COULD DIFFUSION INDEXES HAVE FORECASTED THE GREAT DEPRESSION?*

Gabriel Mathy†
American University

Yongchen Zhao‡
Towson University

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ABSTRACT: Diffusion indexes provide an effective tool to forecast the business cycle today (Zhao 2020). We test how effective diffusion indexes are in forecasting the deepest recession in U.S. history: the Great Depression. Moore (1961) considered the effectiveness of diffusion indexes historically, including for the Great Depression, though he only did so retrospectively and did not forecast out-of-sample. We reconstruct Moore's diffusion indexes for this historical period and make our own comparable indexes for out-of-sample predictions. We find that diffusion indexes, including the horizon-specific ones we produce, can nowcast turning points fairly well. Forecasting remains difficult, but our results suggest that the initial downturn in 1929 may be forecastable months before the Great Crash. This is a novel result, as previous authors had found the Depression was not forecastable.

KEYWORDS: Diffusion Index; Great Depression; Forecasting

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† mathy@american.edu. Department of Economics, American University, 4400 Massachusetts Avenue NW, Washington, DC 20016, United States.
‡ yzhao@towson.edu. Department of Economics, Towson University, 8000 York Road, Towson, MD 21252. United States.

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1. INTRODUCTION

The Great Depression was the deepest downturn in US history and was more severe than any economic crisis before or since. Being able to forecast the turning points of such a deep downturn would be extremely valuable for anyone, but particularly for policymakers, assetholders, and business firms. Previous studies have examined how forecastable the Depression was. Dominguez et al. (1988) found that the Depression was not forecastable, even using state-of-the-art time series techniques (which, at the time, were based on vector autoregressions). They also found that Harvard and Yale based forecasting groups could not forecast the Great Depression. Other authors have also found that the path of output and the price level in the Depression were not forecastable.[4] The dispersion of forecasts widened during the Depression too, consistent with increased difficulty in forecasting (Romer 1993).

Another forecasting method that has largely been forgotten today, the diffusion index, comes from Moore (1961), who applied it to historical data, including the Great Depression period of the 1930s. A diffusion index is an aggregate of individual series. Its value equals the percentage of its component series that are expanding. The more series that are expanding, the less likely a recession is underway; and the more series that are contracting, the more likely a recession is in progress. Diffusion indexes have been successfully used in the modern period for forecasting,[5] so we apply this technique to the Great Depression to see how effective diffusion indexes could be in forecasting this severe downturn.

Although diffusion indexes can be used to forecast different aspects of the business cycles, here we mainly focus on the turning points.[6] They are notoriously difficult to identify in advance,

[4] See Goldfarb et al. (2005), Hamilton (1992), Klug et al. (2005), and Mathy and Stekler (2018), *inter alia*.

[5] See Zhao (2020) and references therein.

[6] We also briefly examine the ability to forecast the severity of the business cycle in the Depression.

but they are important for economic actors to forecast (Stekler 1972). NBER recession dates are used: The business cycle peak was reached in August 1929, two months before the Great Crash on Wall Street, which is often seen by the laypersons as heralding the start of the Depression. The trough occurred in March 1933. The next expansion lasted until May 1937, followed by a recession until June 1938. The US economy then would not see a recession until after World War 2. Using data up to December 1940, we focus solely on the pre-war period. Of primary interest is the ability of diffusion indexes to forecast the Great Contraction period from 1929-1933 when real GDP fell by a third.

The rest of the paper is organized as follows: Our data set is introduced in the next section. We present the design of our empirical exercises in Section 3, including how we construct various diffusion indexes. Section 4 contains our main results on the forecasting performance of the diffusion indexes. The next three sections consider extensions and robustness checks: We augment our data set with real-time data vintages and repeat the main exercise in Section 5. We consider making the forecasts at the quarterly frequency in Section 6. Section 7 focuses on our ability to predict the severity of the depression. The last section contains some concluding remarks.

2. DATA

We first reconstruct the diffusion index used by Moore (1961) using the latest data. The series he used are listed in Table 1. We are able to locate the series he used or close substitutes in all cases. The Standard Statistical Company Industrial Output Index is only available in the publications of the Standard Statistical Company, but this publication ran for a few years only and is hard to find today. Instead, we substitute the "Index of Industrial Production and Trade for United States" compiled by Barron's Magazine. As this is a similar index compiled by a private sector organization, it should contain similar information. After reconstructing Moore's index, we then see if we can improve on Moore's diffusion index by adding other variables discussed below.

We begin with monthly variables. We add bank debits for both New York and 140 cities outside of New York. These data are transactions equivalent to expenditure and they correspond closely to economic activity in this period. We include bank rates as well, since they are also related to the business cycle in this period. To get additional disaggregated information on production, we include a diffusion index of different components of industrial production, as well as a diffusion

index of eight leading indicators.[7] The index of American Business Activity by the Cleveland Trust Company, created by a respected contemporary forecaster, Col. A. P. Ayres, is also included as an additional business cycle indicator. Furthermore, we include a few manufacturing variables that are highly cyclical, including factory employment in automobiles, the gross hiring rate in manufacturing, and the layoff rate in manufacturing. We also include security issuance by corporations as well as state and local governments, as these are correlated with the business cycle. Retail sales are included as well. They co-move closely with the overall business cycle in this period. In addition, we include the percentage of steel ingot production capacity utilization – another highly cyclical industrial indicator. Finally, we include the wholesale price index for all commodities excluding farm products and food. This can be seen as an analogue to the modern "core" price index, excluding changes in food prices that may fluctuate in ways uncorrelated with business cycles.

Although our main empirical exercise focuses on constructing monthly diffusion indexes, we also consider additional quarterly data. We add a diffusion index of the profits of major manufacturing corporations as well as a diffusion index of freight car loadings for 19 commodity groups. We also add an index of railroad freight tons originated. In addition, we use some early estimates of Gross National Product from Barger (1942) and three measures of investment: manufacturing inventory investment, new capital formation of plant, and new capital formation of equipment. The full list of series used is shown in Table 1. Data sources include the NBER Macrohistory database, the Saint Louis Fed's FRED database, and the Bureau of Economic Analysis's Survey of Current Business.

[Table 1 here]

In the exercises below, we use historical data as our baseline. Real-time data, when available, are used to check the robustness of our main conclusions. During our period of interest, data revisions were less common than they are today, though some did occur. Industrial Production is updated and revised frequently by the Federal Reserve Board, and we use the real-time data vintages from ALFRED by the Saint Louis Federal Reserve Bank. Among the rest, variables

[7] These series are: (Inverted) Liabilities of Business Failures; Industrial Stock Prices; New Orders for Durable Goods Manufacturers; Residential Construction Contracts; Commercial and Industrial Construction Contracts; Average Workweek in Manufacturing; Number of New Business Incorporations; and Basic Prices (Moore 1961).

reported as indexes are the most frequently revised. For those, we use data from the appendixes of the Survey of Current Business as this publication contained an extensive appendix of real-time data for almost any series relevant for a diffusion index. Specifically, we have real-time data for Pig Iron Production, Steel Ingots Production, and Automobile Tire Inner Tubes Production from December 1926 to February 1941 and for Steel Ingot Production Capacity from January 1927 to February 1941.

3. DIFFUSION INDEXES FOR PREDICTING THE GREAT DEPRESSION

Our main empirical exercise involves constructing three predictors and evaluating their ability to forecast the Great Depression. Of the three, we are primarily interested in the first – a standard diffusion index. This exercise is designed for two primary purposes. First, we determine whether the peak in 1929 and the trough in 1933 are foreseeable, and if they are, how far in advance. Second, we test whether the variables used by Moore, as well as the additional ones we select, contain information useful for this forecasting task – and in particular, whether using the additional variables allows us to achieve improved forecasting performance.

While Moore constructed his index with the benefit of hindsight, we restrict our use of future information as much as is practical to simulate a contemporary forecast. Specifically, we construct our index in a manner similar to how a typical recursive out-of-sample forecast is made: For making a forecast for time period t with a horizon h, the estimation sample includes observations up to $t-h-1$. Taking a nowcast (i.e., $h=0$) for period t as an example, this nowcast would be made using a training sample that contains data up to $t-1$, since the data *for* period t would not be available *during* period t. Generally, as the training sample expands, the forecasting model is re-estimated, so the nowcast for $t+1$ is made using information up to and including that from period t. In addition to limiting the data we use to make each forecast, we impose a few other restrictions detailed below. Despite our best effort, it is unavoidable that some aspects of our exercises, such as what variables we use to augment Moore's data set, benefit from knowledge unavailable to forecasters in the 1930s.

The first of the three indexes we construct largely resembles Moore's work. The index itself is a standard diffusion index that shows the percentage of its components expanding. It is bound between 0% and 100%, where a value of 100% means all the components of the index are expanding. Thus, the lower the value of the index, the more likely the economy is in a recession.

Moore's work showed that this index, despite its simple construction, performed well in signaling the approach of a possible turning point with its peak precedes that of the business cycle.[8] When constructing this index, we follow Moore's procedure in spirit. However, we make two important changes to make our forecasts "out-of-sample." The first change we make arises out of the difficulty associated with seasonal adjustment. While most of our variables do not contain a visible seasonal component, some exhibit seasonality in a way that vary significantly during our sample period. This makes reliable seasonal adjustment in recursive out-of-sample forecasting very difficult – we either run into the issue of significant residual seasonality or excessive revisions to the seasonally adjusted values. The limited length of our time series further complicates this task. To avoid unnecessary data distortions and to keep the procedure straightforward (and thus easy to interpret), we use differences and transformations such as percent change from a year ago as an alternative where appropriate.

