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Estimation of Heterogeneous Panel Data Models With Mixed Sampling Frequencies

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ABSTRACT

This paper studies heterogeneous mixed-frequency panel data models, focusing on linear specifications that allow heterogeneity in both aggregation weights and slope coefficients. To address potential correlations between the heterogeneity and the covariates, we first show that, under additional normalization conditions, the mean-group estimator delivers consistent and asymptotically normal slope estimates but biased weights estimators. As an alternative, we propose a correlated random effects estimator using a generalized Mundlak specification. We further discuss the implementation of these two estimators when covariates are observed at substantially higher sampling frequencies. Monte Carlo simulations are conducted to assess their finite-sample properties. As an empirical illustration, we revisit the impact of temperature fluctuations on economic growth using the proposed framework.

JEL Classification: C13, C23

1 | Introduction

Standard panel data models typically assume that all variables are observed at a common frequency. This assumption is often violated in practice, particularly in macroeconomic, financial, and environmental applications, where researchers routinely work with data recorded at mixed frequencies. For example, studies of the effects of temperature fluctuations on economic growth commonly combine quarterly or annual macroeconomic indicators with monthly or daily temperature measures.

Since the seminal work of Ghysels et al. (2005, 2006, 2007) and Ghysels and Wright (2009), Mixed Data Sampling (MIDAS) models have attracted substantial attention in econometric research. Early contributions are surveyed by Foroni and Marcellino (2013), while more recent developments include MIDAS-VAR models (Schorfheide and Song 2015), volatility dynamics (Pettenuzzo et al. 2016), and high-dimensional extensions incorporating machine learning techniques (Babii et al. 2022a, 2022b). Empirical applications of MIDAS models span a broad range of settings (e.g., Ferrara and Guérin 2018; Marcellino and Sivec 2016). The MIDAS framework is closely related to the literature on temporal aggregation (e.g., Hsiao 1979; Pesaran et al. 1989); see Andreou et al. (2010) for detailed discussions.

Panel data models with mixed data sampling remain relatively underexplored. Veredas and Petkovic (2010) study cross-sectional and temporal aggregation in panel MIDAS models, while Blasques et al. (2016) propose a likelihood-based approach to estimating dynamic panel factor models with MIDAS structures. More recent work addresses identification in dynamic panel MIDAS models (Khalaf et al. 2021), extends projection-based methods to this setting (Yang et al. 2023), and incorporates machine learning techniques to handle heavy-tailed dependence and improve forecast accuracy (Babii et al. 2023, 2024).

Despite these advances, much of the literature continues to assume homogeneous aggregation schemes and identical slopes across units. As noted by Swamy (1970), restricting heterogeneity to individual-specific intercepts may fail to capture variation in slopes. In our empirical analysis of temperature shocks and economic growth, we accommodate such heterogeneity by allowing country-specific responses that reflect differences in income, economic structure, and adaptive capacity. Poorer economies, which are more reliant on climate-sensitive sectors and constrained by limited resources, are particularly vulnerable, whereas wealthier countries benefit from infrastructure and technology that buffer temperature shocks. We also relax the common aggregation scheme assumption, recognizing that high-frequency shocks may transmit differently across countries—for instance, climate fluctuations during winter may have smaller effects in countries with limited winter production.

This paper extends panel MIDAS models within a unified framework to allow richer heterogeneity by incorporating unit-specific aggregation parameters and heterogeneous slopes. This advancement is well suited to our empirical application since climate shocks during economically critical periods may generate heterogeneous effects across sectors and regions. These features capture how cross-sectional units process mixed-frequency information and respond to aggregated variables in different manners, thereby enhancing the empirical relevance of the model. To our knowledge, this is the first fully heterogeneous panel MIDAS model that addresses both sources of heterogeneity. Building on the heterogeneous panel literature, it explores the largely unexamined interaction between slope heterogeneity and mixed-frequency structures by jointly modeling unit-specific aggregation weights and slope variation.

