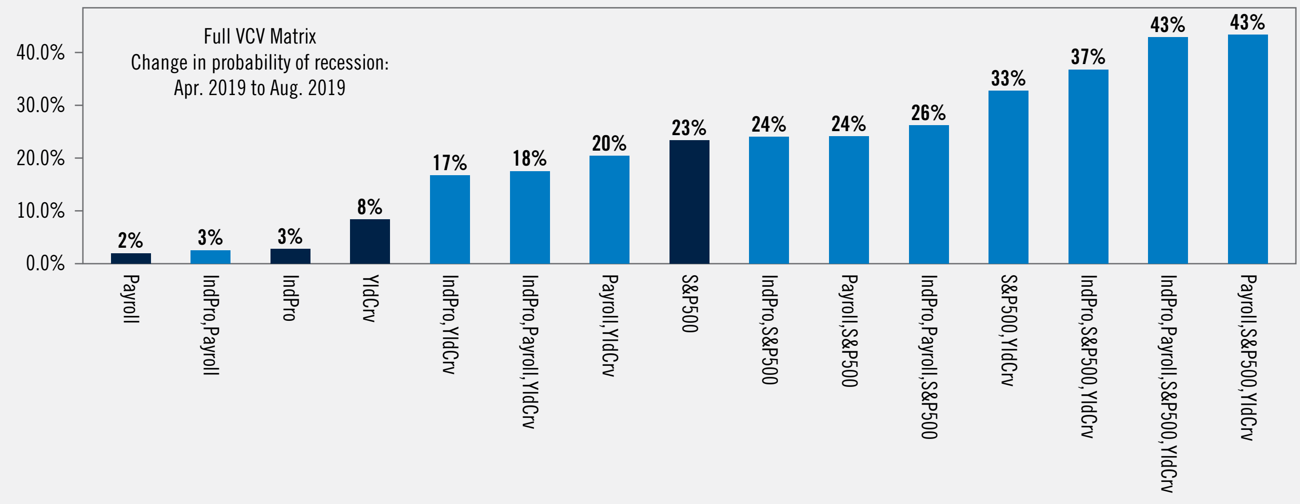
Figure 6: The Probability of Recession, KKT^{IAS}
April 2019 through January 2020



Source: Federal Reserve Board, Haver Analytics, NBER, Standard and Poor's, and PGIM IAS. For illustrative purposes only.

Figure 7a: Decomposing the 2019-2020 Changes in KKT[IAS]

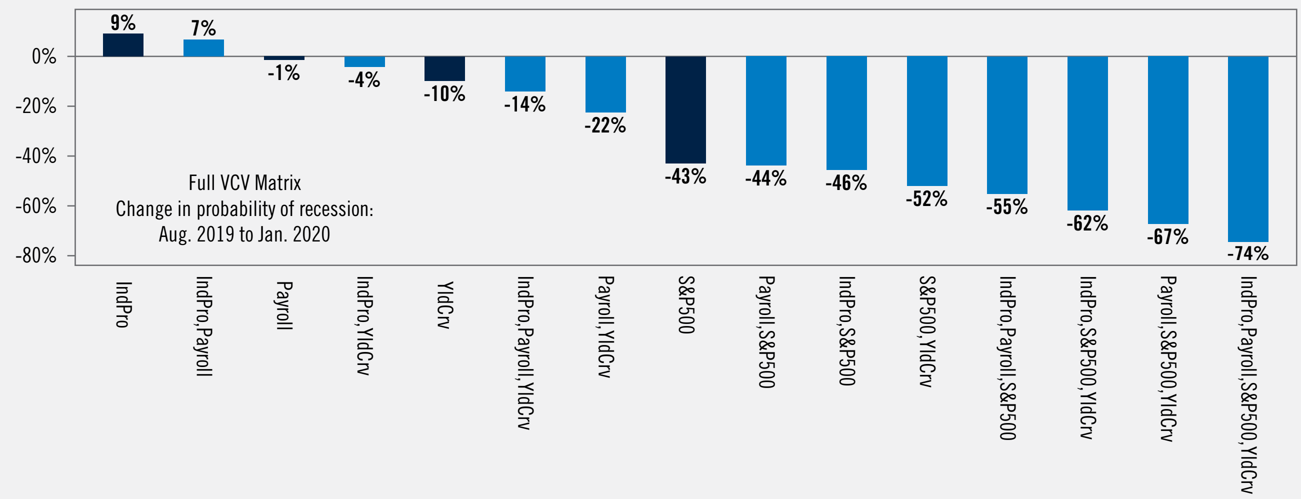
April 2019-August 2019



Note: Navy bars represent KKT[IAS] model based on only a single input. The blue bars represent the model based on all four inputs.
Source: Federal Reserve Board, Haver Analytics, NBER, Standard and Poor's, and PGIM IAS. For illustrative purposes only.