Figure 1 shows a few examples of the original data and transformed data. Our transformations ensure that the transformed data do not exhibit visible seasonal variations and are such that their increases (decreases) largely correspond to periods of business cycle expansion (contraction). The second change concerns the definition of "expansion." Moore defined expansion as the period between the previous trough and the subsequent peak. We are unable to do so since it is impossible to determine the "subsequent peak" without using data that would not have been available, not to mention that dating the turning points would introduce a significant delay in the sense that a turning point can only be identified well after the fact. Therefore, we instead follow the common practice today and consider "increase" as "expansion" so that our diffusion index shows the percentage of components increasing.

[Figure 1 here]

There are two issues associated with a standard diffusion index like this. First, it is not targeted to any particular forecast horizon. The index is constructed using the latest data of all of its components. Even if these components all lead the business cycle, the amount of lead time may be uneven and time-varying. Second, the index by construction assigns equal weights to all its components, which may be undesirable when, for example, the components include measures of

[8] Note that the peak of the index can only be identified ex post. Given this, Moore's observation cannot be simply interpreted as the index having strong forecasting power.

different sectors of the economy that are of different sizes. As a result, when the index does not perform satisfactorily, it is difficult to ascertain the cause, as both the selection of the data set and the methodology of the index construction affect its performance. We therefore construct a few additional diffusion indexes and make two additional sets of forecasts using alternative methodologies. We hope these additional results help us better understand the effectiveness of our diffusion indexes and data set.

The additional indexes are constructed to target particular forecast horizons. Instead of simply using the latest observations of all components, these horizon-specific indexes use the data that are best suited to forecast at the chosen horizon whenever possible. More specifically, before we construct the index by calculating the percentage of its components that are expanding, we identify the lead time of each component and determine the observation that we should use based on the component's lead time and the forecast horizon. For example, suppose we are in period t trying to make a forecast for period $t + 2$ (i.e., $h = 2$); and a component of the index has a lead time of 4 periods. Given this lead time, the observation of this component that is best suited for forecasting period $t + 2$ is that of the period $t - 2$. So, we use the value of the component from period $t - 2$ to construct the diffusion index, even though we have the value from period $t - 1$ in our information set. For the components with a lead time of 2 periods or less, the value best suited for forecasting period $t + 2$ is not known at period t, so we simply use the latest known value, i.e., the value from period $t - 1$.[9] We subsequently refer to the standard diffusion index as the diffusion index with an *indefinite* horizon ($h = i$). The additional indexes we just introduced are identified by their specific forecast horizon.

When selecting the variables to use for his index, Moore attempted to identify the lead time of each candidate by visually inspect the data, pinpointing the specific dates of the variable's peaks and troughs, and comparing these dates with the dates of the business cycle turning points. Since our exercise aims to produce out-of-sample forecasts, we must avoid dating the cycles of each component. A different strategy is used instead: Before any estimation, we apply the

[9] One could argue that we should drop the index without a sufficiently long lead time in such cases. We experimented with this approach. Given our relatively small data set, dropping the index without a sufficiently long lead time simply leaves too few components at horizons longer than six months, and the resulting index did not perform well even at some shorter horizons (where more components are left).

aforementioned transformation to each component to remove seasonal variations and align positive (negative) values with expansions (contractions). Then, we run a set of probit regressions of recession on a specific lag of the component from zero up to one year.[10] Since our data set only contains the indicators that we expect to lead the business cycle, we impose this as an assumption and do not consider the possibility of them lagging behind the cycle in setting up these regressions. We then evaluate each model's prediction using the ROC analysis and calculate the corresponding AUC score. The AUC score is a measure of how well a continuous indicator classifies a binary event, where higher values mean better forecasts. The lead time of the component is then estimated to be the amount that results in the maximum AUC score. For these estimations, we consider two training samples: Sample (a) goes back to July 1919 and sample (b) January 1925.[11] Both samples end in December 1928. The first training sample contains three recessions and the second only one. Table 2 lists the lead time of each variable in our data set estimated using the two training samples.

[Table 2 here]

The horizon specific diffusion indexes address the issue of the standard diffusion index not built with a clear forecast horizon in mind. However, the issue remains that the index assigns equal weights to all its components. To address this issue, we make two additional sets of forecasts. The first simply uses a probit model to produce a forecast of recession probability. The predictors in the model are the same as the components of the diffusion index. Compared with the equal weights used by the diffusion index, the probit model effectively allows different components to have different weights. The differing weights can be seen as coming from two sources. The first is immediately clear: the coefficients of the variables act directly as weights. The second source of differing weights has to do with the data: the levels of the transformed variables are used in the regression, while only their signs are used by the standard diffusion index. Thus, the differing magnitudes of the variables naturally act as weights – for example, a sector in steep decline would be "weighted" more heavily. The second set of forecasts we make in addition to the standard

[10] A lag of the component on the right-hand side of the regression means that the variable leads the business cycle.

[11] The data for some variables start afterwards (see Table 1). In such cases, the training sample starts when the data become available.

diffusion index is based on the dynamic factor model (DFM) used in Zhao (2020).[12] The data set is again identical as before. From the data, we extract two common factors, which are then used in a probit model to produce a forecast of recession probability. In other words, instead of running the probit model directly on the dozens of variables in the data set, we run the model using only two common factors. Compared with the probit regression using directly the individual variables, this approach offers two benefits. First, it lessens our concern about the degrees of freedom due to the limited length of our time series. Second, by extracting and using only the common factors, we hope to "filter out" potential noise in the data. Of course, the DFM forecasts retain all the benefits of the simple probit model when compared to the standard diffusion index, e.g., the model does not simply assign equal weights to all the variables.

Corresponding to the empirical strategies discussed above, we report three sets of forecasts in the following sections: (A) Percent expanding, i.e., the standard diffusion index; (B) Predicted probabilities, i.e., from the simple probit model; and (C) DFM forecasts, i.e., from the factor model. All three vary from 0% to 100%. Index (A) assumes low values during recessions, while (B) and (C), being recession probabilities, assume high values during recessions. The parameters of the models used by (B) and (C) are estimated using all available historical data up until the observation used by (A).[13] For each of the three, we make forecasts at the following horizons: 0, 1, 3, 6, and 9 months, where a horizon of 0 month means a nowcast.

4. FORECAST PERFORMANCE OF THE INDEXES

4.1 Can we use the diffusion index to forecast the Depression? If so, how far ahead?

The first question we hope to answer using our results is whether the business cycle peak in 1929 and the subsequent trough in 1933 are predictable using diffusion indexes. We are interested in the information content of the data available at the time: was there enough information that would have allowed forecasters to predict the turning points? If, given the information contained in the

[12] The setup of the model is the same as in (Zhao 2020), i.e., the system of equations contains two factors, two shocks, and the two factors follow a first order vector autoregression.

[13] As explained above, for any variable, the observation used by (A) depends on both the forecast horizon and the variable's lead time. The only exception is the diffusion index with an indefinite horizon, which always use the latest observation of each variable.

data set, the turning points should have been predictable, we would also be interested in knowing how far ahead the prediction could have been made. This requires us to look closely at the dynamics of the various indexes around these two turning points. Since we are mainly concerned with two particular points in time, when comparing the performance of our indexes, we rely on visual inspections. Each plot in Figure 2 presents a comparison of three sets of predictions around the business cycle turning points of 1929 and 1933: (A) the standard diffusion index, (B) the predictions from a probit model, and (C) the predictions from a dynamic factor model. The top plot compares the forecasts with an indefinite horizon. The middle and bottom plot compares the forecasts with a horizon of one and three months, respectively. The horizontal axis shows the date of the target, not the forecast – for example, the three-month-ahead forecast corresponding to 1930m1 is made for this month using information available three months ago.[14] Recall that during a recession, forecasts (A) should have low values while forecasts (B) and (C) should have high values. In the figure, we also include a reference line at 0.5. Note that this is purely a visual reference. The value 0.5 need not be the threshold one uses to convert the probability forecasts or the index values into a binary recession forecast.

[Figure 2 here]

As shown in Figure 2, the diffusion indexes perform well when it comes to predicting the peak in 1929 – the indexes send strong signals of the upcoming peak months before it can be officially dated: even with modern data and techniques, the NBER's Business Cycle Dating Committee decides on the dates of peaks and troughs many months after the fact. We can draw similar conclusions regarding the other two sets of forecasts. Let us focus our attention for now on the diffusion index: The top plot shows that one can identify the peak of the index (1929m5) no later than 1929m7, after two consecutive declines that brought the index to its new low. This, along with the further declines in subsequent months, sends a strong signal that the business cycle peak is likely very near, although the specific month of the peak would remain unknown, as this index

[14] The forecasts with an indefinite horizon is evaluated like a nowcast (i.e., $h = 0$). The same applies to all other figures.

has an indefinite horizon.[15] As shown in the middle plot, the one-month-ahead prediction is past its peak once the value for 1929m11 is known in 1929m10. Similarly, we can see in the bottom plot that the 1929m11 value is clearly below the previous peak – and this value is known three months ahead in 1929m8. When it comes to the prediction of the trough in 1933, the diffusion index with an indefinite horizon starts to trend up in 1933m5, while the one- and three-month ahead index start to trend up no later than 1933m6 and 1933m7, respectively. Here, the diffusion indexes again send a strong signal of the trough almost simultaneously as the actual turning point.