We propose two approaches to account for potential correlations between the heterogeneity and covariates. First, under additional normalization conditions, the mean-group (MG) estimator (Pesaran and Smith 1995) consistently estimates mean slopes, though the estimators of aggregation parameters remain biased. Second, a correlated random-effects (CRE) estimator extends Mundlak (1978) method, consistently identifying the mean of heterogeneous parameters under suitable assumptions. When covariates are observed at much higher frequencies, we follow Babii et al. (2023) to approximate the unknown weighting functions with basis expansions allowing unit-specific coefficients and integrate them with our estimators using machine learning techniques.

We revisit the relationship between temperature fluctuations and economic development. A central debate in this literature is whether temperature shocks generate only transitory level effects (Yang et al. 2023) or persistent effects on growth (Dell et al. 2012). Most previous studies (e.g., Sachs and Warner 1997; Nordhaus 2006) rely on annual temperature measures computed as simple arithmetic averages, which may lead to biased results. Consider a simple case where a country's winter temperature decreases by 1°C while its summer temperature increases by the same amount. Although the simple annual average temperature remains unchanged, such variation clearly has implications for economic performance. Some other studies, such as Miguel et al. (2004) and Barrios et al. (2010), use high-frequency data but do not allow for cross-country heterogeneity beyond additive fixed effects.

Our analysis advances this literature by accounting for heterogeneous responses to temperature shocks and recognizing that aggregation of high-frequency climate data into annual measures may differ across regions. The main findings are as follows. First, we document detailed heterogeneity in the economic impacts of temperature across multiple dimensions, finding a substantially larger temperature-induced growth gap between poor and rich countries than previously reported. Second, we uncover robust evidence that the negative effects of rising temperatures are markedly stronger in already hot countries, challenging previous studies that reported insignificant differences across climate zones (e.g., Yang et al. 2023). Third, in contrast to Dell et al. (2012), we do not find long run growth effects of temperature shocks in poor countries, indicating that their impacts appear primarily through level effects.

The remainder of the paper is organized as follows. Section 2 introduces the heterogeneous panel MIDAS model, Section 3 outlines two estimation procedures and discusses their implementation when covariates are observed at substantially higher frequencies. Section 4 reports Monte Carlo evidence on the finite-sample performance of the proposed estimators, while Section 5 provides an empirical application. Section 6 concludes. Detailed proofs, along with supplementary simulation and empirical results, are deferred to the appendix.

2 | Econometric Framework

Our heterogeneous panel MIDAS model is specified as follows:

$$y_{it} = x_{it}(\alpha_i)\beta_i + u_{it}, \quad t = 1, \ldots, T; \quad i = 1, \ldots, N \tag{1}$$

$$x_{it}(\alpha_i) = \left[x_{it,1}(\alpha_{i,1}), \ldots, x_{it,K}(\alpha_{i,K})\right] \tag{2}$$

$$x_{it,p}(\alpha_{i,p}) = \sum_{m=1}^{M} \alpha_{i,p}^{(m)} x_{it,p}^{(m)}, \quad p = 1, \ldots, K \tag{3}$$

The dependent variable y_{it} is a linear function of the $1 \times K$ vector of aggregated covariates $x_{it}(\alpha_i)$ and the error u_{it}. Each component $x_{it,p}(\alpha_{i,p})$ is a linear combination of high-frequency covariates $\{x_{it,p}^{(m)}\}_{m=1}^{M}$ with unit-specific weights $\{\alpha_{i,p}^{(m)}\}_{m=1}^{M}$. We can relax equation (3) by including additive errors independent of the covariates, which can be absorbed into u_{it} without affecting the analysis. The model allows for two distinct sources of heterogeneity: unit-specific aggregation parameters $\alpha_i = [\alpha_{i,1}', \ldots, \alpha_{i,K}']'$ and heterogeneous slope coefficients in the spirit of Swamy (1970), without imposing independence between β_i and the covariates.

