On the (Mis)Use of Machine Learning with Panel Data

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Abstract

Machine Learning (ML) is increasingly employed to inform and support policymaking interventions. This methodological article cautions practitioners about common but often overlooked pitfalls associated with the uncritical application of supervised ML algorithms to panel data. Ignoring the cross-sectional and longitudinal structure of this data can lead to hard-to-detect data leakage, inflated out-of-sample performance, and an inadvertent overestimation of the real-world usefulness and applicability of ML models. After clarifying these issues, we provide practical guidelines and best practices for applied researchers to ensure the correct implementation of supervised ML in panel data environments, emphasizing the need to define ex ante the primary goal of the analysis and align the ML pipeline accordingly. An empirical application based on over 3,000 US counties from 2000 to 2019 illustrates the practical relevance of these points across nearly 500 models for both classification and regression tasks.

JEL-Codes: C33, C53.

Keywords: machine learning, prediction policy problems, panel data, data leakage.

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1. Introduction

In recent years, economics and other social sciences have enthusiastically embraced the use of Machine Learning (ML) to address "prediction policy problems" (Kleinberg et al., 2015).¹ Many scholars have started to apply supervised ML algorithms to rich panel data to analyze and support ex ante policy targeting and design. Topics covered include enhancing investments in energy, increasing the efficiency of workplace inspections and tax audits, as well as improving targeting at both local (e.g., bankruptcy, corruption) and national levels (e.g., financial crises, asylum seeker flows) (Antulov-Fantulin et al., 2021; Ash et al., 2024; Battaglini et al., 2024; Boss et al., 2024; Bluwstein et al., 2023; Christensen et al., 2024; de Blasio et al., 2022; Jarvis et al., 2022; Johnson et al., 2023). The overall idea underlying papers in this new tradition is simple and compelling: to leverage increasingly available rich panel datasets for accurately predicting complex social phenomena on new, previously unseen data, thus offering policymakers predictions that can be used to refine policies and shape outcomes in the desired direction (Kleinberg et al., 2015). In practice, the main purpose of most of these studies is to identify the areas or units most susceptible to a given hard-to-detect phenomenon. Accordingly, the ML algorithms are asked to find recurrent patterns in data and predict where the phenomenon under analysis is most likely to occur. By pinpointing the hotspots or 'red flags' (e.g., high-risk areas), these models can help policymakers to allocate resources in a costefficient way, ensuring that policy efforts are concentrated where they are needed most and allowing for proactive rather than reactive measures.

Although we believe that the insights provided by this new and active research area are valuable and that ML has much to offer in improving policy targeting and design, we deem it important to raise awareness about common mistakes associated with the default application of supervised ML to panel data, such as the use of contemporaneous covariates, i.e., covariates observed at time t, as predictors to forecast outcomes at time t, or the split of the observations into training and testing sets in a way that does not make them completely disjoint. Such modelling choices can potentially lead to severe data leakage and overly optimistic measures of out-of-sample performance, which, in turn, can result in misleading policy prescriptions and overconfidence in the actual ML's ability to support policy efforts. Data leakage is the unintended use of information during model training and validation that would not be expected to be available at the prediction stage and has been deemed 'one of the top ten

¹ This article is primarily intended for users of ML in genuine prediction settings. Another strand of literature has adapted and developed ML techniques for causal inference, i.e., to estimate treatment effects rather than predict outcomes (e.g., Wager & Athey, 2018; Chernozhukov et al., 2018), giving rise to the subfield of causal machine learning. Many of the issues discussed here are also relevant for causal machine learning techniques when used in conjunction with panel data.

data mining mistakes' (Kaufman et al., 2012).

The perils of data leakage associated with the use of ML have recently come under intense scrutiny across many different scientific fields, including, among others, biology, medicine, computer security, peace studies, nutrition, and satellite imaging (Apicella et al., 2024; Bernett et al., 2024; Kapoor & Narayanan, 2023; Rosenblatt et al., 2024). Data leakage has even been pointed out as one of the main culprits of the reproducibility crisis in machine-learning-based science (Kapoor & Narayanan, 2023), potentially contributing to producing 'illusions of understanding' in AI-driven scientific research (Messeri & Crockett, 2024). In the social sciences, these issues are rarely discussed, despite the fact that empirical analyses increasingly rely on panel data, which is particularly susceptible to data leakage.

We fill this gap by adopting a perspective centered around data leakage issues that specifically pertain to panel data. We start by clarifying the conceptual and practical pitfalls associated with the uncritical use of supervised ML with panel data. We then propose empirical guidelines for practitioners to ensure the correct implementation of supervised ML techniques in practically relevant panel data environments, emphasizing the need to clarify the primary goal *ex ante* and align the ML analysis accordingly. We illustrate these points with an empirical application based on a balanced panel dataset of over 3,000 US counties focusing on both a classification and a regression problem. Our target reader is the applied economist willing to correctly harness these powerful tools on their panel data to inform and target policy interventions.

For this analysis, we focus on aggregate panel data, also known as 'time-series cross-sectional data,' as the benchmark case. This type of data involves observations on multiple administrative entities (such as regions or countries) across multiple time periods and is increasingly used in studies on policy targeting. In addition, by analyzing aggregate panel data we can underline their specific challenges related to contamination or leakage issues, due to their spatial dimension, and to the possibility of covering the entire population of interest (e.g., all counties within a given state). Despite the peculiarities of aggregate panel data, most of the insights discussed below fully apply to longitudinal microdata on individuals or firms.

The rest of this paper is arranged as follows. Section 2 discusses the leakage problem. Section 3 provides empirical guidelines for applied researchers. Section 4 illustrates the empirical application. Section 5 concludes.

2. The leakage problem

The goal of supervised ML is to minimize out-of-sample error when predicting an outcome of interest based on a set of inputs, accurately generalizing to unseen data. The standard ML approach involves randomly splitting the original sample into two completely disjoint sets—for instance, 80% for training (the training set) and 20% for testing (the testing set). This approach adheres to a 'firewall' principle: none of the data used to generate the prediction function is employed for its evaluation (Mullainathan & Spiess, 2017). The out-of-sample performance of the model on unseen data from the testing set serves as a reliable measure of its 'true' performance on future data.² This seemingly safe reliance on randomization works fine in classic ML tasks where the data do not have either an explicit temporal or spatial dimension. But aggregate panel data are different from the typical ML datasets employed in other domains, as the observations are not independently distributed. If applied to panel data, the above standard procedure is wrong, both conceptually and practically, because it will lead to two different types of data leakage: temporal and cross-sectional leakage. Temporal leakage occurs when information from the future leaks into the past during the training and validation process,³ while cross-sectional leakage refers to information leaks that occur when the same unit appears in both the training and testing.

The entire point of ML is that the out-of-sample performance constitutes a proxy of the real ability of the model to predict on data it has *never* encountered before. The key problem with data leakage is that testing set data points are not new to the model at all. In general, the most significant consequence of data leakage is the inflation of the model's out-of-sample performance, which creates the illusion that the ML algorithm can accurately predict the target phenomenon. However, due to data leakage, the algorithm's performance will be substantially poorer when making predictions on genuinely unseen data. Therefore, data leakage can potentially result in misleading policy recommendations.

To see how leakage due to a random training-testing split can occur with panel data, consider a typical longitudinal dataset, such as the one reported in Figure 1, consisting of panel data with T=7 and N=20, with each unit (e.g., county) belonging to a larger geographical unit (e.g., state, with G=5 in this case). Panel data consist of unit-time observations, where each unit is observed at multiple points in time. In the usual tabular form, the rows of the dataset are therefore unit-time observations. Panel A of Figure 1 illustrates what happens to the data when applying the random split at the unit-time level.