Although the diffusion index does not utilize information on the magnitude of its components nor does it attempt to assign different weights to them, the performance of the index remains robust. This can be observed by comparing the factor model forecasts and the diffusion index in Figure 2. Both series of forecasts have almost identical peaks and troughs, so that neither has a clear advantage in terms of how far ahead the turning point can be identified. This implies that, for the purpose of predicting the two business cycle turning points, there is little information loss from using a standard/naïve diffusion index with equal weights relative to using an index that weights its components. Moreover, unlike the diffusion indexes, the one- and three-month-ahead forecasts of the factor model showed a significant decline around late 1931, sending a misleading signal of a recovery while the trough was more than a year away. In addition, we note that the predicted probabilities from the simple probit model do not as perform well. Partly because of the length of our time series, the model tends to fit extremely well *in sample*, thus giving undue weights to a few variables that may turn out to be poor predictors out-of-sample. The resulting forecasts thus tend to be as volatile as they are extreme, e.g., they can change from 0 to 1 then back to 0 in a three-month period as shown in the top plot. Most importantly, the probit model forecasts do not allow us to identify the turning points any earlier than the other forecasts do. Therefore, in subsequent analyses, we mainly focus on the diffusion index.

In our observations above regarding Figure 2, our timing of the turning points in the forecasts is conservative. Depending on how uncertain forecasters feel, they may be inclined towards sounding the alarm for the incoming peak earlier than we choose to. To illustrate this point,

[15] Recall that the index for indefinite horizon is constructed using the latest observation of all its components. The procedure does not rely on us determining the lead time of each component, and thus is not specific to neither training sample (a) or (b).

we compare the diffusion indexes for forecasting three-, six-, and nine-month ahead in Figure 3. At all three horizons, the forecasts peak well before 1930m1. This means that forecasters who rely on these longer horizon indexes could identify signals of the business cycle peak as early as mid-1929, six to nine months ahead of time.

[Figure 3 here]

To further explore the implications of constructing a diffusion index with a specific forecast horizon versus an indefinite forecast horizon, we make a comparison as presented in Figure 4. Specifically, we plot, side by side over the entire forecast period from 1920 to 1934, the diffusion index with an indefinite horizon (i.e., always using the latest observation of its components) and the index with a horizon of zero. As Figure 4 shows, while the index with an indefinite horizon clearly leads the business cycle more than the index with a horizon of zero does, the amount of lead time varies. The index with a horizon of zero, i.e., for nowcasts, is better aligned with the recessions, especially after 1926. This observation should serve to reinforce our earlier conclusion that the business cycle peak and trough around the Depression are identifiable using a diffusion index.

[Figure 4 here]

4.2 The usefulness of additional data

So far, we have exclusively examined the indexes constructed using Moore's 21 variables. Next, we turn to the question of whether the additional monthly and quarterly variables we selected provide further improvement in the indexes' forecast performance. Since we are still primarily interested in the prediction of the turning points, we continue to rely on visual inspections of the forecasts.

[Figure 5 here]

In Figure 5, we compare the diffusion indexes with an indefinite horizon constructed using three progressively larger data sets. The first is based on the 21 series used by Moore. The second is based on the first index with additional monthly indicators of our choosing. The last data set adds to the second index some indicators available at a quarterly frequency. Our indexes remain

monthly in all three cases. The quarterly series are converted to a monthly frequency using linear interpolation. Figure 5 shows that the additional data we introduced helps with the forecasting of turning points in subtle, yet important ways. First, with the additional data, the indexes decline more smoothly throughout the initial months of the recession, potentially eliminating doubts regarding the state of the business cycle that one might have had in 1929m10 if one were to rely solely on the 21 series. Second, as the economy moves out of the recession, the indexes made with additional data, especially the quarterly series, do not have the same sharp decline in 1933m3 and 1933m4.

4.3 The effect of using different training samples to determine the components' lead time

Recall that when constructing diffusion indexes with specific horizons, we relied on a training sample to determine the lead time of each of the components. We explored two different training samples, where training sample (a) covers the three recessions before 1929 and training sample (b) covers only the recession immediately preceding that of 1929. Figure 6 compares the indexes constructed based on these training samples. Both indexes use all the data we have available, including the quarterly series. The indexes for nowcasting are in the top plot and the ones with a horizon of three months are in the bottom plot.

[Figure 6 here]

Figure 6 shows that a shorter training sample, i.e., training sample (b), helps to identify the peak in 1929 more accurately in the case of the nowcasts – the index constructed using this training sample shows an earlier and steadier decline around the onset of the recession in the second half of 1929. In addition, the indexes based on a shorter training sample have a more rapid decline during the first year of the recession and a slightly more pronounced rebound immediately out of the recession in early 1933. However, the differences between the indexes constructed using the two training samples become almost negligible for the three-month-ahead forecasts (and those at longer horizons, which are omitted from the figure). That said, although we believe a shorter training sample helps here, we caution against generalizing the conclusion beyond the context of forecasting the 1929 peak.

4.4 Overall classification accuracy of the indexes

Finally, we turn to the overall classification accuracy of the indexes when it comes to predicting the binary state of the economy, i.e., recession vs. non-recession. This is measured using the AUC statistic. Specifically, for each forecast series, we construct a nonparametric ROC curve and calculate the area under the curve. For the forecasts made using data sets augmented with the variables we selected, we take their AUC statistic and test the null hypothesis that it is the same as the AUC statistic of the forecasts made using Moore's series alone. In other words, we test whether the additional variables we selected help to improve forecast accuracy. For this purpose, we choose the nonparametric test of correlated ROC curves developed by DeLong *et al*. (1988) since all the forecasts are targeting the same set of outcomes. The results are reported in Table 3 using an evaluation sample of 1929 to 1934.

[Table 3 here]

Most of our previous observations are confirmed by these results. As the horizon increases, the accuracy of all forecasts deteriorates. Considering its simplicity, the diffusion indexes perform very well, especially at short horizons, where the AUC statistics reach above 0.9. Augmenting Moore's data set with the additional variables, especially the quarterly variables, helps to further improve the indexes' forecast performance at nearly all horizons. For the purpose of nowcasting, using the standard diffusion index with an indefinite horizon provides better overall accuracy than using the horizon-specific diffusion index. For the purpose of forecasting the 1929-1933 recession using horizon specific indexes, the shorter training sample, i.e., training sample (b) prove to be more helpful.

It is worth noting that the AUC statistics do not reflect the forecast's ability to identify the turning points. Since the two turning points represent only 2 out of 60 observations in the evaluation sample, forecasts that are better used for predicting the turning points do not necessarily exhibit better overall accuracy. For example, the forecasts from the probit model (B) based on Moore's data have consistently higher AUC across all horizons than those of the diffusion index, despite the latter being the one better suited for predicting turning points as shown in our analyses above.

5. REAL-TIME DATA VINTAGES

We carried out our forecasting exercises discussed above by making out-of-sample forecasts using revised data. In this section, we repeat this process using appropriate real-time data vintages. Note that despite the use of real-time data vintages, the forecasts we report in this section are not true real-time forecasts. A few difficulties make it impractical for us to carry out a true real-time forecasting exercise. The first concerns the publication lags of the variables in our data set. We are unable to ascertain the lag structure for all of our variables. This issue becomes more complex if we were to attempt to account for possible lags in data transmission in this historical context. The second difficulty stems from our limited access to real-time data vintages. As discussed in Section 2, we have obtained real-time data for a number of variables that we believe are important "drivers" of our results. Many variables were not revised, but in some cases, we simply did not have access to real-time data for all our variables. In addition, to the best of our knowledge, real-time data for the NBER recession dates do not exist for our target period.[16] Finally, a few variables in our data set are themselves (diffusion) indexes that are constructed after the 1929-1933 recession. As long as we use these series, we cannot avoid using the hindsight of those who developed the indexes. Therefore, we do not attempt to create forecasts in real time. Instead, we simply use the real-time data available to us as a robustness check to see if the substitution of our real-time data vintages for historical data would alter our baseline results in any fundamental way.

[Figure 7 here]

In Figure 7, we repeat some of the earlier exercises using forecasts constructed with appropriate real-time data vintages. The top plot repeats the same exercise shown in the top plot of Figure 2. The middle plot repeats the same exercise shown in Figure 3. The bottom plot repeats the same exercise shown in Figure 5. Generally speaking, the diffusion indexes that are constructed using the sign of the components are little changed. Since the transformations applied to most variables rely on values from a year ago in order to mitigate seasonality, minor data revisions do not alter the sign of the transformed values. Of course, the changes in the magnitude of these

[16] There was some recession dating by the NBER in the 1920s and 1930s by Burns and Mitchell, but the recession dates were made after the fact and were not revised in this period (Romer and Romer 2020).

transformed values lead to slight differences in the forecasts made using the probit model and the factor model. However, we do not observe anything that contradicts the conclusions reported earlier. These results based on real-time data vintages only serve to reinforce our main conclusions from the previous section.