Equation (3) assumes a common sampling frequency across high-frequency variables; allowing M to vary with p could accommodate differing frequencies, but we omit this extension for notational simplicity. We focus initially on a fixed M, which permits OLS estimation and simplifies the theoretical analysis. Section 3.4 relaxes this restriction and considers cases with substantially higher-frequency covariates as $M \to \infty$.

We introduce the following notations. Denote $X_i(\alpha_i) = [x_{i1}(\alpha_i)', \dots, x_{iT}(\alpha_i)']'$ as the $T \times K$ matrix of aggregated covariates. Let $x^H_{it,p} = (x^{(1)}_{it,p}, \dots, x^{(M)}_{it,p})$ denote the pth high-frequency covariate over $(t-1, t)$, and $x^{(m)}_{it} = (x^{(m)}_{it,1}, \dots, x^{(m)}_{it,K})$ be the $1 \times K$ vector of covariates at the mth observation. Define $X^H_{it} = (x^H_{it,1}, \dots, x^H_{it,K})$ and $X^H_i = (X^{H'}_{i1}, \dots, X^{H'}_{iT})'$. We use $\otimes$ and $\odot$ to denote the Kronecker and Hadamard products, respectively, with element-wise inverse $A^{\odot -1}$ for matrices with nonzero entries. Let ι_M be an $M \times 1$ vector of ones and define $\Lambda = I_K \otimes \iota'_M$. Finally, define $\gamma_i = (\gamma'_{i,1}, \dots, \gamma'_{i,K})'$ with $\gamma_{i,p} = \alpha_{i,p}\beta_{i,p}$. With these notations, the model can be rewritten by combining Equations (1–3):

$$y_{it} = x_{it}(\alpha_i)\beta_i + u_{it} = X^H_{it}[\alpha_i \odot (\beta_i \otimes \iota_M)] + u_{it} = X^H_{it}\gamma_i + u_{it}, \quad (4)$$

We refer to $\{\gamma_i\}_{i=1}^N$ as reduced form parameters and $\{\alpha_i, \beta_i\}_{i=1}^N$ as structural parameters. Equation (4) can be written as $Y_i = X^H_i \gamma_i + U_i$ in matrix form, where Y_i, X^H_i, and U_i are matrices formed by stacking y_{it}, x^H_{it}, and u_{it} over time t, respectively. Standard assumptions are detailed in the appendix. Here, we state two normalization assumptions required for the identification of β. Let $\alpha^{(m)}_p = E[\alpha^{(m)}_{i,p}]$ and $\beta = E(\beta_i)$.

Normalization assumption (a): $\sum_{m=1}^M E[\alpha^{(m)}_{i,p}] = \sum_{m=1}^M \alpha^{(m)}_p = 1$ for each $p = 1, \dots, K$.

Normalization assumption (b): $\sum_{m=1}^M \alpha^{(m)}_{i,p} = 1$ for each $p = 1, \dots, K$.

Assumption (a) requires that, for each covariate, the mean aggregation weights sum to one. This normalization is necessary for identification of β, since $\alpha \odot (\beta \otimes \iota_L)$ is observationally equivalent to $(c\alpha) \odot (c^{-1}\beta \otimes \iota_L)$ for any $c \neq 0$. Assumption (b) stipulates that the individual-specific aggregation weights sum to one for each covariate. Taking expectations of (b) yields (a). Further discussion of these two assumptions is provided in the appendix.