 $^{^{2}}$ To address the bias-variance trade-off and prevent overfitting, automatic tuning techniques, such as random k-fold cross-validation (CV), can be applied to the training sample to select optimal hyperparameter values.

³ As we discuss later, other than through sample splits, temporal leakage can also result from the use of contemporaneous predictors (see Section 3).

Some rows, i.e., unit-time observations, will end up in the training set, while others will end up in the testing set. For many units, the same unit will appear in both training and testing sets. All time periods will appear in both the training and testing sets. The ML model will be trained and tuned on the training set, and then it will be employed to predict out-of-sample on the held-out unit-time observations.





Notes: This example mirrors a short version of the data from the empirical application described in Section 4, where the time variable corresponds to years, the unit variable to counties, and the group variable to states.

At this stage, however, the model will not really be encountering previously unseen data: it has

already 'seen' most units and all time periods belonging to the testing set during its training phase (e.g., in Panel A, unit 7 ends up in the training set in all time periods but T=5, in which it ends up in the testing set). It already 'knows' both most or all of the units and their characteristics—especially if some of the predictors are time-invariant or slowly changing over time—and any temporal trend of the outcome trajectories, because it has been trained on the latest available data already. Possibly worse, data at time t+k, with $k \ge 0$, in the training set will be employed to predict the outcome at time t in the testing set. Lastly, considering the forecasting goal associated with policy targeting, it does not make sense to include the latest available time period in the training sample. Therefore, with an observation-level random split on panel data, there will be both temporal and cross-sectional leakage, leading to a potentially severe overestimation of the authentic ability of the ML model to predict on new data points.

Yet, there are alternative solutions that can be employed: as Figure 1 shows, one can also split at the unit or group level or, alternatively, at the time level only. Table 1 below reports the four cases depicted in the figure and compares what happens to the observations. With a random split at the unit level, some units will appear only in the training set, while the rest of the units will only feature in the testing set.⁴ All time periods will be present in both sets. This type of split—using an 80/20 rule is shown in Panel B of Figure 1. This split strategy will lead to temporal leakage, but not crosssectional one: the units the ML model will encounter on the testing set will be previously unseen, but the algorithm may have already captured common shocks or a general trend in the trajectory of the outcome. A variation of this type is the split at the group level, where all units of some groups appear in the training set, and all units of other groups feature in the testing set. An example is provided in Panel C of Figure 1, where counties are grouped in states. This approach is usually done to remove residual cross-sectional leakage, as we will discuss below, but it still suffers from temporal leakage. In the fourth case, the researcher can split non-randomly on time: in this case, the first time periods will appear in the training set, while the latest will appear in the testing set (see Panel D of Figure 1 for an example where the first 5 time periods are part of the training set and the last two time periods constitutes the testing set).⁵ All units will be present in both sets. In this scenario, there will be crosssectional leakage, but not temporal one: the model will already know all the units it will encounter in the testing set, but it has never encountered before data from the latest points in time.

⁴ In practical implementation, this involves sampling blocks of rows, with the blocks defined by unit groups.

⁵ This corresponds to sampling data by the values in the 'Time' column of the dataset.

Strategy	Implication	Consequence
[1] Random split at the observation (unit-time) level	Many units appear in both training and testing sets. All the time periods appear in both the training and testing sets.	Temporal and cross- sectional leakage
[2] Random split at the unit level	Some units appear in the training set, while others feature only in the testing set. All time periods are present in both sets.	Temporal leakage
[3] Random split at the group level	All units of some groups appear in the training set, while all units of other groups feature only in the testing set. All time periods are present in both sets.	Temporal leakage
[4] Non-random split on time	Earlier time periods appear only in the training set, while later periods appear exclusively in the testing set. All units are present in both sets.	Cross-sectional leakage

Table 1: Split strategies for ML with panel data

Given that some form of leakage will inevitably always occur when applying ML to panel data, what is the best possible splitting strategy? To answer this question, we need to take a step back and consider the research goal. We stress that prediction policy problems can be divided into two main— and very different—types:

A. Cross-sectional prediction policy problems:

- The rationale for cross-sectional prediction⁶ is to address the challenge that arises when data for a specific outcome of interest are available only for a subset of units within a given population. For example, one variable might be collected over time only for certain areas (e.g., large ones). However, both policymakers and researchers aim to comprehensively understand and map the phenomenon across the entire population of units.⁷ In this scenario, ML can be applied to units with available outcome information. The model, trained on a subset of these data, can then predict out-of-sample outcomes for the rest of units with observed labels. If the

⁶ We label this type of out-of-sample prediction problem as 'cross-sectional' because, even though we are in a panel setting, its main goal is to produce 'horizontal' predictions of the outcome for other units—hence, cross-sectionally—rather than forecasting outcomes for the same units over time.

⁷ This is also known as 'transfer learning' in data-scarce environments.

model performs "well", it can be used to predict outcomes for units where no outcome data exists. This type of prediction task can be seen as using ML algorithms for missing data imputation rather than as a genuine policy targeting exercise.

For this cross-sectional prediction policy problem, the most appropriate choice is to split the sample at the unit level (split strategy [2]). This approach ensures no cross-sectional contamination, albeit at the expense of temporal leakage. The shared temporal information between the training and testing sets is not problematic in this context because our goal is not to forecast outcomes at future time points; rather, we aim to map the phenomenon cross-sectionally across units.

B. Sequential forecasting policy problems:

In this case, both the policymaker and the researcher are interested in machine predictions based on historical data that can accurately forecast future outcomes. The final policy goal might be the development of an early-warning model or the implementation of preventive policies. Here, the split must rigorously be non-random with respect to time (split strategy [4]). The model will be trained and tuned using earlier periods and evaluated on future periods. Operationally, there will be cross-sectional leakage because all units will appear in both the training and testing sets. However, given that the ultimate goal is to produce accurate outcome forecasts for the same units at future time points, this cross-sectional leakage is not conceptually or methodologically problematic.

On the other hand, a random split based on unit-time (split strategy [1]) is always problematic, whether the goal is cross-sectional prediction or forecasting. In this scenario, both types of leakage occur. The real-world utility of the model will be overstated, and the machine predictions will be biased. Furthermore, the researcher's goal remains unclear, leading to a ML strategy that produces misleading results. Unfortunately, the discrepancy between evaluated and actual performance on new data will most likely remain concealed until the end of the 'production' stage—i.e., if and when the ML tool is deployed for policy purposes, with all the unintended consequences for the cost, targeting, and effectiveness of said policy.