Figure 7b: Decomposing the 2019-2020 Changes in KKT[IAS]

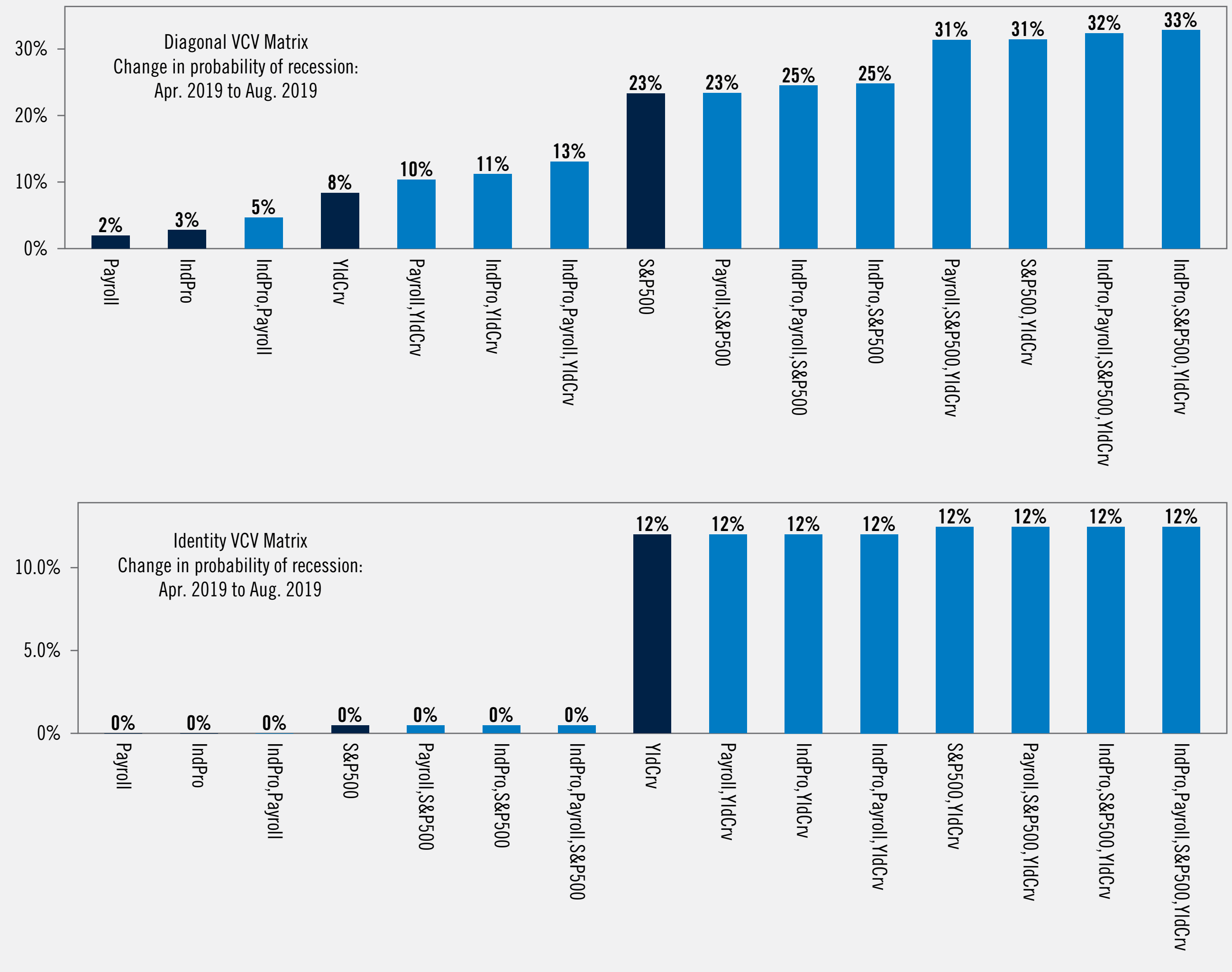
August 2019-January 2020



Note: Navy bars represent KKT[IAS] model based on only a single input. The blue bars represent the model based on all four inputs.
Source: Federal Reserve Board, Haver Analytics, NBER, Standard and Poor's, and PGIM IAS. For illustrative purposes only.