6. QUARTERLY FORECASTS USING DIFFUSION INDEXES

In this section, we briefly consider whether we can better forecast the depression using the standard diffusion indexes if we focus on lower frequency quarterly data. The motivation for this choice is that the index at a lower frequency may be smoother. As discussed in Zhao (2020), the smoothness of the index is important when it comes to extracting binary predictions, as a smoother series may allow us to better identify turning points and thus reduce the uncertainty of the forecasts. Although the index is to be constructed at the quarterly frequency, we do not want to throw away information contained in the higher frequency monthly variables. We thus allow each monthly variable to enter the data set three times, with the values for the three months in a quarter. This strategy also increases the number of candidate series for the diffusion index, which helps to further smooth the index. In Figure 8, we plot the quarterly diffusion indexes. The top plot compares the three indexes with indefinite horizon that are constructed using the three data sets. The middle plot shows the comparison for the indexes constructed for nowcast (i.e., $h = 0$). The bottom plot shows the comparison for $h = 1$. Note that for these quarterly forecasts, the horizons are stated in quarters, and given the reduced number of observations, training sample (b) is not applicable.

[Figure 8 here]

As expected, Figure 8 shows that the quarterly indexes are smoother, which makes it easy to identify the turning points of the indexes. For example, the top plot shows that the diffusion index with an indefinite horizon clearly started to decline in 1929q4. If we also consider the indexes with specific horizons shown in the lower two plots, this decline can be identified during this quarter, though not one quarter ahead of time. The quarterly indexes appear to be able to "forecast" the 1933 trough only since 1933q3, which is one quarter after the actual trough. Comparing the indexes made with different data sets, we observe some differences between the Moore's series and the augmented data sets, but not between the two augmented data sets. This is understandable since the number of additional monthly variables exceeds that of the additional

quarterly variables, not to mention the design that creates three quarterly series from each monthly series. The added data provide some benefits especially during the first year of the recession. However, they appear to do little to help with the forecasting of the 1933 trough. While temporal aggregation could smooth out some of the noise in higher-frequency data, we do not find that this effect is large enough to offset the resulting loss in information and in the timeliness of the forecasts.

7. PREDICTING THE SEVERITY OF THE GREAT DEPRESSION

Finally, we turn to the challenge of forecasting the severity of the Great Depression. In line with the exercises in existing literature, we consider forecasting the next 18 months at a 3-month interval from Mar 1929 to Mar 1931. In other words, at the end of each quarter during this period, we make a set of forecasts covering the next 18 months. Our target variables for this exercise are industrial production and wholesale prices, percent change from a year ago. Since the diffusion index is devoid of magnitude information from its components, it cannot be used for this purpose. The standard method in the literature uses time series models such as the vector autoregression. We follow this approach in spirit. Specifically, we do not attempt to create a structural model. Instead, we use the factor model that we reported above when forecasting the turning points. This model has been successfully applied to nowcasting and forecasting variables like real GDP and consumption.[17] We use this model to estimate the common factors in the same way as before, and then use the factors in a linear regression model to forecast our target variables. The forecasting equation contains three lags of the dependent variable and three lags of each of the factors. As in our exercises above, we consider three different data sets: The first contains only Moore's series; the second is augmented with additional monthly variables; and the third further augmented with additional quarterly variables. Figure 9 shows these forecasts.

[Figure 9 here]

The key question for us is whether the severity and the continuation of the depression are predictable, and if so, how much in advance. In particular, we consider whether the predictability changes after the stock market crash of October 1929. As discussed in Section 1, conventional wisdom suggests little predictability at longer horizons, while small output declines are foreseeable

[17] See Giannone *et al*.(2008) and Lahiri *et al*. (2016).

at shorter horizons, c.f., Dominguez *et al*. (1988). Our results are largely similar. The models here successfully predict the decline in output even at longer horizons. However, the decline is predicted to be modest in magnitude, and the predictions remained modest even after the stock market crash in Oct 1929. In fact, as shown in Figure 9, output forecasts point to a soon-to-come recovery even after steep and sustained declines in the actual values. This is similar to the qualitative forecasts made by the business press in this period as well, which forecasted recovery "right around the corner" (Mathy and Stekler 2017). The severity of the price drop is better predicted in the sense that none of the forecasts in the year of 1930 point to an imminent recovery. However, at no point in our exercise do we obtain a price forecast as low as the realized value. As for the role of the additional variables we used to augment Moore's data set, Figure 9 shows that the forecasts made with these variables better state the severity of the depression, especially when we focus on the forecasts made in 1929 and early 1930. However, the differences are modest – even with these additional variables, it remains difficult to foretell the true severity and extent of the depression in its early months.

8. CONCLUDING REMARKS

This paper studied whether diffusion indexes can provide a quality forecast of the US Great Depression, as measured by the nowcasts and forecasts of turning points and the forecast ability of diffusion indexes for the Great Contraction period of 1929-1933. We have found that Moore's original diffusion index has decent performance, and that models based on the addition of other series performs at least as well. We are able to forecast the initial turning point when recession begins in 1929 in advance. This forecast is accurate several months ahead of the iconic stock market crash of October 1929. We also have some success in forecasting other turning points in advance, though the performance degrades in the late 1930s. This contrasts with previous forecasters that viewed the Depression as unforecastable, even using modern techniques and with the benefit of hindsight. Our results demonstrate the value of diffusion indexes in forecasting, specifically in an important historical episode. This suggests that diffusion indexes should be used more widely to provide useful forecasts, both in the present and historically.

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Table 1. List of variables and data availability

This table lists the variables in our data set, whether they are used by Moore, and the amount of data we have on each variable. A star * after a variable name indicates that we have real-time data for the variable.

Description	Data Start	Data End	Number of Observations
Variables used by Moore			
Automobile Production, Passenger Cars, Factory Production	1920m1	1940m12	252
Automobile Production, Trucks	1920m1	1940m12	252
Automobile Tire Inner Tube Production*	1922m1	1940m12	228
Average Hours of Work Per Week, Manufacturing Industries	1921m6	1940m12	235
Bank Clearings Outside New York City	1920m1	1940m12	252
Contracts for Industrial Buildings (sq. ft.)	1920m1	1940m12	252
Dow-Jones Industrial Stock Price Index	1920m1	1940m12	252
Index of Department Store Sales	1920m1	1940m12	252
Index of Factory Employment, Machinery	1920m1	1940m12	252
Index of General Business Activity (AT&T)	1920m1	1937m12	216
Index of Industrial Production and Trade	1920m1	1940m12	252
Index of Value of Residential Construction Contracts	1920m1	1940m12	252
Index of Wholesale Prices	1920m1	1940m12	252
Industrial Production Index*	1920m1	1940m12	252
Liabilities of Business Failures	1920m1	1933m1	157
Paper Production, All Grades	1920m1	1940m12	252
Pig Iron Production*	1920m1	1940m12	252
Production Worker Employment, Manufacturing	1920m1	1940m12	252
Railroad Operating Income	1920m1	1940m12	252
Revenue and Non-Revenue Net Ton-Miles of Freight Hauled	1920m1	1940m12	252
Steel Ingot Production*	1920m1	1939m12	240
Additional monthly variables			
Bank Debits for New York	1920m1	1940m12	252
Bank Debits, 140 Centers Outside of New York City	1920m1	1940m12	252
Bank Rates on Customer Loans, Leading Cities	1920m1	1939m2	230
Cum. Net Diff Ind, Industrial Production	1919m3	1940m12	262
Diff Ind of Eight Leading Indicators	1919m4	1940m12	261
Index of American Business Activity, Cleveland Trust	1920m1	1940m12	252
Index of Factory Employment, Automobiles	1920m1	1940m12	252
Labor Turnover, Gross Accession Rate, Manufacturing	1920m1	1930m12	132
Labor Turnover, Layoff Rate, Manufacturing	1920m1	1930m12	127
Productive security issues, corporate	1922m1	1940m7	217
Productive security issues, municipal, state, etc.	1922m1	1940m7	223
Retail Index US	1920m1	1939m12	240
Steel Ingot Production Capacity Utilization*	1927m1	1940m12	168
WPI, Commodities ex Farm Products and Foods	1920m1	1940m12	252
Additional quarterly variables			
Cum. Net Diff Ind, Profits of 17-700 Manuf. Corps.	1920m7	1940m10	244
Diff Ind, Freight Car loadings, 19 Commodity Groups	1927m1	1939m10	154
Gross National Product	1922m1	1940m10	226
Manufacturing Inventory Investment	1921m4	1938m10	211
New Capital, Equipment	1919m4	1940m10	259
New Capital, Plant	1919m4	1940m10	259
Railroad Freight Tons Originated, Carload	1921m1	1940m10	238

Table 2. Estimated lead time of our variables

The table shows the estimated amount of lead time, in months, of each variable in our data set. Two sets of estimates are provided as the estimation is carried out using two subsamples. Subsample (a), which starts in July 1919, contains the three recessions before that of 1929 to 1933, while subsample (b), which starts in Jan 1925, covers only the recession immediately before it. Only subsample (a) applies to quarterly variables.