The preceding discussion is centered around the random split, dividing the original sample into two distinct sets. However, the same principles apply when considering traditional cross-validation for

hyperparameter tuning and model selection on the training set.⁸ Let us focus on temporal leakage as our benchmark. When we ignore the temporal dimension of panel data and perform random k-fold CV (as is automatically, but implicitly, done in most user-friendly ML packages⁹), we end up training the model on k-1 folds that include future time periods. Subsequently, we test its performance on the left-out k^{th} fold, which contains past time periods. Unfortunately, this approach does not optimize hyperparameters for forecasting, potentially leading to suboptimal model selection, as the model will not be specifically trained to forecast future observations, but also past ones. These issues related to information leakage across the temporal dimension are not novel and have been known for decades in time series analysis. Concepts such as time-series cross-validation (Hyndman & Athanasopoulos, 2018) were specifically developed to address these challenges. However, it appears that most practitioners of ML in the social sciences have so far overlooked these insights. There are signs of growing awareness among economists that we should think more carefully before applying standard ML routines to panel data.¹⁰ In a recent review of causal panel data methods, Arkhangelsky and Imbens (2024) warn that the panel dimension creates additional challenges in implementing crossvalidation routines. Given the increasing use of ML on panel data, we find it crucial to emphasize these concepts.¹¹

Finally, a consideration on cross-sectional prediction problems in scenarios where spatial dimensions play a significant role, such as when working with aggregate panel data. For instance, when strong spatial autocorrelation exists among units (as is often the case with aggregate data), we encounter a subtle form of contamination. Even if the same unit never appears in both training and testing sets, if units closely spatially autocorrelated with that unit do appear, spatial leakage occurs. Essentially, the

⁸ See <u>here</u> for a detailed discussion on possible cross-validation strategies in predictive settings with temporal and/or spatial autocorrelation in the data. Concerning *causal* ML methods, instead, we are not aware of any discussion of data leakage issues when applying cross-validation strategies, such as cross-fitting in the context of double machine learning (Chernozukhov et al., 2018), on panel data. This emerges as an interesting and important area for future research.

⁹ There are a few well-known exceptions to random cross-validation, such as the *createTimeSlices* function in the popular R package *caret*, or the *TimeSeriesSplit* function in the *scikit-learn* Python library. However, these functions are only suitable for time series, not for panel data. The only routines for panel data cross-validation we are aware of at this time are two new packages for R and Python, respectively, which can be found <u>here</u> and <u>here</u>.

¹⁰ See, for instance, the panel cross-validation approach proposed by Cerqua et al. (2024).

¹¹ Furthermore, and distinct from leakage issues, there is also a compelling case for preserving the temporal structure of the data so that the ML models can implicitly account for the time dimension. Supervised ML models (XGBoost, random forest, etc.) usually employed in recent literature, in fact, do not explicitly incorporate the temporal (and spatial) dimension of longitudinal data. While there are deep learning algorithms, such as the class of models called Recurrent Neural Networks, that are designed to model and learn sequential data, such as language processing and time series, they are seldom used in conjunction with panel data. This is because, like most time series forecasting techniques, they typically require a substantial number of time periods to obtain accurate predictions. In any case, when applied on tabular data, some supervised ML algorithms, such as tree-based methods, still consistently outperform deep learning techniques (Grinstazjn et al., 2022).

algorithm has not directly "seen" that specific unit, but it "knows" very similar ones encountered during training. To mitigate this issue, consider applying the random split not at the individual unit level, but at a higher level of clustering (split strategy [3]). For example, if the unit is a county, split at the state level. By stratifying the sample in this way, we reduce the risk of spatial leakage.¹²

Having highlighted these common yet often overlooked pitfalls, the next section provides a set of practically relevant recommendations for researchers dealing with these challenges in applied settings.

3. Practical guidelines

Table 2 below summarizes our recommendations for practitioners. Note that these guidelines pertain to both classification and regression problems. First and foremost, the researcher should clarify the research goal at the outset: which type of prediction policy problem you are working on? Are you interested in cross-sectional prediction or forecasting? Depending on the answer to this preliminary question, all the subsequent ML analysis on panel data will then be designed accordingly.

An important step that precedes the sample split and cross-validation stages, which we did not discuss earlier, concerns the choices governing the selection of predictors included in the dataset. This choice also depends on the overall goal of the project and is particularly important when the objective is forecasting for ex ante policy targeting. In case the researcher is interested in forecasting, it is crucial that only lagged (or time-invariant) predictors are included in the ML model. In this case, in fact, including predictors contemporaneous with the outcome—or even subsequent to it—would be both methodologically and practically incorrect. Methodologically, it would result in simultaneity issues, which can be seen as a form of temporal leakage originating from the predictors, as the ML model would learn any distribution shift or structural break at time t that is common to both the outcome and the predictors. In addition, the predictors themselves might be affected by the predicted event. It is indeed well-established in forecasting practice that, to forecast future values of a variable, only information available at the time the forecast is made can be used, and that the forecasting ability of a model must be evaluated by generating forecasts over some past period (with known outcomes) only using data known at each forecast origin (Petropoulos et al., 2022). Moreover, it is generally beneficial to include lagged outcome values as additional predictors to enhance the forecasting accuracy of the ML algorithm.

¹² This is the equivalent solution to what is done in causal inference to address potential violations of the stable-unit-treatment-value assumption in contexts with spatial spillovers.

ML Pipeline Step	Do's	Don'ts
1. Research design	Clarify your research and policy goal at the outset: are you interested in a cross-sectional prediction problem or a sequential forecasting problem?	Skip this stage and start the empirical analysis without having your goal in mind <i>ex ante</i> .
2. Dataset building	Do not include variables that are a direct derivation or transformation of the outcome. If you are interested in sequential forecasting, all predictors should be at least at $t - I$. Include lagged values of the outcome as additional predictors. ¹³ Do not include variables that are a direct derivation or transformation of the outcome.	Include both contemporaneous and lagged predictors, regardless of the problem's nature, or variables that are a direct derivation of the outcome.
3. Sample split	For cross-sectional prediction, split randomly at the unit level. If you suspect residual cross- sectional (e.g., spatial) leakage, consider stratified sampling at a higher level of aggregation. For sequential forecasting, split non-randomly on time.	Apply a random split at the observation (unit-time) level.
4. Cross-validation	If your goal is cross-sectional prediction, apply stratified cross-validation at the unit or group level on the training set. If interested in forecasting, apply temporal cross- validation at the time level on the training set (using either an expanding or rolling window approach). ¹⁴	Apply random k-fold CV.
5. Out-of-sample testing	Evaluate the out-of-sample performance of the model on truly previously unseen data.	Test the out-of-sample performance of the model on data it has already encountered before.

Table 2: Do's and Don'ts with ML analysis on panel data

On the practical side, if the goal is to provide policymakers with machine predictions that can anticipate the unfolding of a given phenomenon, then the applicability of those predictions should depend on data promptly available to the policymaker before the outcome materializes. Including contemporaneous predictors would mean waiting for those data to be collected, effectively turning the forecasting problem into a retrospective one by the time the predictor data become available.

¹³ Ideally, the choice of the optimal lag structure should also be cross-validated and based on a grid search.

¹⁴ As most existing ready-to-use package routines automatically implement random k-fold CV, this will likely involve a preliminary pre-processing step in which researchers manually prepare the temporally-ordered folds to implement a panel version of cross-validation which carefully preserves the temporal ordering of the data.

Finally, no direct derivations or mechanical transformations of the outcome should be included as predictors (e.g., the use of contemporaneous income levels to predict income growth).

In the next section, we provide an empirical illustration that demonstrates how to detect and quantify the degree of data leakage associated with the uncritical application of ML to panel data.

4. Empirical Application

To illustrate the practical implications of the issues discussed above, we carry out a comprehensive analysis on a panel dataset from the US. Specifically, the analysis is conducted at the county level for all US states. We have created a balanced panel of 3,058 counties (out of the 3,143 existing counties) from 2000 to 2019.¹⁵ We have collected a variety of variables to analyze economic performance across the US. The list of variables and their sources is reported in Table A.1 in Appendix A, while the descriptive statistics are in Table A.2 in Appendix A.