This analysis sheds light on the role of the VCV and, hence, on the importance of its efficient and accurate estimation. The shifting probability of recession that was observed towards the end of 2019 depends significantly on which VCV matrix is used. Figure 6 above illustrates the impact of using the full VCV matrix as the weighting scheme in the probability calculation relative to using a diagonal matrix of variances, or to using the identify matrix which is just an averaging of the data without any weighting scheme. To further sharpen the point, Figure 8 looks at the drivers of the spike in recession probability towards the end of 2019 when using either (1) *a diagonal matrix* or (2) *an identity matrix* in lieu of the estimated VCV, thus removing interaction effects. As discussed above, the role of the weighting matrix looms large. Weighting by a diagonal VCV, (top panel), market variables drive the entire change in recession probability. Macroeconomic variables on their own do very little, even when combined with market data. The bottom panel does the same exercise but with an identity matrix, with the yield curve alone driving the change in recession probability.

Figure 8: Decomposing Late-2019 Increase in KKT[IAS] under Alternative VCV Assumptions
(Diagonal VCV matrix, top panel; identity VCV matrix, bottom panel)



Note: Navy bars represent KKT[IAS] model based on only a single input. The blue bars represent the model based on all four inputs.
Source: Federal Reserve Board, Haver Analytics, NBER, Standard and Poor's, and PGIM IAS. For illustrative purposes only.

What is the Value of KKT^IAS for Portfolio Managers?

From the perspective of an investment practitioner, one measure of the utility of cyclical measures such as KKT is to gauge future market conditions, in terms of expected returns, volatility and risk considerations, and the implications for portfolio construction and allocation decisions. Given that trailing market data play a significant (though not exclusive) role in driving the KKT^IAS measure, does KKT^IAS provide forward market information?

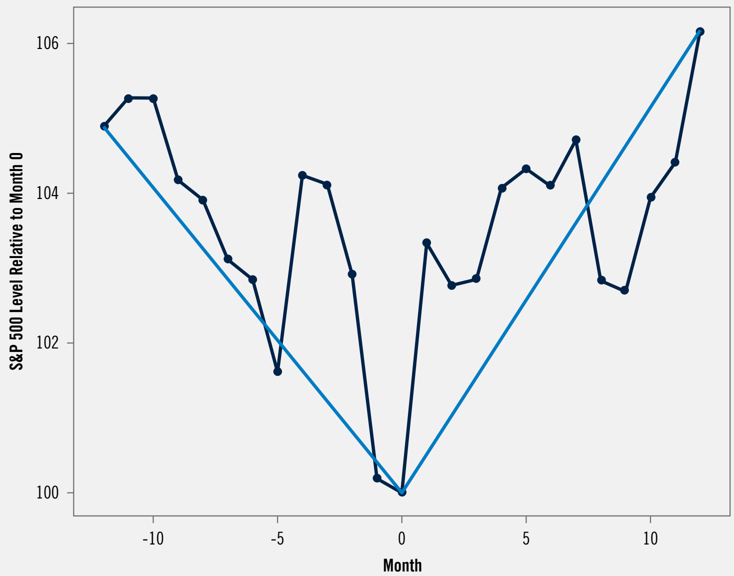
We analyze how an investor could use the KKT^IAS index as a market timing signal. Figure 9 displays the average level of the S&P 500 12m before and 12m after the month ("month 0") for which probability of recession first climbs to 80%. On average, cumulative returns are *negative (-3%)* 12m prior to month 0, with most of the market damage occurring 3m to 6m prior to month 0. After month 0, S&P 500 returns tend to be *positive*, reaching a cumulative return of about +6% by month 12.