3 | Estimation Methods

To clarify the parameters of interest, let $\alpha_i = \alpha + v_{i,\alpha}$, $\beta_i = \beta + v_{i,\beta}$, and $\gamma_i = \gamma + v_{i,\gamma}$, where $\alpha = E(\alpha_i)$, $\beta = E(\beta_i)$, and $\gamma = E(\gamma_i)$. The primary objective is to estimate the average structural slopes $E(\beta_i)$, distinguishing our approach from studies focusing on average reduced-form parameters in models like (4). For example, Babii et al. (2023) emphasize forecast performance and reduced-form slope estimation, but do not address identification of the underlying structural parameters, which is the focus here. As shown below, consistent estimation of γ does not, in general, imply consistent estimation of β without additional assumptions. To build intuition, we first focus on estimators of the reduced-form parameter γ, from which the structural estimators can be recovered under suitable assumptions.

3.1 | Reduced-Form Estimators

If the heterogeneities are ignored, then Equation (4) reduces to $y_{it} = X^H_{it}\gamma + \kappa_{it}$, where $\kappa_{it} = u_{it} + X^H_{it} v_{i,\gamma}$. The pooled OLS estimator is given by:

$$\hat{\gamma}_{ols} = \left(\sum_{i=1}^N X^{H'}_i X^H_i\right)^{-1}\left(\sum_{i=1}^N X^{H'}_i Y_i\right) \quad (5)$$

When heterogeneity is uncorrelated with the covariates, a more efficient estimator can be obtained within the random-effects framework. Following Swamy (1970), we assume: (i) $E(v_{i,\gamma} v'_{i,\gamma}) = \Gamma$ and Γ is positive definite; (ii) u_{it} is serially uncorrelated and homoskedastic with variance σ^2_u. The GLS estimator is given by[1]

$$\hat{\gamma}_{gls} = \left[\sum_{i=1}^N X^{H'}_i (X^H_i \Gamma X^{H'}_i + \sigma^2_u I)^{-1} X^H_i\right]^{-1} \times \left[\sum_{i=1}^N X^{H'}_i (X^H_i \Gamma X^{H'}_i + \sigma^2_u I)^{-1} Y_i\right], \quad (6)$$

Consistency of pooled OLS and GLS requires orthogonality between the heterogeneity and covariates, an assumption often violated in practice. In contrast, the MG estimator allows arbitrary correlations between the heterogeneity and covariates, which is given by

$$\hat{\gamma}_{mg} = \frac{1}{N}\sum_{i=1}^N \hat{\gamma}_i = \frac{1}{N}\sum_{i=1}^N (X^{H'}_i X^H_i)^{-1} X^{H'}_i Y_i. \quad (7)$$

When heterogeneity is uncorrelated with covariates, both $\hat{\gamma}_{ols}$ and $\hat{\gamma}_{gls}$ are consistent and asymptotically normal, with GLS being more efficient under correct second-moment assumptions. The MG estimator, in contrast, remains consistent regardless of any correlations between individual heterogeneity and covariates.

3.2 | Structural Estimators

Given normalization assumptions (a) and (b), we can recover estimators of (α, β) from their corresponding reduced-form estimators of γ. The pooled estimators of (α, β) are given as follows:

$$\hat{\beta}_{ols} = \Lambda \hat{\gamma}_{ols}; \quad \hat{\alpha}_{ols} = \hat{\gamma}_{ols} \odot (\hat{\beta}^{\odot -1}_{ols} \otimes \iota_M), \quad (8)$$

where $\Lambda = I_k \otimes \iota'_M$ and $\hat{\beta}^{\odot -1}_{ols}$ denotes the Hadamard inverse of $\hat{\beta}_{ols}$ as defined in Section 2. In a similar way we can recover the GLS estimator of β and α as follows:

$$\hat{\beta}_{gls} = \Lambda \hat{\gamma}_{gls}; \quad \hat{\alpha}_{gls} = \hat{\gamma}_{gls} \odot (\hat{\beta}^{\odot -1}_{gls} \otimes \iota_M). \quad (9)$$