This setting is relevant as it utilizes socio-economic data from a widely studied high-income country, which could, for example, be employed to forecast areas that might soon enter a recession. This has self-evident policy implications and relevance for both the US and the global economy. To this end, the timespan of our dataset covers the period of the global financial crisis and the Great Recession.¹⁶

The overall objective of our analysis is to predict or forecast economic outcomes. We carry out two separate analyses: a classification and a regression task, to quantify and document data leakage across both types of prediction settings. There are two outcomes:

- for the regression task, we use personal income per capita¹⁷;
- for the classification task, we use a recession dummy that indicates whether a county experienced a decrease in personal income per capita in a given year.¹⁸

¹⁵ We lose a few counties due to boundary changes over the period under analysis and a few others because they lack data for at least one of the variables considered.

¹⁶ Cross-sectionally, this type of data could be used, for instance, to impute missing subnational inflation data that are collected only for larger or economically more relevant areas.

¹⁷ Personal income includes the total income received by all individuals and entities in a county from all sources (sum of wages and salaries, supplements to wages and salaries, proprietors' income with inventory valuation and capital consumption adjustments, rental income of persons with capital consumption adjustment, personal dividend income, personal interest income, and personal current transfer receipts, less contributions for government social insurance plus the adjustment for residence), which is then divided by the number of individuals (both civilian and military) who reside in the county.

¹⁸ Although a recession is generally considered to occur when there is a decline in real GDP for at least two consecutive quarters, we cannot adopt such definition for two reasons: i) our panel is at the year level; ii) the U.S. Bureau of Economic Analysis provides data on GDP at the county level only from 2017 onwards.

There are also two different prediction policy problems, as outlined in our previous discussion:

- i) sequential forecasting;
- ii) cross-sectional prediction.

Additionally, since we discussed above that temporal leakage in forecasting problems can be particularly severe if there are unforeseen changes in the relationships among variables, we also explore the forecasting problem with a special focus on a single year of our panel dataset—2009, during which the US experienced a drop in per capita income due to the Great Recession.

This means that we have in total *six* predictive problems to solve:

- 1) Forecasting a binary outcome;
- 2) Forecasting a continuous outcome;
- 3) Predicting cross-sectionally a binary outcome;
- 4) Predicting cross-sectionally a continuous outcome;
- 5) Forecasting a binary outcome in a single year (2009);
- 6) Forecasting a continuous outcome in a single year (2009).

To solve these six problems, we use the same set of raw predictors for all models. This ensures that any differences in performance that emerge can only be due to different partitioning of the data and the selection of the raw predictors.

For each predictive task (classification and regression), we run several different models featuring various combinations of the following parameters:

- 1. Use of contemporaneous predictors: in forecasting problems, this is one of the main types of data leakage. We alternatively include and remove contemporaneous predictors for the different models. For example, when we include contemporaneous predictors, we use unemployment in 2014 to predict income per capita in 2014. However, we never include contemporaneous predictors that are a direct derivation of the outcome variables (e.g., we do not use log income per capita in 2014 as a predictor in the classification task for the same year).
- Sample split strategy: we compare all the split strategies illustrated in Figure 1 and Table 1:
 [1] random split: a random split of the dataset at the county-year level; [2] county split: we randomly split at the county level, assigning counties to either the training or the testing set;
 [3] state split: we randomly split at the state level, and then assign their counties to either the

training or the testing set, to reduce potential spatial leakage; [4] time split: a non-random split at the year level.¹⁹

- **3.** Inclusion of lagged outcomes: this criterion is only used to assess how performance varies across models with and without outcome lags included.
- 4. Adjustment of the testing set size: without adjustments, the different choices in the above criteria result in different testing set sizes for the separate models. We alternatively adjust or not the testing set size of the different models, and run both the adjusted and unadjusted versions of the models to ensure an adequate comparative performance assessment.
- **5.** Algorithm: we employ two different ML algorithms: Extreme Gradient Boosting (XGBoost) and Random Forest. These algorithms are among the most popular ML techniques used by applied researchers. Refer to Appendix B for a description of these models. For comparability, we also run simpler models, namely a Logit model for the classification problem and Ordinary Least Squares (OLS) for the regression task.

Note that among the above-described parameters, only choices involving points 1) and 2) can be sources of data leakage, with 1) being a source of (temporal) leakage only in forecasting problems. Taking into account the six different prediction problems and the five modelling criteria just described, in total we run 480 different models. Due to the large number of models and to ensure better comparability across different configurations, we use default settings for the hyperparameter values of the ML algorithms, without cross-validating them. However, remember that when cross-validation is performed, it should follow the guidelines provided in Section 3. We start by discussing temporal leakage in the forecasting problems, and next, we move to cross-sectional leakage.

4.1 Temporal leakage (Predictive problems 1, 2, 5, 6)

Figure 2 shows the performance of the various model configurations for the classification (Panel A) and regression tasks (Panel B) across all time periods, when the goal is forecast an outcome over time and there is a risk of temporal leakage. Remember that temporal leakage in our context can arise from two parameters: a) when we include contemporaneous predictors, and b) when we do not split the dataset based on time. As we can see, in models with temporal leakage, the performance, as measured by the Area under the Curve (AUC), is significantly higher compared to non-leaked models. For instance, focusing on Figure 2 (classification – Panel A); when employing a random forest model, the average AUC among leaked models is 0.759, while the average among non-leaked models is 0.708, a difference of 0.051 points. This is a considerable difference as the AUC ranges from 0 to 1,

¹⁹ For the non-random split at the year level we assign all the observations in the years 2016,2017, 2018 and 2019 to the testing set.

with 0.5 being as good as random guessing. Similar results are observed with XGBoost (center image in Figure 2 Panel A) and Logit models (right image in Figure 2 Panel A). Analogous insights, with even larger leakage, apply to the regression task (see Figure 2 Panel B), where performance is measured by Mean Squared Error (MSE). The MSE of the leaked models is substantially lower. For instance, in the case of XGBoost the leakage ratio—expressed as the ratio between the difference in MSE between leaked vs. non-leaked models, over the MSE of the non-leaked models—is over 17%.

Figure 3 focuses on the Great Recession year (2009). As we can see, the difference in performance due to temporal leakage can be significantly larger when an unexpected shock occurs. For instance, the AUC for the classification task with the Random Forest model drops from 0.69 for the leaked models to 0.42 for the non-leaked ones (Figure 3 - Panel A). In contrast, the leakage ratio for the regression problem (Figure 3 - Panel B) remains similarly substantial as for the models run across all periods. This is not surprising since the decrease in personal income in the recession year was not large enough to entail significant differences in the value of the continuous outcome variable. These impressive differences for the classification task in 2009 underscore that inflation in performance due to temporal leakage is particularly harmful when trying to forecast otherwise difficult-to-anticipate events. In fact, structural breaks, such as the Great Recession, are known in the ML field as distribution shifts. A distribution shift occurs when the training data distribution differs from the data distribution the model encounters during testing. This leads to a sharp drop in out-of-sample performance because the input-to-output relationships and patterns the model learned during training no longer hold true in the new environment. By definition, distribution shifts are impossible to predict as they imply a fundamental and unforecastable change in the data-generating process. Even a wellperforming ML model cannot anticipate the impact of the Great Recession on economic outcomes when trained and tuned only on past information. This type of event thus represents a decisive litmus test to highlight the problem with leakage issues: if the model performs well on post-break data and the prediction error is small, something is probably wrong. Likely, it is not because the model can magically predict the future, but because some form of leakage-information from the future-has sneaked into the model, either via observations or predictors (or both). Failing to realize this means severely overestimating the power of ML models.²⁰

²⁰ More generally, one should be skeptical *a priori* of extremely good out-of-sample performances in predicting or forecasting complex socio-economic outcomes, which are partially characterized by inherently unpredictable idiosyncratic patterns that make the irreducible error substantially higher than in most standard ML applications.