Variable	Subsample		Variable	Subsample	
	(a)	(b)		(a)	(b)
Automobile Production, Passenger Cars, Factory Production	12	0	Index of Value of Res. Cons. Contr.	3	8
Automobile Production, Trucks	12	0	Index of Wholesale Prices	12	3
Automobile Tire Inner Tubes Production	1	0	Industrial Production Index	12	0
Average Hours of Work Per Week, Manufacturing Industries	0	1	Labor Turnover, Gross Accession Rate, Manufacturing	0	0
Bank Clearings Outside New York City	12	0	Labor Turnover, Layoff Rate, Manufacturing	0	4
Bank Debits for New York	1	0	Liabilities of Business Failures	0	0
Bank Debits, 140 Centers Outside of New York City	12	0	Manufacturing Inventory Investment	12	
Bank Rates on Customer Loans, Leading Cities	3	5	New Capital, Equipment	0	
Contracts for Industrial Buildings	12	5	New Capital, Plant	0	
Cum. Net Diff Ind, Industrial Production	0	8	Paper Production, All Grades	12	10
Cum. Net Diff Ind, Profits of 17-700 Manuf. Corps.	0		Pig Iron Production, 1000s Gross Tons, M, NSA	12	0
Diff Ind of Eight Leading Indicators	3	4	Production Worker Employment, Manufacturing	12	9
Diff Ind, Freight Car loadings, 19 Commodity Groups*	0		Productive security issues, corporate	3	9
Dow-Jones Industrial Stock Price Index	0	12	Productive security issues, municipal, state, etc.	10	0
Gross National Product	12		Railroad Freight Tons Originated, Carload	9	
Index of American Business Activity	12	12	Railroad Operating Income	0	0
Index of Department Store Sales	7	0	Retail Index US	9	1
Index of Factory Employment, Automobiles	12	0	Revenue and Non-Revenue Net Ton-Miles of Freight Hauled	8	1
Index of Factory Employment, Machinery	11	1	Steel Ingot Production	12	8
Index of General Business Activity	12	12	WPI, Commodities ex Farm Products and Foods	12	2
Index of Industrial Production and Trade	12	0			

* The length of the time series is too short for estimation. We assume the variable is coincident.

Table 3. Forecasting performance of various indexes measured by AUC statistics – 1929 to 1933

This table shows the area under the nonparametric ROC curve (AUC statistic) for each set of forecasts. The evaluation sample is from Jan 1929 to Dec 1933. Each column corresponds to a horizon. Horizon "i" means "indefinite" – these forecasts are evaluated like nowcasts and they do not have a corresponding training sample as the training sample refers to the one used to determine the lead time of the index components. For the forecasts made using data sets with the monthly and quarterly variables we selected, a test of the null hypothesis that the AUC is the same as that of the forecasts made using Moore's series alone is carried out. When this null hypothesis is rejected at the 10% level, the AUC statistic is set in bold.

Index and Data Set		Training sample (a)					Training sample (b)				
	$h = i$	$h = 0$	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 0$	$h = 1$	$h = 3$	$h = 6$	$h = 9$
A. % Expanding											
1. Moore series	0.95	0.69	0.66	0.68	0.62	0.58	0.92	0.88	0.84	0.71	0.63
2. Additional monthly variables	0.96	**0.73**	**0.70**	**0.68**	**0.67**	0.58	0.92	0.88	0.84	0.74	0.65
3. Additional quarterly variables	**0.98**	**0.79**	**0.78**	**0.75**	**0.72**	**0.62**	**0.95**	**0.93**	**0.88**	**0.79**	0.65
B. Predicted Probability											
1. Moore series	0.93	0.92	0.92	0.85	0.70	0.62	0.82	0.79	0.82	0.74	0.59
2. Additional monthly variables	**0.84**	0.82	0.83	**0.67**	**0.66**	0.69	**0.85**	**0.73**	**0.74**	0.59	0.61
3. Additional quarterly variables	0.73	0.78	0.75	**0.67**	0.51	0.68	0.82	0.67	0.80	0.62	0.59
C. DFM Forecast											
1. Moore series	0.98	0.99	0.97	0.94	0.81	0.61	0.93	0.95	0.92	0.90	0.68
2. Additional monthly variables	**0.99**	**0.99**	**0.98**	**0.95**	0.74	0.61	0.97	**0.95**	**0.92**	**0.92**	**0.69**
3. Additional quarterly variables	**0.99**	**1.00**	**0.99**	**0.98**	**0.89**	0.67	**0.97**	**0.95**	**0.93**	**0.94**	**0.77**

Figure 1. Selected indicators with visible seasonal variations

The three plots below present the raw data (dashed line) and the transformed values (bars) for three variables related to automobile production. They show that the transformed data do not exhibit visible seasonal variations and are such that positive values are typically associated with business cycle expansions. Shaded areas correspond to NBER dated recession periods.

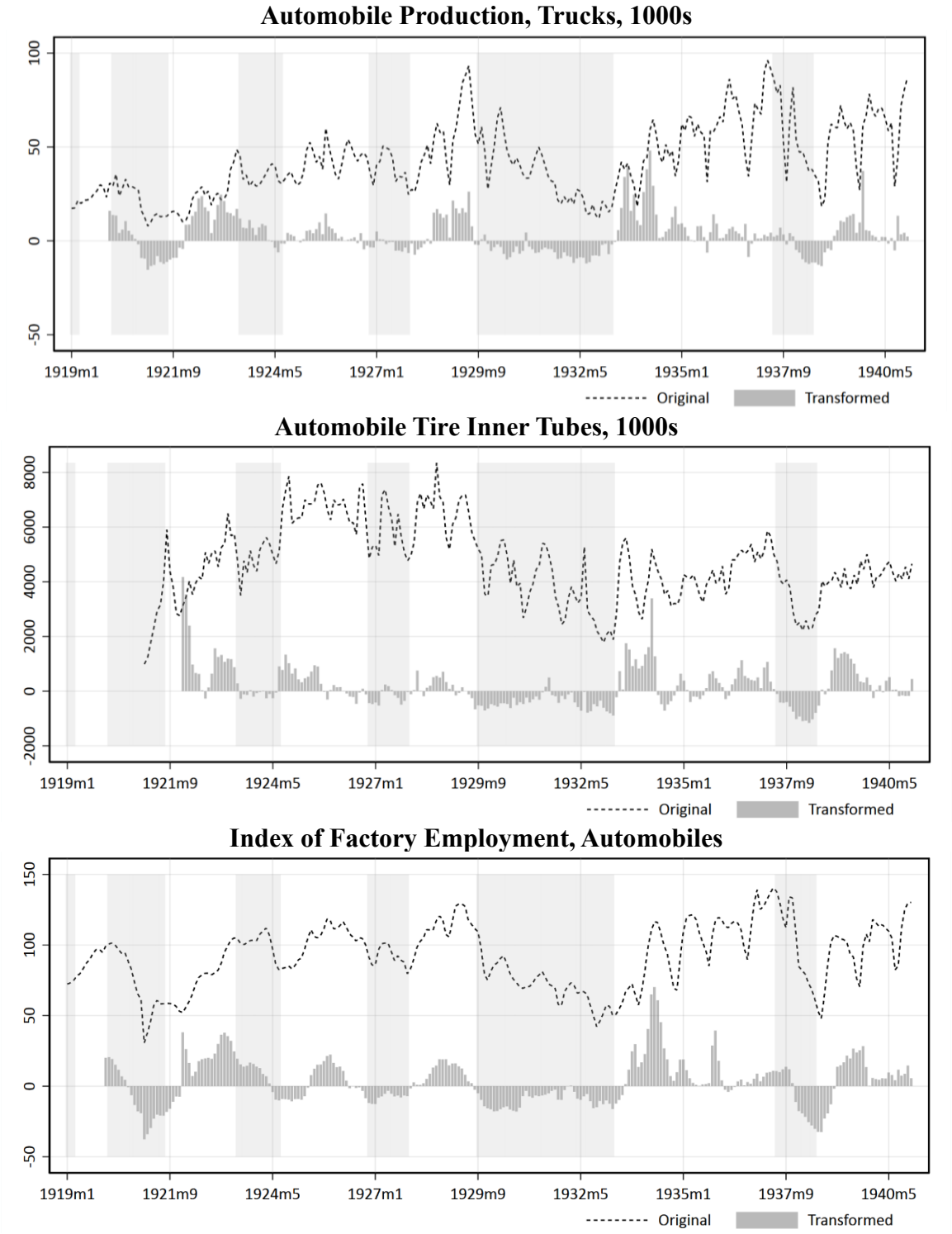


Figure 2. Comparing the indexes around the business cycle turning points of 1929 and 1933

Each plot presents a comparison of three sets of predictions, the standard diffusion index, the predictions from a probit model, and the predictions from a dynamic factor model, around the business cycle turning points of 1929 and 1933. The top plot compares the forecasts with an indefinite horizon. The middle plot compares the forecasts with a horizon of one month. The bottom plot compares the forecasts with a horizon of three months. The black horizontal grid line corresponds to the value 0.5. Note that during a recession, forecasts (A) should have low values while forecasts (B) and (C) should have high values. Shaded areas correspond to NBER dated recession periods.