This analysis suggests that a good deal of market damage has already been inflicted by the time KKT^IAS hits the 80% mark. In fact, a high KKT^IAS value is a signal to increase market exposure. That said, it is worth considering if there is an "optimal" KKT^IAS threshold to use as a market timing signal. After all, to get to 80%, the KKT^IAS measure needs to first hit 50%, 60%, etc. This warrants further exploration.

Technical Details: Estimating the Variance-Covariance Matrix

Critical to calculating the Mahalanobis distance are the estimated vector of means and the VCV, which together determine the assumed (Normal) distribution of the data in a specific phase of the cycle (recession and robust growth, in this context). To prevent "look ahead" bias in the probability of recession, these parameters are estimated using data available at that point in time. Hence, estimates of these matrices are likely to be very noisy and unstable even as more data are added to the estimation. This is particularly likely for the recession VCV, given that (a) there are few recessionary periods, even over a long period of time; (b) most recessions are short, further reducing the number of *independent* observations per recession (recall, the inputs are all *trailing-12m* calculations); (c) each recession is different and the covariance of data during a specific recession may change considerably from one recession to the next; and (d) there has been a decline in economic volatility (but not market volatility) mid-way thru the estimation period.

Figure 9: S&P 500 Performance Before and After the Probability of Recession Climbs to 80%
24m window, indexed to month 0, 13 episodes from 1954 to 2020
(Month 0 is the first month when KKT^IAS ≥ 80%)



Note: The two straight lines in blue represent a linear path from month 0 to months -12 and 12.
Source: Haver Analytics, NBER, Standard & Poor's, and PGIM IAS. For illustrative purposes only.

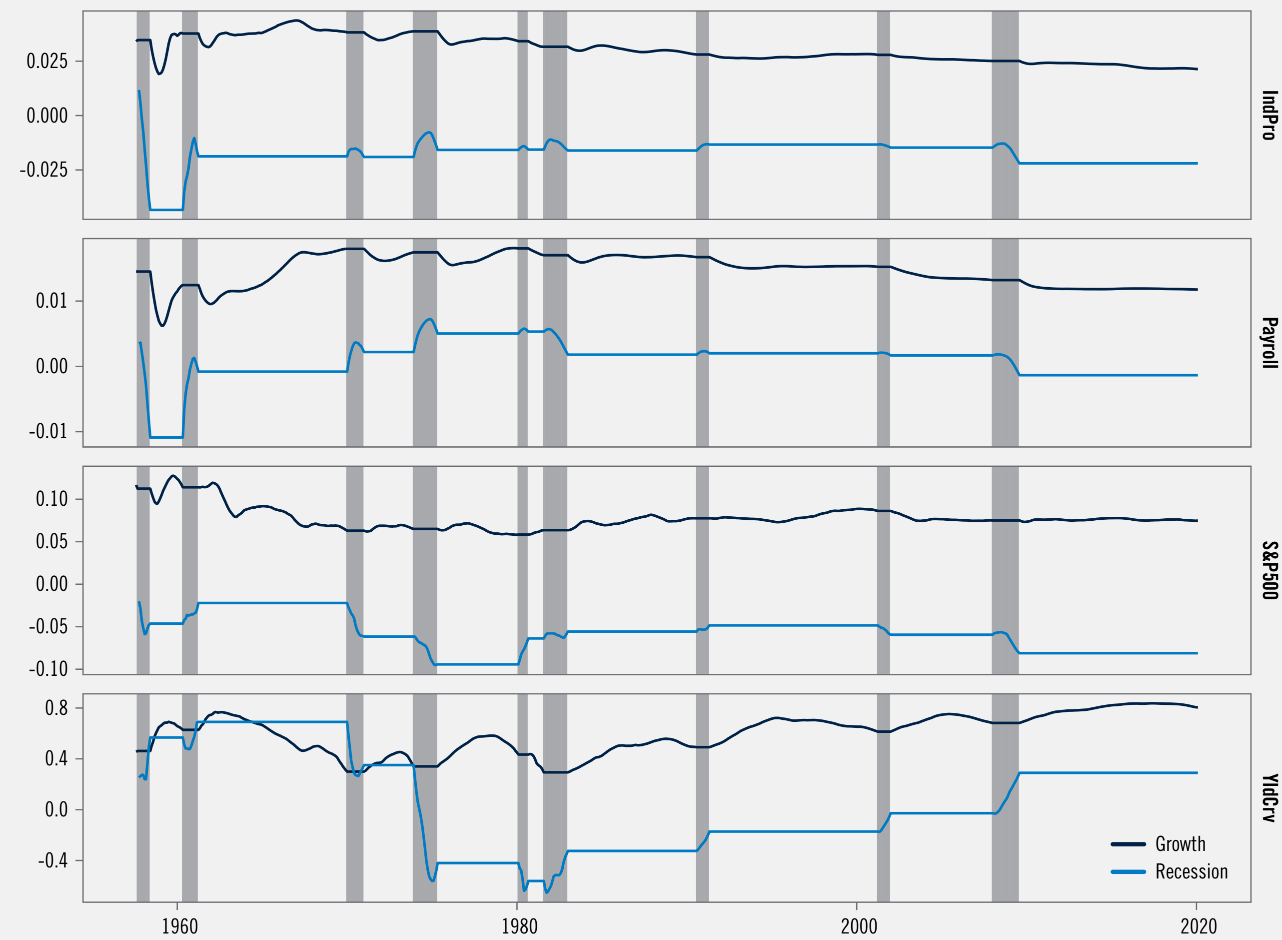
Figures 10 and 11 show the evolution of estimated parameters as the data window expands. We note the following:

a. Stable means: Estimates of the means seem to converge rather quickly as the data window expands (see Figure 10). This is true for both recession-period and robust-growth-period means. The one exception seems to be the mean of the yield curve during recessions, which seems to climb over time.

b. Converging variances: Volatility estimates have also been fairly stable as the data window expands (see Figure 11, with variance estimates graphed along the diagonal). Interestingly, the volatility of the market variables (stock returns and the yield curve) seem to be converging at a higher level as more data are added, while the volatility of the pure macroeconomic variables seems to be converging to a lower level. Given that Mahalanobis distance measure weights data by the inverse of the VCV, all else equal, this suggests that over time the role of market variables in KKT^{IAS} is becoming more muted.

c. Unstable recession-period covariances: In contrast, the covariance terms look far less stable, particularly with respect to recessionary periods (see Figure 11). While the biggest shift in recession-period covariance estimates occurred in the wake of the 2008 recession, even prior to 2008, the addition of each recession seems to produce its own shift of the covariance estimates. At the risk of overinterpretation, this suggests that recessions are *sui generis*, at least with respect to co-movement across the macro economic and market landscape. As a result, future data may not be informative for past recessions, and *vice versa*. Hence, some sort of weighting/filtering of the data may be warranted.

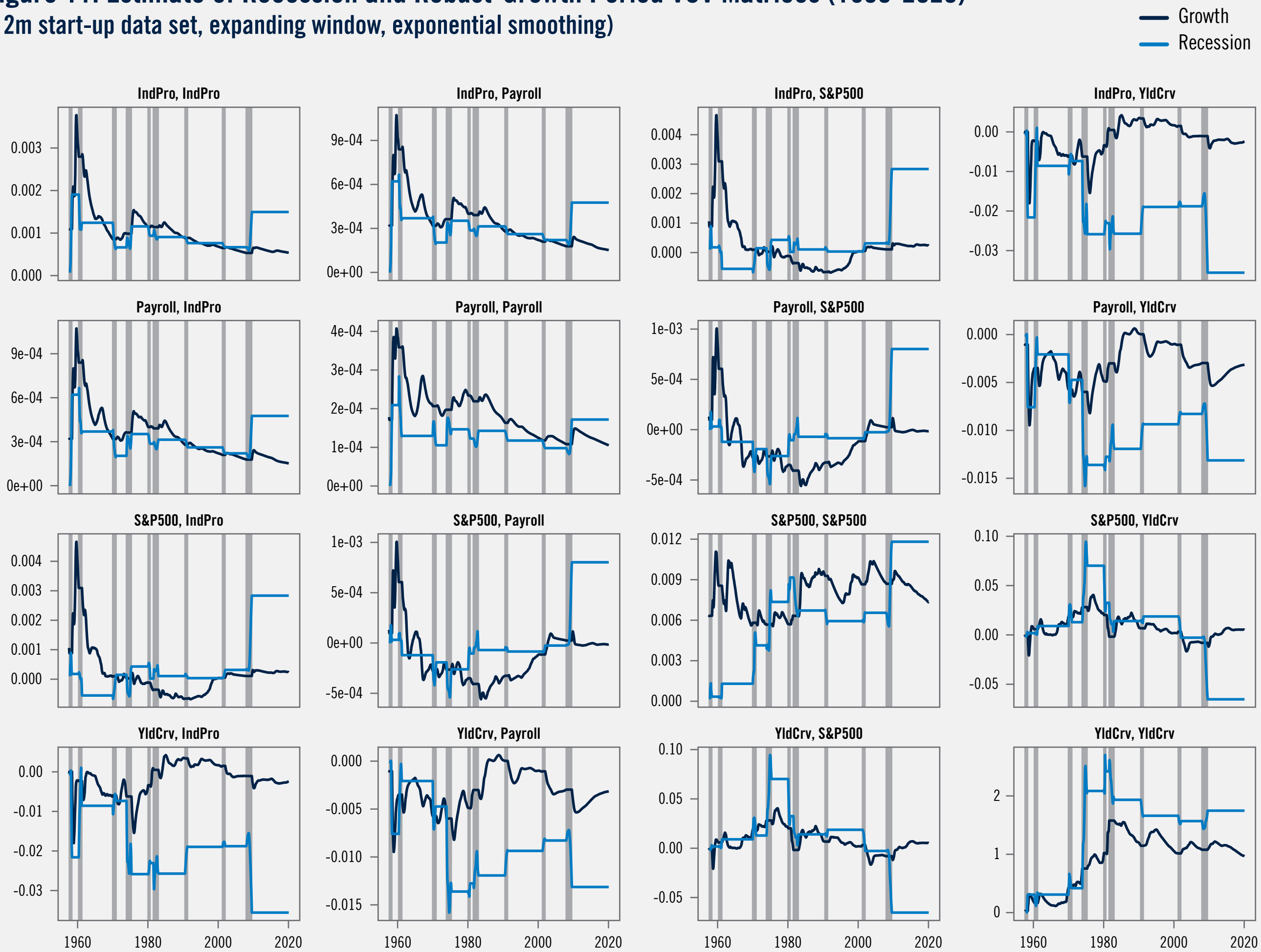
Figure 10: Estimate of Recession and Robust-Growth Period Means (1960-2020)
(12m start-up data set, expanding window, exponential smoothing)



Note: Gray bars represent periods of NBER recessions.
Source: BLS, Federal Reserve Board, Haver Analytics, NBER, Standard & Poor's, and PGIM IAS. For illustrative purposes only.

Figure 11: Estimate of Recession and Robust-Growth Period VCV Matrices (1960-2020)

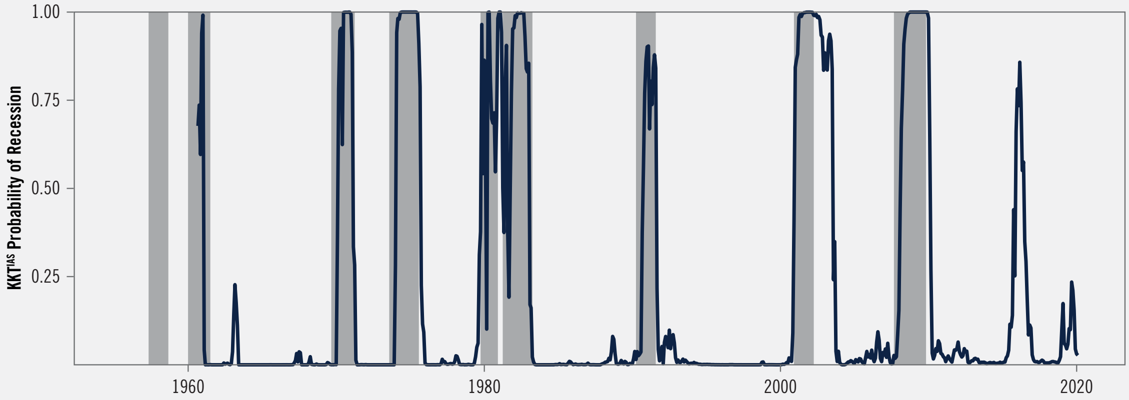
(12m start-up data set, expanding window, exponential smoothing)



Note: Gray bars represent periods of NBER recessions.
Source: BLS, Federal Reserve Board, Haver Analytics, NBER, Standard & Poor's, and PGIM IAS. For illustrative purposes only.