Figure 2: Temporal leakage in the forecasting problem (all years)

Notes: Each axis shows the performance, measured in terms of AUC (Panel A) or MSE (Panel B), of different models where we forecast a binary dummy for recession (Panel A) or the log of the income per capita (Panel B) with a set of predictors (as described in Appendix A). The models are ordered from the worst to the best performing according to the chosen metric. The performance of the model is reported by the square marker. Each model differs according to the criteria specified in the table at the bottom of the axis. The different combinations of the parameters are highlighted by the colored rectangles below each marker, where darker colors indicate activation of that parameter. The bottom black/grey bar summarizes whether the model is temporally leaked. Specifically, a black rectangle represents a temporally leaked model that includes at least one of the following: contemporaneous variables; a non-time determined split. In Tables A.3 and A.4 of Appendix A we report the full results.



Figure 3: Temporal leakage in the forecasting problem (focus on the Great Recession, year 2009)

Notes: Each axis shows the performance, measured in terms of AUC (Panel A) or MSE (Panel B), of different models where we forecast a binary dummy for recession (Panel A) or the log of the income per capita (Panel B) with a set of predictors (as described in Appendix A). The models are ordered from the worst to the best performing according to the chosen metric. The performance of the model is reported by the square marker. Each model differs according to the criteria specified in the table at the bottom of the axis. The different combinations of the parameters are highlighted by the colored rectangles below each marker, where darker colors indicate activation of that parameter. The bottom black/grey bar summarizes whether the model is temporally leaked. Specifically, a black rectangle represents a temporally leaked model that includes at least one of the following: contemporaneous variables; a non-time determined split. In Tables A.5 and A.6 of Appendix A we report the full results.

4.2 Cross-Sectional Leakage (Predictive problems 3-4)

Turning to cross-sectional leakage, which in our case, since we are using aggregate panel data, takes the form of spatial leakage—a specific type of cross-sectional leakage. Spatial leakage occurs due to the same or similar (spatially autocorrelated) units appearing in both the training and testing sets. To assess the varying intensity of this type of leakage, we analyzed how the performance of the models changes with different splitting methods. The benchmark leaked model is trained and tested based on a random split, where all units (i.e., counties) are likely to appear in both the training and the testing sets. For the county split (i.e., unit-level split), we expect less spatial leakage, as counties in the training set do not appear in the testing set. For the state split, we ensure that all the counties in the testing set are not in the same state as any county in the training set. In plain words, in the "county" split, the model predicts the outcome of a county that it has never seen before, while in the "state" split, the model predicts the outcome of a county from a state whose counties the model has never seen before. Results are shown in Figure 4 for the classification (Panel A) and regression tasks (Panel B). As we can see, in all models except the Logit²¹, all leaked models tend to overperform the nonleaked ones, indicating the presence of spatial leakage, although the differences as smaller compared to temporal leakage. Interestingly, the worse performances are observed for models using the state splits, suggesting the presence of residual spatial leakage at the county level due to spatially autocorrelated nearby counties.

In sum, our empirical application shows that in a typical panel dataset, the data leakage issues we discussed in this paper tend to lead to significant overestimation of the performance of ML models across all the predictive problems considered. While these issues might not always be as severe as in this case study, since the extent of leakage and the degree of out-of-sample performance overestimation will vary depending on the application, we suspect that in most datasets, leakage issues will be substantial enough to significantly alter the evaluation of the ML models. Furthermore, even when leakage is proven to be minimal, it remains conceptually and methodologically inappropriate to disregard the unique characteristics of panel data in such applications.

²¹ Note that the logit model, unlike the other two ML algorithms, has difficulty handling the unbalanced distribution of the outcome variable (recession dummy) for the classification task. In these cases, performance metrics like the AUC can be uninformative. To understand this problem with logit, check Table A.3, where we also report detailed results on sensitivity and specificity across the different classification models. Consequently, the logit results for classification should be interpreted with a grain of salt.

Figure 4: Cross-sectional leakage (all years)



Notes: Each axis shows the performance, measured in terms of AUC (Panel A) or MSE (Panel B), of different models where we cross-sectionally predict a binary dummy for recession (Panel A) or the log of the income per capita (Panel B) with a set of predictors (as described in Appendix A). The models are ordered from the worst to the best performing according to the chosen metric. The performance of the model is reported by the square marker. Each model differs according to the criteria specified in the table at the bottom of the axis. The different combinations of the parameters are highlighted by the colored rectangles below each marker, where darker colors indicate activation of that parameter. The bottom black/grey bar summarizes whether the model is spatially leaked. Specifically, a black rectangle represents spatially leaked model with a training/testing set split not determined at the state level. In Tables A.7 and A.8 of Appendix A we report the full results.

5. Conclusions

Data leakage in the use of ML is increasingly recognized as a fundamental challenge across many scientific fields (Bernett et al., 2024; Kapoor & Narayanan, 2023; Rosenblatt et al., 2024). No such widespread awareness has yet emerged in the social sciences, especially concerning longitudinal data. We argue that more effort and critical thinking should be devoted to the preliminary design of ML analysis on panel data to avoid data leakage issues that might bias out-of-sample performance upward and unintentionally mislead policymakers into overestimating the power and applicability of ML techniques. We caution applied researchers against simply importing traditional ML practices into their research domain without taking care of the underlying analytical and practical implications. We also suggest that each ML paper should clearly report the full ML pipeline and explicitly write how they prevented data leakage issues. Given the ongoing ML revolution in economics and other social sciences and the growing availability of panel data, these issues deserve attention.

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Appendix - Supplementary application information

A. Data and full results

The analysis is conducted at county level for all US states. We have created a balanced panel of 3,058 counties (out of the 3,143 existing counties) from 2000 to 2019.²² We have collected a variety of variables to analyze economic performance across the US. The list of variables and their sources is reported in Table A.1, while the descriptive statistics are in Table A.2. As described in the main text, there are two dependent variables:

- i) one for the regression problem, i.e., personal income per capita growth rate measured as the annual percentage change in personal income per capita²³;
- ii) one for the classification problem, namely, a recession dummy that indicates whether a county experienced a drop in personal income per capita in a given year.²⁴

Economic variables including personal income per capita, average wage, percentage of income from unemployment benefits and workplace employment rate (number of employees divided by the resident population from 18 to 65 years old) are all sourced from the U.S. Bureau of Economic Analysis (BEA). The rest of the predictors are instead sourced from US Census. Demographic information encompasses total population, the percentage of the population under 18 and over 65, as well as detailed breakdowns by gender and racial composition (White, Black, Hispanic, and Asian percentages of the population). Additionally, it includes birth and death rates per 1,000 inhabitants. Lastly, also the mobility aspects is taken into account via the net internal and domestic migration per 1,000 inhabitants. This diverse set of variables ensures a robust framework for understanding the factors influencing economic dynamics at the county level and serves the scope for showcasing the data leakage consequences of an erroneous split of the training-test data.

²² We lose a few counties due to boundary changes over the period under analysis and a few others because they lack data for at least one of the variables considered.

²³ Personal income includes the total income received by all individuals and entities in a county from all sources (sum of wages and salaries, supplements to wages and salaries, proprietors' income with inventory valuation and capital consumption adjustments, rental income of persons with capital consumption adjustment, personal dividend income, personal interest income, and personal current transfer receipts, less contributions for government social insurance plus the adjustment for residence), which is then divided by the number of individuals (both civilian and military) who reside in the county.