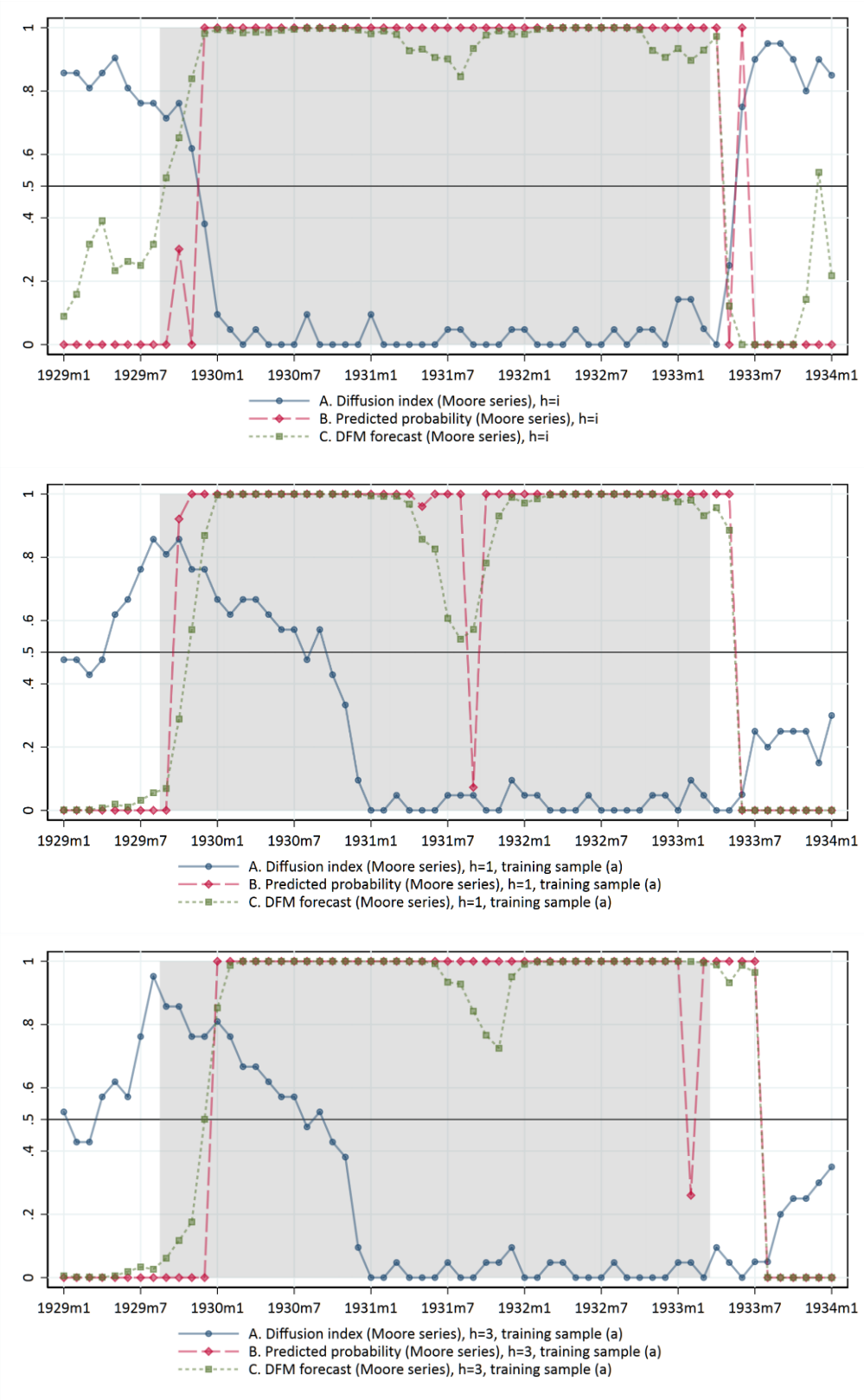


Figure 3. Comparing the diffusion index at horizons three, six, and nine months

This figure compares the diffusion indexes with horizons of three, six, and nine months. Note that the horizontal axis shows the date of the target, not the forecast – for example, the three-month-ahead forecast corresponding to 1930m1 is made for this month using information available three months ago. Shaded areas correspond to NBER recession periods.

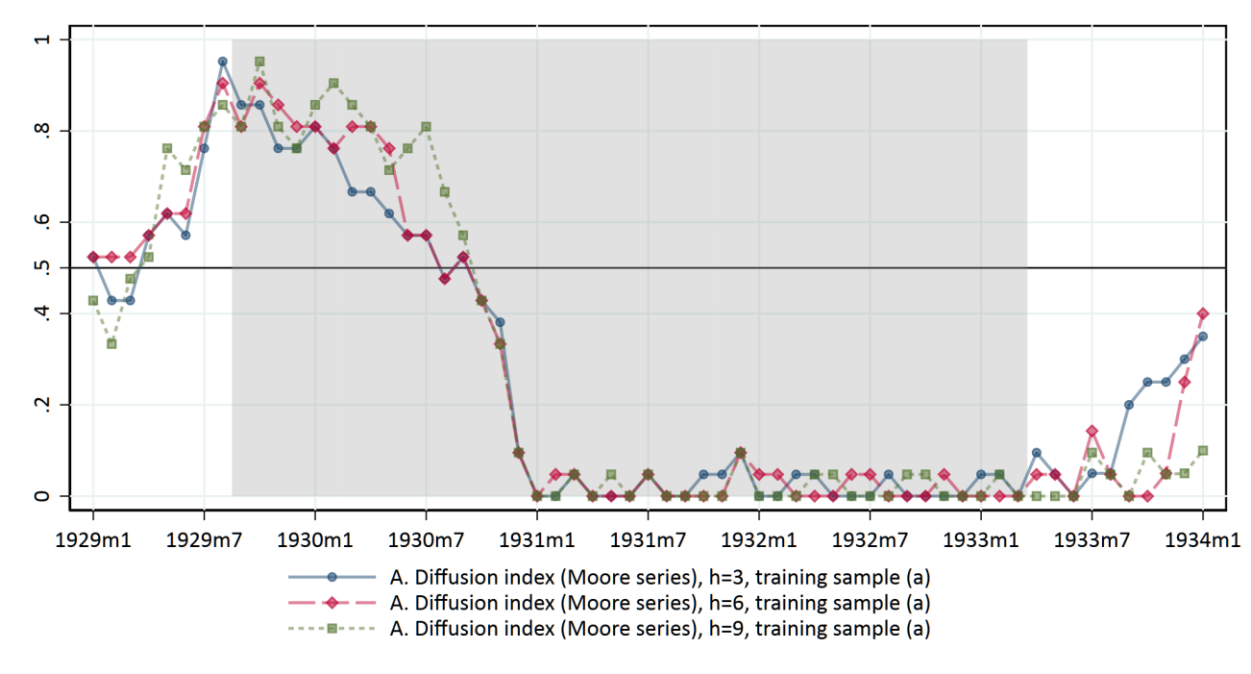


Figure 4. Comparing the diffusion index with an indefinite horizon and the index for nowcasting

This figure compares the diffusion index with an indefinite horizon and the index for nowcasting, i.e., with a horizon of zero month. Both series are aligned the same way, that is, the horizontal axis shows the date when the forecasts are made (which, given the horizon, is the same as the target date). Shaded areas correspond to NBER recession periods.

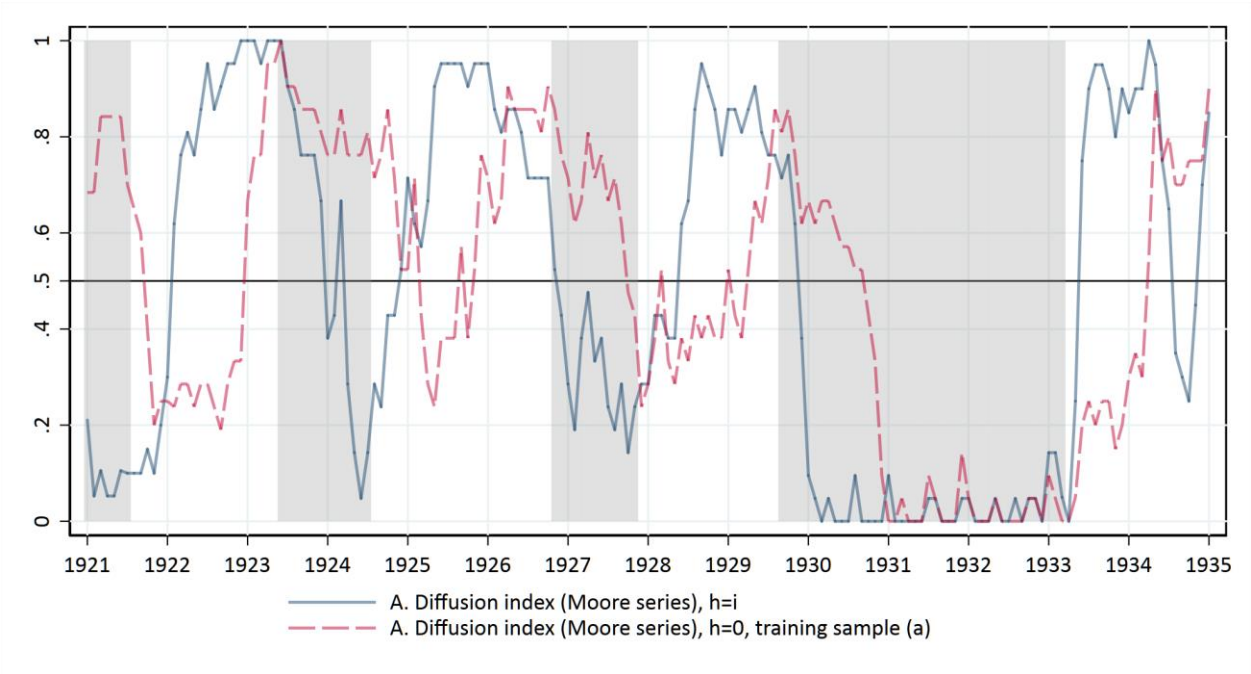


Figure 5. Comparing the diffusion index constructed using different data sets

This figure compares the diffusion indexes constructed using the data set containing Moore's 21 series and data sets with the additional monthly and quarterly series we selected. The three data sets are progressively larger, i.e., the forecasts labeled as made with additional quarterly series use all the data we have available. Shaded areas correspond to NBER recession periods.