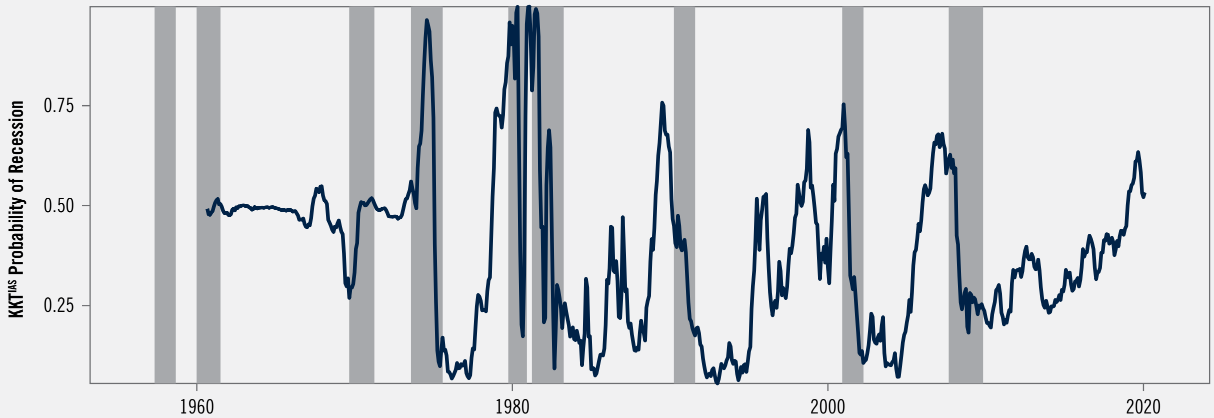
Figure 12: KKT^{IAS} Index

(12m start-up data set, expanding window, exponential smoothing, diagonal VCV)



Note: Gray bars represent periods of NBER recessions.
Source: Haver Analytics, NBER, and PGIM IAS. For illustrative purposes only.

Figure 13: KKT^{IAS} Index
(12m start-up data set, expanding window, exponential smoothing, identity VCV)



Note: Gray bars represent periods of NBER recessions.
Source: Haver Analytics, NBER, and PGIM IAS. For illustrative purposes only.

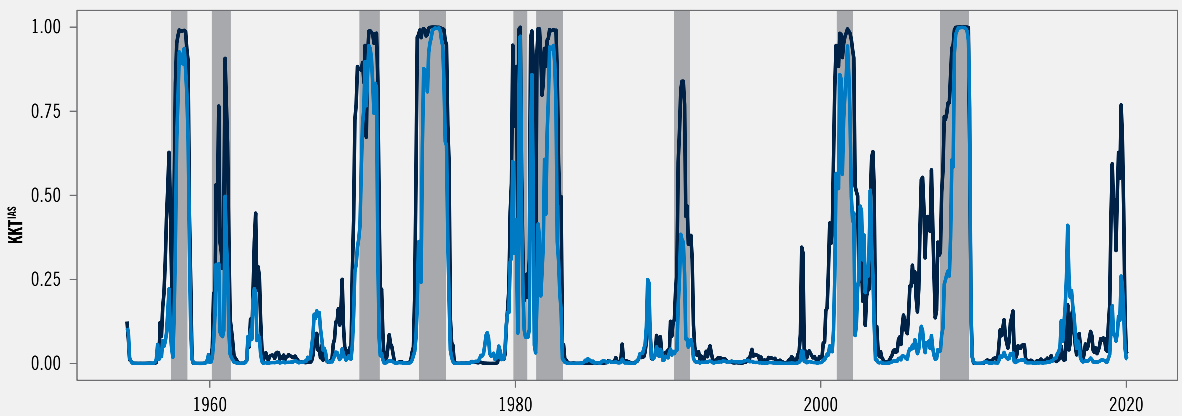
To examine the impact of VCV instability on recession probabilities, we re-estimate KKT in two different ways: (1) assuming no covariances and just weighing data by their volatilities, substituting a diagonal VCV for the full VCV in the equations above (see Figure 12) and (2) by equally weighing the data, substituting an identity VCV for the VCV in the equations above (see Figure 13).