²⁴ Although a recession is generally considered to occur when there is a decline in real GDP for at least two consecutive quarters, we cannot adopt such definition for two reasons: i) our panel is at the year level; ii) the U.S. Bureau of Economic Analysis provides data on GDP at the county level only from 2017 onwards.

Variable	Source
Personal income per capita growth rate (%)	U.S. Bureau of Economic Analysis (BEA)
Recession dummy	U.S. Bureau of Economic Analysis (BEA)
Personal income per capita	U.S. Bureau of Economic Analysis (BEA)
Average wage	U.S. Bureau of Economic Analysis (BEA)
Income from Unemployment Benefit (%)	U.S. Bureau of Economic Analysis (BEA)
Workplace employment rate (%)	U.S. Bureau of Economic Analysis (BEA)
Population	US Census data
Population under 18 (%)	US Census data
Population over 65 (%)	US Census data
Women (% of population)	US Census data
White (% of population)	US Census data
Black (% of population)	US Census data
Hispanic (% of population)	US Census data
Asian (% of population)	US Census data
Birth (per 1,000 inhabitants)	US Census data
Deaths (per 1,000 inhabitants)	US Census data
Net internal migration (per 1,000 inhabitants)	US Census data
Net domestic migration (per 1,000 inhabitants)	US Census data

Variable	Mean	Std Dev
Personal income per capita growth rate (%)	3.38	5.66
Recession dummy	0.15	0.36
Personal income per capita	34,089	11,280
Average wage	34,140	9,236
Income from Unemployment Benefit (%)	46.43	40.02
Workplace employment rate (%)	86.65	27.59
Population	98,965	317,471
Population under 18 (%)	23.53	3.40
Population over 65 (%)	16.51	4.54
Women (% of population)	50.13	2.07
White (% of population)	78.61	19.37
Black (% of population)	8.75	14.35
Hispanic (% of population)	8.12	13.13
Asian (% of population)	3.35	4.89
Birth (per 1,000 inhabitants)	11.16	3.80
Deaths (per 1,000 inhabitants)	9.57	3.57
Net internal migration (per 1,000 inhabitants)	1.00	1.82
Net domestic migration (per 1,000 inhabitants)	-0.99	18.54
Ν	3,0)58
Т	2	20
N·T	61,	160

Table A.2: Descriptive statistics

Tuble 11.5. Temporal leakage in the forecasting classification problem (an years)	run
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Results

Model	Contemporaneous	Outcome Lags	Split Type	AUC	Adj. Test Size	Sensitivity	Specificity	Train Size	Test Size
Logit	yes	yes	time	0.335	yes	0.000	0.998	34244	2448
Logit	yes	yes	time	0.338	no	0.000	1.000	42812	12232
Logit	no	yes	time	0.357	yes	0.009	0.991	34244	2448
Logit	no	yes	time	0.361	no	0.000	1.000	42812	12232
Logit	yes	no	time	0.361	yes	0.997	0.001	34244	2448
Logit	ves	no	time	0.377	no	0.999	0.000	42812	12232
Logit	no	no	time	0.392	yes	0.997	0.003	34244	2448
Logit	ves	ves	random	0.399	no	0.000	1.000	42934	12110
Logit	no	no	time	0.409	no	0.000	1.000	42812	12232
Logit	ves	ves	random	0.414	ves	0.079	0.937	34244	2448
Logit	no	ves	random	0.423	no	0.096	0.911	42934	12110
Logit	no	ves	random	0.437	ves	0.171	0.877	34244	2448
Logit	ves	no	random	0.473	no	0.000	0.999	42934	12110
Logit	ves	no	random	0.487	ves	0.661	0.355	34244	2448
Logit	no	no	random	0.493	no	0.132	0.878	42934	12110
Logit	no no	no	random	0.508	ves	0.685	0.368	34244	2448
XGBoost	no	no	random	0.500	no	0.661	0.500	42934	12110
XGBoost	no	Ves	time	0.695	Ves	0.674	0.622	3/2/1	2//8
Random forest	no	yes	time	0.698	yes	0.680	0.650	34244	2440
XGBoost	no	no	time	0.698	yes	0.759	0.050	34244	2440
Pandom forest	no	Nec	time	0.098	yes	0.739	0.571	34244	2440
VCPoost	lio	yes	time	0.099	yes	0.710	0.019	24244	2440
AUDOOSI Dandam famat	yes	yes	undom	0.705	yes	0.504	0.793	42024	12110
Random forest	lio	no	random	0.705	IIO	0.646	0.647	42954	2448
Kandom lorest	no	no	random	0.711	yes	0.605	0.692	34244	2448
XGBoost	no	no	random	0.712	yes	0.568	0.743	34244	2448
XGBoost	yes	no	time	0.713	yes	0.649	0.722	34244	2448
AGBoost	no	yes	time	0.713	no	0.649	0.701	42812	12232
XGBoost	no	yes	random	0./14	no	0.587	0.724	42934	12110
XGBoost	no	no	time	0.715	no	0.632	0.714	42812	12232
Random forest	no	no	time	0.717	no	0.745	0.593	42812	12232
Random forest	no	yes	time	0.718	no	0.733	0.608	42812	12232
XGBoost	yes	yes	time	0.719	no	0.611	0.744	42812	12232
XGBoost	yes	no	time	0.722	no	0.650	0.706	42812	12232
Random forest	yes	no	time	0.723	yes	0.689	0.681	34244	2448
XGBoost	no	yes	random	0.724	yes	0.598	0.736	34244	2448
Random forest	yes	yes	time	0.734	yes	0.723	0.648	34244	2448
Random forest	yes	no	time	0.736	no	0.724	0.644	42812	12232
Random forest	yes	yes	time	0.745	no	0.625	0.748	42812	12232
Random forest	no	yes	random	0.749	no	0.624	0.743	42934	12110
Random forest	no	yes	random	0.757	yes	0.661	0.722	34244	2448
XGBoost	yes	no	random	0.769	no	0.662	0.743	42934	12110
XGBoost	yes	yes	random	0.787	no	0.756	0.671	42934	12110
XGBoost	yes	no	random	0.789	yes	0.668	0.780	34244	2448
Random forest	yes	no	random	0.796	no	0.740	0.714	42934	12110
Random forest	yes	no	random	0.803	yes	0.764	0.711	34244	2448
XGBoost	yes	yes	random	0.804	yes	0.629	0.846	34244	2448
Random forest	yes	yes	random	0.820	no	0.720	0.761	42934	12110
Random forest	yes	yes	random	0.830	yes	0.757	0.757	34244	2448