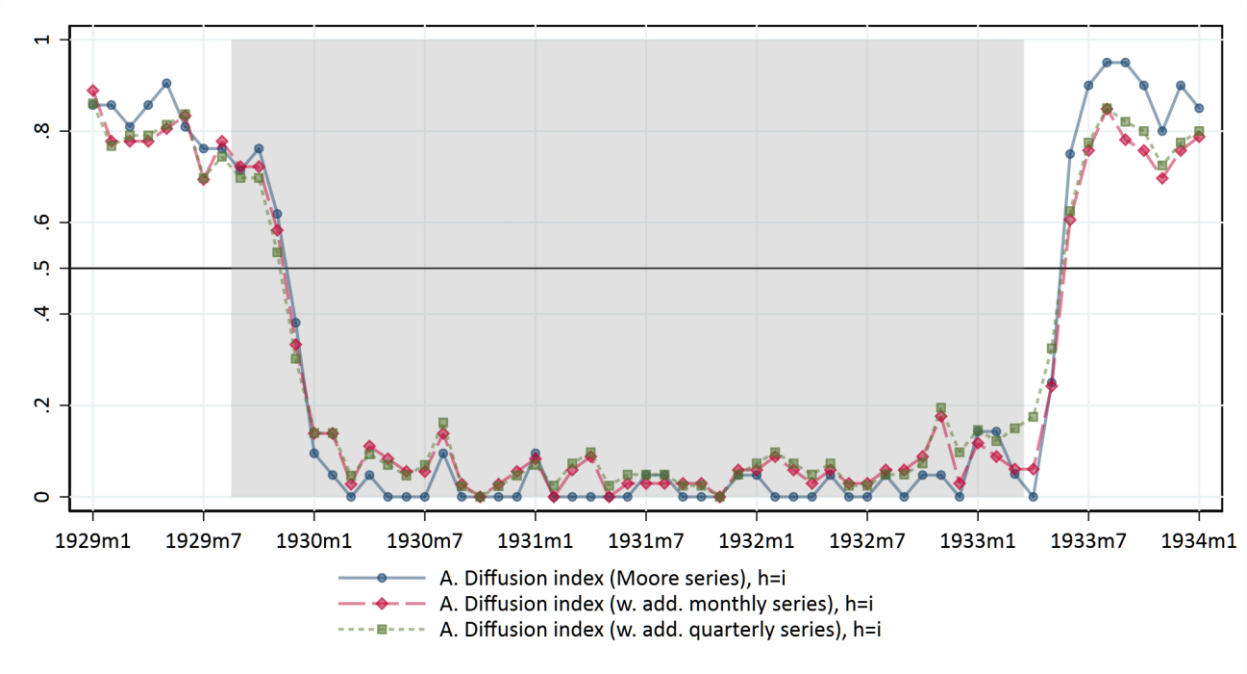
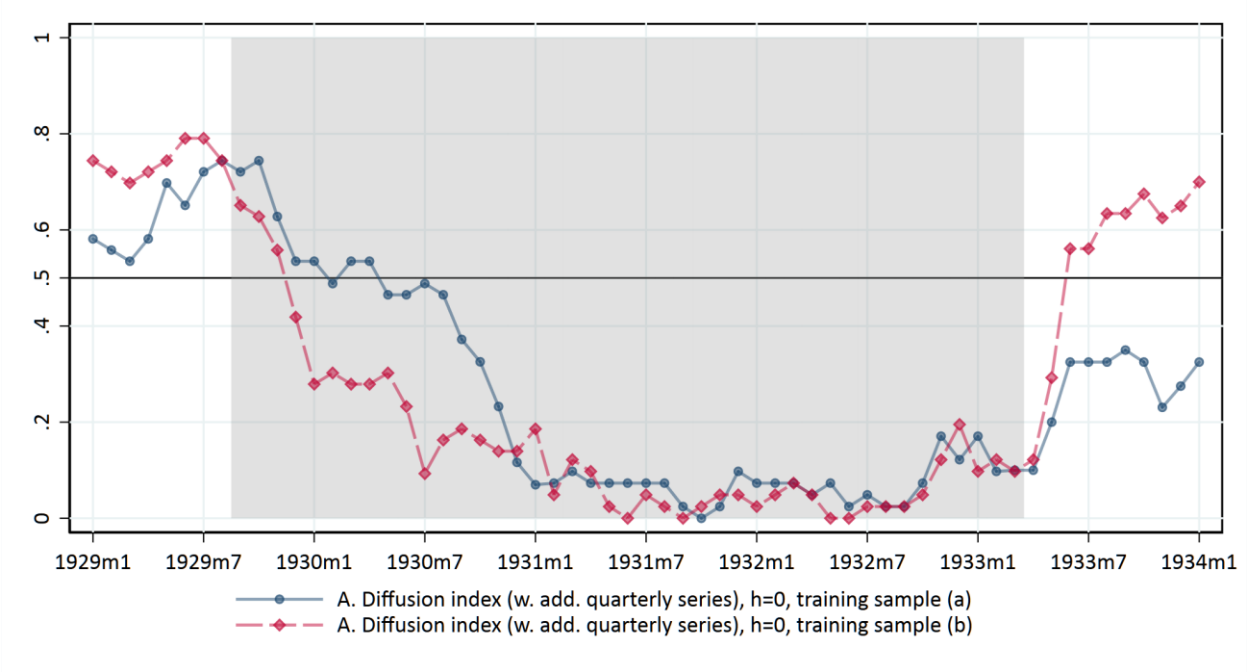


Figure 6. Comparing the effect of different training samples on diffusion indexes with specific horizons

This figure compares the horizon-specific diffusion indexes whose components' lead time is determined using different training samples. Training sample (a) covers the three recessions before the 1929 and training sample (b) covers only the recession immediately preceding that of 1929. The top plot shows the indexes for nowcasting and the bottom plot shows the indexes used to forecast with a horizon of three months. Shaded areas correspond to NBER recession periods.



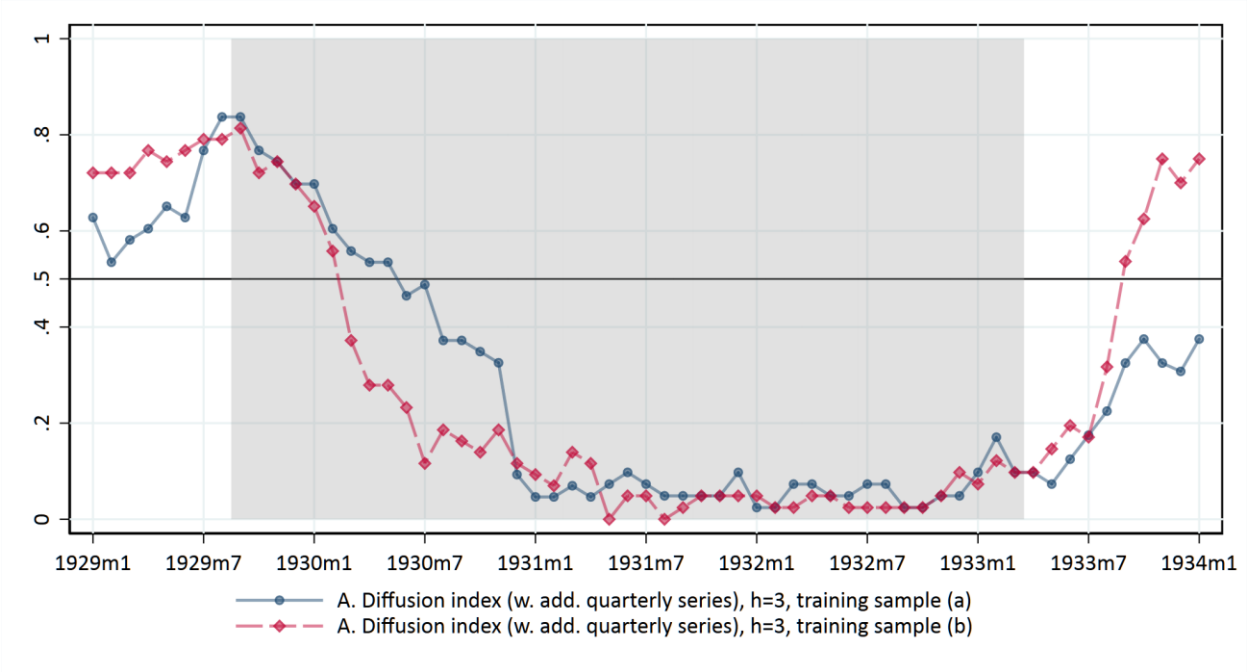


Figure 7. Indexes constructed using real-time data vintages

In this set of plots, we repeat some of the earlier exercises using forecasts constructed with appropriate real-time data vintages. The top plot repeats the same exercise shown in the top plot of Figure 2. The middle plot repeat the same exercise shown in Figure 3. The bottom plot repeats the same exercise shown in Figure 5. Shaded areas correspond to NBER recession periods.