Let $\{\hat{\alpha}_i, \hat{\beta}_i\}_{i=1}^N$ be the least squares estimator of $\sum_{i=1}^N (Y_i - X_i(\alpha_i)\beta_i)'(Y_i - X_i(\alpha_i)\beta_i)$ subject to the normalization assumption (b). The MG estimator is given by $\hat{\alpha}_{mg} = \frac{1}{N}\sum_{i=1}^N \hat{\alpha}_i$ and $\hat{\beta}_{mg} = \frac{1}{N}\sum_{i=1}^N \hat{\beta}_i$. In the appendix, we present a lemma showing that

$$\hat{\alpha}_{mg} = \frac{1}{N}\sum_{i=1}^N \left[\hat{\gamma}_i \odot ((\Lambda \hat{\gamma}_i)^{\odot -1} \otimes \iota_M)\right]; \quad \hat{\beta}_{mg} = \Lambda \hat{\gamma}_{mg}. \quad (10)$$

Equation (10) shows that the nonlinear problem can be reformulated as a linear regression, which is appealing for empirical applications. The expression for α implies that if β is near zero, α may be ill-defined—a well-known issue (Davies 1987).

For simplicity, we assume all elements of $\hat{\beta}$ are bounded away from zero with probability approaching one.

The asymptotic properties of the three estimators are summarized in the theorem reported in the appendix. Several key insights emerge. First, all three structural estimators are generally biased, even when the covariates are independent of the parameter heterogeneity. This bias is a distinctive feature of the heterogeneous panel MIDAS framework. Second, under the normalization assumption (b), the MG estimator of β is consistent, whereas $\hat{\alpha}_{MG}$ remains inconsistent, reflecting an intrinsic identification difficulty of our panel MIDAS setup.

3.3 | Correlated Random Effects Approach

The normalization assumption (b) may alter the statistical properties of the random coefficients (see the appendix). Moreover, the MG estimator is inconsistent for the weighting parameter, which can be of empirical interest in certain applications. To address these limitations, we adopt the generalized Mundlak device of Breitung and Salish (2021), which decomposes heterogeneous slopes into a systematic component, parameterized by second-order moments of the covariates, and an idiosyncratic component that is orthogonal to them, as formalized in the following assumption.

Generalized Mundlak Assumption: $v_{i,\alpha} = \tilde{S}_{iT}\phi_1 + e_{i,\alpha}$ and $v_{i,\beta} = \check{S}_{iT}\phi_2 + e_{i,\beta}$, where $\tilde{S}_{iT} = \frac{1}{T}\sum_{t=1}^{T} X_{it}^{H\prime} X_{it}^{H} - \frac{1}{NT}\sum_{j=1}^{N}\sum_{s=1}^{T} X_{js}^{H\prime} X_{js}^{H}$ and $\check{S}_{iT} = \frac{1}{MT}\sum_{t=1}^{T}\sum_{m=1}^{M} x_{it}^{(m)\prime} x_{it}^{(m)} - \frac{1}{NMT}\sum_{j=1}^{N}\sum_{t=1}^{T}\sum_{m=1}^{M} x_{it}^{(m)\prime} x_{it}^{(m)}$. $e_{i,\alpha}$ and $e_{i,\beta}$ are independent of each other and are independent of X_i^H for all $i = 1, \ldots, N$.

The generalized Mundlak device has the advantage of maintaining a manageable number of additional parameters. It can be shown that $\dim(\phi_1) + \dim(\phi_2) = MK + K$, which is substantially smaller than the number of unknown parameters under the standard Mundlak device. Let $\Phi = (\alpha', \beta', \phi_1', \phi_2')'$. We can rewrite the model as $Y_i = F(X_i^H, \Phi) + \eta_i$, where $F(X_i^H, \Phi) = X_i^H\left\{(\alpha + \tilde{S}_{iT}\phi_\alpha) \odot [(\beta + \check{S}_{iT}\phi_\beta) \otimes \iota_L]\right\}$ and the formula of η_i is given in the appendix. The independence between $e_{i,\alpha}$ and $e_{i,\beta}$ ensures that $E(\eta_i \mid X_i^H) = 0$. The CRE estimator of Φ is obtained by minimizing the following objective function:

$$\hat{\Phi}_{CRE} = \operatorname{argmin} \sum_{i=1}^{N} \left\| Y_i - F(X_i^H, \Phi) \right\|^2. \tag{11}$$