Model	Contemporaneous	Outcome Lags	Split Type	MSE	Adj. Test Size	Train Size	Test Size
OLS	yes	yes	time	0.042	yes	34244	2448
OLS	yes	yes	time	0.044	no	42812	12232
OLS	no	yes	time	0.044	yes	34244	2448
Random forest	yes	yes	time	0.045	no	42812	12232
Random forest	yes	yes	time	0.045	yes	34244	2448
OLS	no	yes	time	0.046	no	42812	12232
Random forest	no	yes	time	0.047	no	42812	12232
Random forest	no	yes	time	0.048	yes	34244	2448
XGBoost	yes	yes	random	0.048	yes	34244	2448
OLS	yes	yes	random	0.049	yes	34244	2448
Random forest	yes	yes	random	0.049	yes	34244	2448
XGBoost	yes	yes	random	0.049	no	42934	12110
OLS	yes	yes	random	0.050	no	42934	12110
XGBoost	yes	yes	time	0.051	no	42812	12232
XGBoost	yes	yes	time	0.051	yes	34244	2448
Random forest	yes	yes	random	0.052	no	42934	12110
Random forest	no	yes	random	0.052	yes	34244	2448
OLS	no	yes	random	0.053	yes	34244	2448
Random forest	no	yes	random	0.054	no	42934	12110
OLS	no	yes	random	0.055	no	42934	12110
XGBoost	no	yes	random	0.056	yes	34244	2448
XGBoost	no	yes	random	0.057	no	42934	12110
XGBoost	no	yes	time	0.060	no	42812	12232
XGBoost	no	yes	time	0.062	yes	34244	2448
XGBoost	yes	no	random	0.086	yes	34244	2448
XGBoost	yes	no	random	0.088	no	42934	12110
XGBoost	no	no	random	0.091	no	42934	12110
XGBoost	no	no	random	0.092	yes	34244	2448
Random forest	yes	no	random	0.107	yes	34244	2448
Random forest	yes	no	random	0.107	no	42934	12110
Random forest	no	no	random	0.111	no	42934	12110
Random forest	no	no	random	0.112	yes	34244	2448
XGBoost	no	no	time	0.123	yes	34244	2448
XGBoost	yes	no	time	0.124	yes	34244	2448
XGBoost	yes	no	time	0.125	no	42812	12232
XGBoost	no	no	time	0.125	no	42812	12232
Random forest	yes	no	time	0.128	no	42812	12232
Random forest	yes	no	time	0.128	yes	34244	2448
Random forest	no	no	time	0.130	yes	34244	2448
Random forest	no	no	time	0.130	no	42812	12232
OLS	yes	no	random	0.153	no	42934	12110
OLS	yes	no	random	0.154	yes	34244	2448
OLS	yes	no	time	0.160	yes	34244	2448
OLS	yes	no	time	0.162	no	42812	12232
OLS	no	no	random	0.167	no	42934	12110
OLS	no	no	time	0.168	yes	34244	2448
OLS	no	no	random	0.169	yes	34244	2448
OLS	no	no	time	0.172	no	42812	12232

Table A.4: Temporal leakage in the forecasting regression problem (all years) – Full Results

Notes: The table reports the details of the results shown in Figure 2 – Panel B.

M. 1.1	0	Outcome	Split		Adj. Test	G	G	Train	T C!
Model	Contemporaneous	Lags	Туре	AUC	Size	Sensitivity	Specificity	Size	Test Size
XGBoost	no	no	time	0.393	yes	0.020	1.000	14676	612
XGBoost	yes	no	time	0.399	yes	0.046	0.968	14676	612
Random forest	no	no	time	0.409	yes	0.033	0.991	14676	612
XGBoost	no	yes	time	0.422	yes	0.025	0.995	14676	612
XGBoost	no	no	time	0.424	no	0.016	0.991	18348	3058
XGBoost	yes	yes	time	0.429	yes	0.079	0.950	14676	612
XGBoost	yes	no	time	0.431	no	0.069	0.939	18348	3058
Random forest	no	yes	time	0.440	yes	0.025	1.000	14676	612
Random forest	no	no	time	0.441	no	0.021	0.985	18348	3058
Logit	yes	yes	random	0.449	yes	0.082	0.936	14676	612
Random forest	yes	no	time	0.462	yes	0.015	0.995	14676	612
Random forest	yes	yes	time	0.463	yes	0.086	0.950	14676	612
Logit	yes	yes	random	0.465	no	0.159	0.865	16696	4710
XGBoost	no	yes	time	0.466	no	0.135	0.905	18348	3058
Logit	no	yes	random	0.470	yes	0.082	0.944	14676	612
XGBoost	yes	yes	time	0.472	no	0.074	0.962	18348	3058
Random forest	no	ves	time	0.479	no	0.149	0.892	18348	3058
Random forest	ves	no	time	0.485	no	0.267	0.746	18348	3058
Logit	no	ves	random	0.488	no	0.263	0.787	16696	4710
Random forest	ves	ves	time	0.496	no	0.157	0.893	18348	3058
Logit	ves	no	random	0.554	ves	0.545	0.612	14676	612
Logit	yes	no	random	0.564	no	0.481	0.649	16696	4710
Logit	yes	no	random	0.572	Vec	0.545	0.627	1/676	612
Logit	no	10	random	0.572	no	0.537	0.627	16696	4710
Logit	Nes	Nec	time	0.584	no	0.548	0.597	183/8	3058
Logit	yes	yes	time	0.589	IIO	0.348	0.397	14676	612
Logit	yes	yes	time	0.500	yes	0.277	0.807	14070	2058
Logit	lio	yes	time	0.500	110	0.330	0.394	10540	5058
Logit	по	yes	time	0.592	yes	0.279	0.867	140/0	012
Logit	yes	no	time	0.638	no	0.640	0.566	18348	3058
Logit	no	no	time	0.645	no	0.625	0.593	18348	3058
Logit	yes	no	time	0.656	yes	0.751	0.482	14676	612
Logit	no	no	time	0.664	yes	0.782	0.459	14676	612
XGBoost	no	no	random	0.696	no	0.729	0.561	16696	4710
Random forest	no	no	random	0.713	yes	0.645	0.663	14676	612
Random forest	no	no	random	0.714	no	0.639	0.687	16696	4710
XGBoost	no	no	random	0.718	yes	0.627	0.707	14676	612
XGBoost	no	yes	random	0.745	no	0.674	0.714	16696	4710
XGBoost	no	yes	random	0.758	yes	0.864	0.532	14676	612
Random forest	no	yes	random	0.780	no	0.738	0.704	16696	4710
Random forest	no	yes	random	0.792	yes	0.618	0.837	14676	612
Random forest	yes	no	random	0.830	yes	0.727	0.787	14676	612
Random forest	yes	no	random	0.840	no	0.747	0.812	16696	4710
XGBoost	yes	no	random	0.844	no	0.752	0.814	16696	4710
XGBoost	yes	yes	random	0.853	yes	0.682	0.884	14676	612
XGBoost	yes	yes	random	0.854	no	0.711	0.865	16696	4710
Random forest	yes	yes	random	0.861	no	0.764	0.830	16696	4710
Random forest	yes	yes	random	0.862	yes	0.709	0.884	14676	612
XGBoost	yes	no	random	0.865	yes	0.845	0.763	14676	612
Notes: The tabl	le reports the detai	ls of the re	sults show	vn in Fig	$\frac{1}{1}$ - Pa	nel A.			