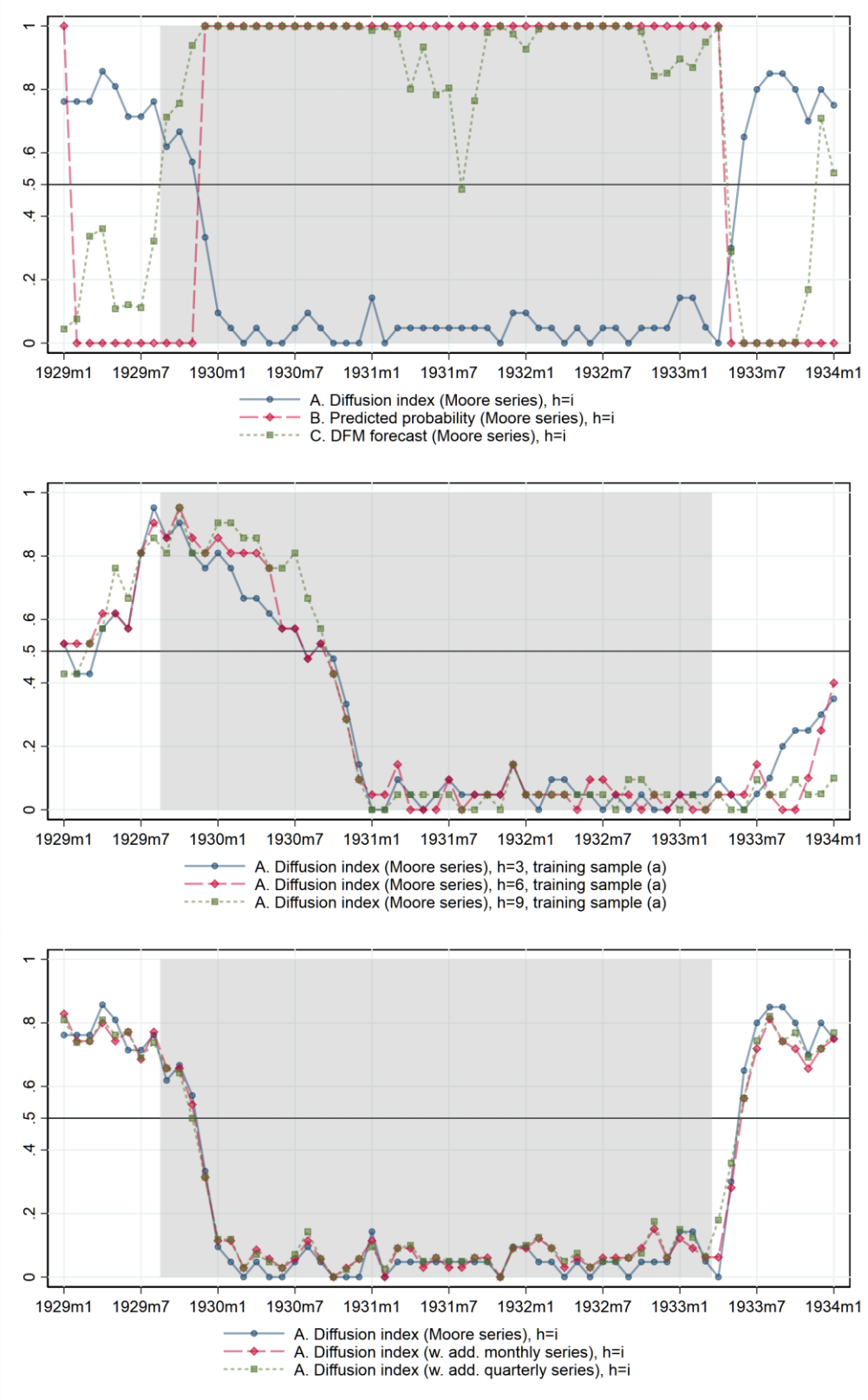


Figure 8. Comparing quarterly diffusion indexes constructed using different data sets

In this figure, we plot the quarterly diffusion indexes. The top plot compares the three indexes with indefinite horizon that are constructed using the three data sets. The middle plot shows the comparison for the indexes constructed for nowcast (i.e., $h = 0$). The bottom plot shows the comparison for $h = 1$. Note that the horizons are stated in quarters, and given the reduced number of observations, training sample (b) is not applicable here. Shaded areas correspond to NBER recession periods.

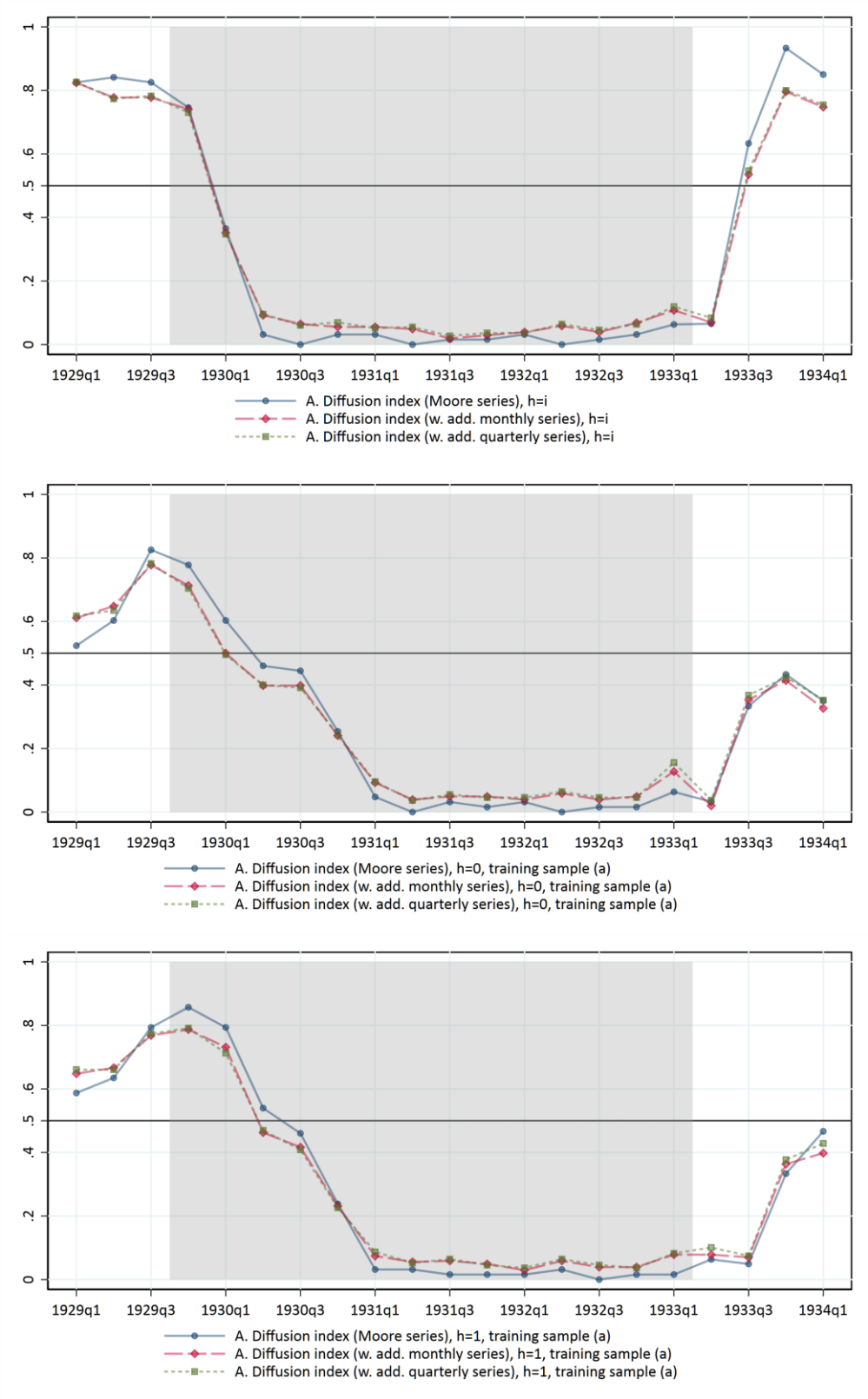


Figure 9. Comparing quarterly diffusion indexes constructed using different data sets

This figure shows the forecasts of the factor model made at a 3-month intervals for the next 18 months from Mar 1929 to Mar 1931. Our target variables for are industrial production and wholesale prices, percent change from a year ago. In each plot, the left panel shows the output forecasts and the right panel shows the price forecasts. The top plot shows the forecasts made using Moore's 21 series. The bottom plot shows the forecasts made using all available data including the additional monthly and quarterly variables. Shaded areas correspond to NBER recession periods.