In our heterogeneous panel MIDAS setting, the CRE estimator is obtained by nonlinear least squares, in contrast to the single-frequency heterogeneous panel context, where it reduces to a linear form (Breitung and Salish 2021). The asymptotic distribution of the CRE estimator is presented in the Appendix S1.

3.4 | Heterogeneous Panel MIDAS With Ultra-High-Frequency Covariates

In certain applications, covariates are sampled at substantially higher frequencies, posing significant challenges in the implementation of our proposed estimators. The MG estimator is feasible only when $T \geq (M-1)K$ under normalization assumption (b). The generalized Mundlak device also introduces an additional $MK + K$ parameters, which may lead to weak identification as $M \to \infty$. Addressing these issues is therefore critical for empirical applications. We follow Babii et al. (2023) and adopt a machine learning based strategy:

$$x_{it,p}(\alpha_{i,p}^*) = \sum_{m=1}^{M} W_p^{(m)}(\alpha_{i,p}^*) x_{it,p}^{(m)}, \quad p = 1, \ldots, K. \tag{12}$$

If we set $W_p^{(m)}(\alpha_{i,p}^*) = \alpha_{i,p}^{*(m)}$, the above equation corresponds to an unrestricted version of the MIDAS model (Foroni et al. 2013). To address the problem of parameter proliferation when M is large, we follow the approach proposed by Babii et al. (2022b) and introduce a weighting function $w : [0,1] \to R$ parameterized by a low-dimensional vector:

$$W_p^{(m)}(\alpha_{i,p}^*) = \sum_{l=1}^{L} \alpha_{i,p}^{*(l)} w_l\left(\frac{m-1}{M}\right) \quad m = 1, \ldots, M, \tag{13}$$

where $\alpha_{i,p}^* = [\alpha_{i,p}^{*(1)}, \ldots, \alpha_{i,p}^{*(L)}]'$ is a $L \times 1$ individual-specific vector and $\{w_l(u)\}_{l=1}^{L}$ is a collection of L basis functions, called the *dictionary* in the machine learning literature. A common choice in econometrics is orthogonal Legendre polynomials (e.g., Babii et al. 2023). Note that the dimension of $\alpha_{i,p}^*$ is now fixed at L as M increases to infinity. Equation (13) may be relaxed to hold approximately if the approximation error vanishes sufficiently fast. As our objective is to recover mean slope parameters, we maintain exact equality and examine the consequences of such approximation errors in simulations.

We next outline our approach to heterogeneous panel MIDAS models with ultra-high-frequency covariates. Define W as an $M \times L$ matrix where the (m, l)th element is given by $w_l\left(\frac{m-1}{M}\right)$. Let $\Lambda^* \equiv I_K \otimes (\iota_M' W)$. The ultra-high-frequency model, as defined by Equations (1), (12), and (13), can now be written as follows.

$$y_{it} = [X_{it}^H (I_K \otimes W)]\gamma_i + u_{it} \equiv X_{it}^{*H}\gamma_i + u_{it}, \tag{14}$$

where $X_{it}^{*H} = X_{it}^H(I_K \otimes W)$. With Equation (14), the pooled, GLS, and MG estimators of γ can be obtained exactly the same as in Section 3.1, subject only to notational adjustments. For example, the reduced-form MG estimator is now written as $\hat{\gamma}_{MG}^* = N^{-1}\sum_{i=1}^{N}(X_i^{*H\prime} X_i^{*H})^{-1}(X_i^{*H\prime} Y_i)$ and the corresponding structural MG estimator is $\hat{\beta}_{MG}^* = \Lambda^* \hat{\gamma}_{MG}^*$. The modified normalization assumptions are given in the appendix. The CRE approach can be implemented in a similar manner by modeling (α_i^*, β_i) using the generalized Mundlak device.