When using the diagonal VCV (*i.e.*, weighting by volatilities alone) the recession indicator continues to perform quite well, at least optically. However, when using the identity VCV (*i.e.*, equal weighting) the resulting indicator is more volatile, never climbs as high, shows a greater number of "false positives," but looks to lead the actual onset of recessions by several months. This analysis of the role of the VCV is an area requiring further work.

Upward Bias? The Impact of "Functional Form"

Returning to the logit model above, the resulting probability of recession also matches the NBER dates and is comparable to the KKT^{IAS} measure (see Figure 14). A direct comparison of the two models, however, reveals some interesting differences. For both measures high and low readings of recession probability both tend to be bunched together but otherwise, the KKT^{IAS} measure

Figure 14: Recession Probability KKT^{IAS} (navy) and Logit Model (blue)
(1960-2020; out of sample)

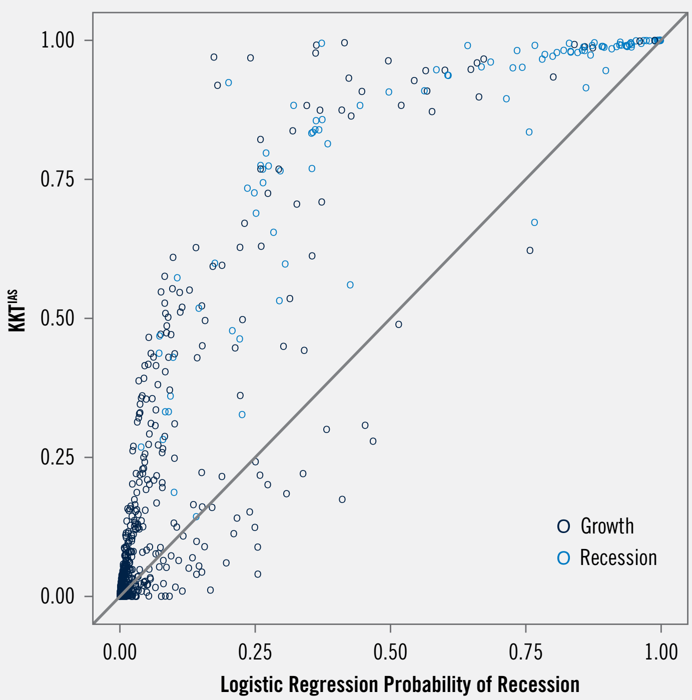


Note: Gray bars represent periods of NBER recessions.
Source: Haver Analytics, NBER, and PGIM IAS. For illustrative purposes only.

nearly always delivers a probability of recession that is higher than the corresponding logit reading (see Figure 15). For example, reading off the "schedule" in Figure 15, a 75% probability reading from the KKT^{IAS} model is consistent with a ~30% logit model reading. In practice, both KKT^{IAS} and logit measures climbed last year; KKT^{IAS} peaked at around 75%, while the logit-based measure reached a more modest 25%.

Given the observed regularity between these two measures, a direct analytical comparison between them is warranted to better understand the advantages of KKT. KKT disregards much time series information as it only uses means and VCV from robust-growth and recessionary-growth periods and ignores data from all other periods. In contrast, a logit model uses the *entire* data sample, scoring recessionary months as "1s" and *all other months* as "0s." Technically, what is the difference between the likelihood function that a logit specification is maximizing, versus the likelihood used here? Some of the difference could be due to how the logit model treats non-recessionary data in the likelihood function relative to the KKT approach. Such an analysis is beyond the scope of this note is likely a fruitful avenue for future research.

Figure 15: KKT^{IAS} Recession Probability (y-axis) vs Logit Recession Probability (x-axis)
(1960-2020; out of sample)



Source: Haver Analytics, NBER, Standard and Poor's, and PGIM IAS. For illustrative purposes only.

References

Kinlaw, W., M. Kritzman and D. Turkington (15 January 2020). "A New Index of the Business Cycle." MIT Sloan School Working Paper 5908-20.

Acknowledgments

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