Table A.5: Temporal leakage in the forecasting classification problem (focus on the Great **Recession, year 2009) – Full Results**

Model	Contemporaneous	Outcome Lags	Split Type	MSE	Adj. Test Size	Train Size	Test Size
Random forest	yes	yes	random	0.052	no	16696	4710
OLS	yes	yes	random	0.053	no	16696	4710
XGBoost	yes	yes	random	0.053	no	16696	4710
Random forest	yes	yes	random	0.054	yes	14676	612
XGBoost	yes	yes	random	0.055	yes	14676	612
Random forest	no	yes	random	0.056	no	16696	4710
OLS	yes	yes	random	0.058	yes	14676	612
OLS	no	yes	random	0.058	no	16696	4710
Random forest	no	yes	random	0.058	yes	14676	612
OLS	yes	yes	time	0.060	no	18348	3058
XGBoost	no	yes	random	0.061	no	16696	4710
OLS	no	yes	random	0.063	yes	14676	612
OLS	yes	yes	time	0.065	yes	14676	612
XGBoost	no	yes	random	0.066	yes	14676	612
XGBoost	yes	yes	time	0.074	yes	14676	612
XGBoost	yes	yes	time	0.076	no	18348	3058
Random forest	yes	yes	time	0.086	yes	14676	612
Random forest	yes	yes	time	0.086	no	18348	3058
OLS	no	yes	time	0.086	no	18348	3058
XGBoost	yes	no	random	0.086	no	16696	4710
OLS	no	yes	time	0.088	yes	14676	612
XGBoost	no	no	random	0.089	no	16696	4710
XGBoost	yes	no	random	0.090	yes	14676	612
Random forest	no	yes	time	0.091	yes	14676	612
Random forest	no	yes	time	0.092	no	18348	3058
XGBoost	no	no	random	0.093	yes	14676	612
XGBoost	no	no	time	0.095	no	18348	3058
XGBoost	no	yes	time	0.097	yes	14676	612
XGBoost	no	yes	time	0.097	no	18348	3058
XGBoost	no	no	time	0.098	yes	14676	612
XGBoost	yes	no	time	0.099	no	18348	3058
Random forest	yes	no	random	0.104	no	16696	4710
Random forest	no	no	random	0.104	no	16696	4710
XGBoost	yes	no	time	0.105	yes	14676	612
Random forest	no	no	random	0.108	yes	14676	612
Random forest	yes	no	random	0.109	yes	14676	612
Random forest	no	no	time	0.111	no	18348	3058
Random forest	yes	no	time	0.114	yes	14676	612
Random forest	yes	no	time	0.114	no	18348	3058
Random forest	no	no	time	0.114	yes	14676	612
OLS	yes	no	random	0.143	no	16696	4710
OLS	no	no	time	0.143	no	18348	3058
OLS	no	no	time	0.144	yes	14676	612
OLS	no	no	random	0.148	no	16696	4710
OLS	yes	no	random	0.150	yes	14676	612
OLS	yes	no	time	0.152	no	18348	3058
OLS	no	no	random	0.156	yes	14676	612
OLS	Ves	no	time	0.156	Ves	14676	612

Table A.6: Temporal leakage in the forecasting regression problem (focus on the GreatRecession, year 2009) – Full Results

Notes: The table reports the details of the results shown in Figure 3 – Panel B.

Model	Split Type	AUC	Adi, Test Size	Sensitivity	Specificity	Train Size	Test Size
Logit	County	0.404	ves	0.000	0.999	34244	2448
Logit	County	0.422	no	0.060	0.945	44028	11016
Logit	Random	0.423	no	0.096	0.911	42934	12110
Logit	Random	0.437	ves	0.171	0.877	34244	2448
Logit	States	0.456	ves	0.112	0.900	34244	2448
Logit	States	0.466	no	0.128	0.899	44208	10836
XGBoost	County	0.686	ves	0.560	0.705	34244	2448
XGBoost	States	0.693	ves	0.529	0.749	34244	2448
XGBoost	States	0.697	no	0.585	0.695	44208	10836
XGBoost	County	0.705	no	0.710	0.580	44028	11016
Random forest	States	0.708	no	0.588	0.717	44208	10836
Random forest	States	0.713	ves	0.620	0.704	34244	2448
XGBoost	Random	0.714	no	0.587	0.724	42934	12110
XGBoost	Random	0.724	ves	0.598	0.736	34244	2448
Random forest	County	0.734	yes	0.721	0.631	34244	2448
Random forest	Random	0.749	no	0.624	0.743	42934	12110
Random forest	Random	0.757	yes	0.661	0.722	34244	2448
Random forest	County	0.758	no.	0.687	0.697	44028	11016

Table A.7: Cross-Sectional leakage in the classification problem (all years) – Full Results

Notes: The table reports the details of the results shown in Figure 4 – Panel A.

Table A.8: Cross-Sectional leak	age in the regression	problem (all years)	– Full Results
	8 8	1	

Model	Contemporaneous	Outcome Lags	Split Type	MSE	Adj. Test Size	Train Size	Test Size
Random forest	no	yes	Random	0.052	yes	34244	2448
Random forest	no	yes	County	0.052	yes	34244	2448
OLS	no	yes	Random	0.053	yes	34244	2448
Random forest	no	yes	County	0.053	no	44028	11016
OLS	no	yes	County	0.054	yes	34244	2448
Random forest	no	yes	Random	0.054	no	42934	12110
OLS	no	yes	County	0.055	no	44028	11016
OLS	no	yes	Random	0.055	no	42934	12110
XGBoost	no	yes	Random	0.056	yes	34244	2448
XGBoost	no	yes	County	0.056	yes	34244	2448
XGBoost	no	yes	random	0.057	no	42934	12110
XGBoost	no	yes	County	0.058	no	44028	11016
OLS	no	yes	State	0.062	no	44208	10836
Random forest	no	yes	State	0.063	no	44208	10836
OLS	no	yes	State	0.063	yes	34244	2448
Random forest	no	yes	State	0.065	yes	34244	2448
XGBoost	no	yes	State	0.072	yes	34244	2448
XGBoost	no	yes	State	0.072	no	44208	10836

Notes: The table reports the details of the results shown in Figure 4 – Panel B

B. Machine Learning pipeline

- B.1. Machine Learning models

Below we report a brief description of the models used, see Hastie et al. (2009) for more details.

- Random Forest is an ensemble learning technique that constructs many decision trees during training and aggregates their predictions to increase out-of-sample accuracy by reducing overfitting risk. Each tree is built using a random subset of the training data, which helps in reducing variance and making the model more robust. Additionally, a second layer of randomness is introduced by forcing the trees to select among and split on only a random subset of the predictors at each candidate split. The final prediction is determined by averaging the outputs of all the trees for regression tasks and by taking a majority vote for classification tasks. We use the following parameters: trees =300 (500 trees for the regression task), maximum_depth = None, min_samples_leaf =4, max_features = square-root of N predictors, and min_samples_split = 10.
- **Extreme Gradient Boosting (XGBoost)** is a tree-based ensemble technique that builds models in a sequential manner, where each new model tries to predict the residuals, i.e., the errors, of its predecessors. XGBoost improves this approach by optimizing computational efficiency through parallelization, using regularization to prevent overfitting, and handling missing data. It is widely used in ML applications on structured/tabular data due to its ability to handle complex datasets with minimal tuning. We use it with the following parameters: learning rate= 0.01, max_depth = 2, min_child_weight = 5, gamma= 1, subsample = 0.5, colsample by tree = 0.8 and 500 boost rounds.

- **B. 2. Variables used in the models**

In each ML models, we use the following variables as predictors:

- **Group a**): Average wage, Income from Unemployment Benefit (%), Workplace employment rate (%), Population, Population under 18 (%), Population over 65 (%), Women (% of population), White (% of population), Black (% of population), Hispanic (% of population), Asian (% of population), Birth (per 1,000 inhabitants), Deaths (per 1,000 inhabitants), Net internal migration (per 1,000 inhabitants) and Net domestic migration (per 1,000 inhabitants).
- **Group b**) Personal income per capita growth rate (%), Recession dummy, Personal income per capita.

Note that when running a model that include contemporaneous predictors, we use all variables in *Group a*) but not those of *Group b*), since these contains the target variable or a direct transformation of it. In all models, all the variables of *Group a*) and *Group b*) described enter the model with *lag t-1* and *t-2*, except for the outcome variable, which enters only when we include the lagged outcome.