3.5 | Empirical Guidance on the Choice Between the MG and CRE Estimators

Since the MG and CRE estimators rely on different identifying assumptions, it is useful to provide a systematic comparison of the two to guide empirical applications. Here we highlight the main strengths and limitations of each approach. Consistency of the MG estimator requires that the individual-specific weights sum to one. This assumption is plausible when the aggregation mechanism inherently ensures that weights sum to one. On the other hand, the consistency of the CRE estimator requires that the heterogeneous coefficients admit a decomposition into a systematic component, determined by the second moments of the covariates, and an idiosyncratic component uncorrelated with the covariates. The generalized Mundlak device further assumes that idiosyncratic terms associated with different random coefficients are mutually independent, conditional on the covariates. Empirically, this implies that any correlation among these heterogeneous effects arises solely from their dependence on the covariates and disappears once the covariates are conditioned on.

A direct robustness comparison between the two approaches is not straightforward, as neither set of assumptions dominates in general empirical contexts. In applications where the weights naturally sum to one, the MG approach is preferable, as it does not rely on the correct specification of the relationship between the heterogeneity and covariates. The MG approach requires that the number of time periods T to be at least as large as the number of reduced-form parameters, $\dim(\gamma_i) = MK$, which is rarely satisfied for short panels with high-frequency covariates. As discussed in Section 3.4, this limitation can be mitigated by integrating the MG framework with machine learning techniques. The CRE estimator offers two notable advantages. First, it remains feasible in short panels, including cases where $T < MK$. Second, it provides consistent estimates of the mean aggregation parameters under the generalized Mundlak assumption, which is valuable when the weighting scheme itself is of interest. These benefits, however, come at the cost of stronger functional restrictions.

Computationally, the MG estimator is straightforward to implement, as it only involves unit-level OLS regressions. In contrast, the CRE estimator entails solving a highly nonlinear optimization problem, which may be sensitive to initial values and prone to convergence issues. From a practical standpoint, we recommend the MG estimator for inference on the mean of the heterogeneous slopes, as it avoids strong functional form assumptions linking heterogeneity to the covariates. The individual-level normalization assumption underlying the MG approach is reasonable in most empirical applications, as the slope parameter is typically viewed as the average effect of an aggregated variable, for which the corresponding weights necessarily sum to one. Even when T is relatively small, the MG estimator can be combined with the machine learning techniques to obtain consistent estimates.

4 | Simulation Study

This section examines the finite-sample performance of the proposed estimators under various data-generating processes (DGPs), with two main objectives. First, since the MG and CRE estimators rely on distinct identifying assumptions, we assess their robustness to misspecification and provide guidance on their relative reliability in practice. Second, the results for high-frequency covariates in Section 3.4 rely on the exact equality in Equation (13). In practice, this condition holds only approximately, as the chosen dictionaries may not fully capture the true aggregation process. To evaluate the consequence of such approximation errors, we simulate data where the dictionaries imperfectly proxy the underlying weights.

4.1 | Simulation Designs

We consider the following heterogeneous panel MIDAS model with a single covariate:

$$y_{it} = \left[\sum_{m=1}^{M} \alpha_i^{(m)} x_{it}^{(m)}\right] \beta_i + u_{it} \tag{15}$$

$$x_{it}^{(m)} = f_t^{(m)} + c_i + c_i f_t^{(m)} + r_{it}^{(m)} \tag{16}$$

$$r_{it}^{(m)} = \rho_i r_{it-1}^{(m)} + e_{it,x}^{(m)} \tag{17}$$

$$\alpha_i = \alpha + \tilde{S}_{iT}\phi_1 + e_{i,\alpha};$$

$$\beta_i = \beta + \check{S}_{iT}\phi_2 + e_{i,\beta} \tag{18}$$

The idiosyncratic errors u_{it} and $e_{it,x}^{(m)}$ are independently drawn from Normal$(0, 0.1)$. Individual fixed effects c_i and common factors $f_t^{(m)}$ are generated from Normal$(1, 0.4)$ and Normal$(1, 0.1)$ respectively, while $r_{i0}^{(m)}$ follows Uniform$(-3, 3)$. The autoregressive parameter ρ_i is sampled from Uniform$(-0.1, 0.1)$ and held fixed across replications. The errors $(e_{i,\alpha}, e_{i,\beta})$ follow a mean-zero multivariate normal distribution with unit variances and zero correlations among elements of $e_{i,\alpha}$. We allow $\mathrm{Cov}(e_{i,\alpha}, e_{i,\beta})$ to differ across DGPs.

Table 1 summarizes the six DGPs of our simulation experiments. The designs differ along two key dimensions: (i) whether the normalization restriction $\sum_{m=1}^{M} \alpha_i^{(m)} = 1$ is imposed, and (ii) whether the generalized Mundlak condition holds. DGP1-DGP3 impose the normalization restriction, while DGP4-DGP6 relax it. The generalized Mundlak assumption entails two conditions. To examine their roles, we introduce cross-equation dependence in DGP2 and DGP5 by setting $\mathrm{Cov}(e_{i,\alpha}, e_{i,\beta}) = -0.1\iota_M$, thereby relaxing the independence assumption on the Mundlak decomposition errors. In DGP3 and DGP6, the heterogeneity depends on the covariates only through their first moments, violating the generalized Mundlak specification. All other aspects of the DGPs are held constant across designs.

The simulation is divided into two parts, based on the relative sizes of M and T. Part A sets $(M, T) = (4, 10)$, allowing unrestricted weighting parameters as $M < T$. In this unrestricted MIDAS case, we set the mean value $\alpha = \left(\frac{1}{5}, \frac{1}{5}, \frac{3}{10}, \frac{3}{10}\right)'$. Part B considers $(M, T) = (12, 10)$ with $\alpha = \left(\frac{1}{24}\iota_4', \frac{1}{9}\iota_6', \frac{1}{12}\iota_2'\right)'$, where the weighting parameters are approximated using the dictionaries. The choice of basis functions and the simulation results for Part B are reported in the appendix for brevity.

In all designs, we set $N \in \{50, 100\}$[2] and $E(\beta_i) = \beta = 1$. Each configuration is replicated 1000 times. Within each DGP, we consider four configurations of the heterogeneity parameters (ϕ_1, ϕ_2): (a) $\phi_1 = 0,\ \phi_2 = 0$; (b) $\phi_1 = 0,\ \phi_2 = 0.1$; (c) $\phi_1 = 0.1\iota_M,\ \phi_2 = 0$; and (d) $\phi_1 = 0, 1\iota_M,\ \phi_2 = 0.1$. These four designs represent, respectively, no heterogeneity, heterogeneity of the aggregation weights only, heterogeneity of the slopes only, and both types of heterogeneity, allowing us to evaluate the performance of the proposed estimators under progressively richer forms of cross-sectional variation.

TABLE 1 | Data-generating processes for simulation experiments.

	Generation of $\alpha_i^{(M)}$	Normalization assumption (b)	Generalized Mundlak specification	Generalized Mundlak assumption
DGP1	Reset $\alpha_i^{(M)} = 1 - \sum_{m=1}^{M-1} \alpha_i^{(m)}$	Satisfied	$\text{Cov}(e_{i,\alpha}, e_{i,\beta}) = 0$	Satisfied
DGP2	Reset $\alpha_i^{(M)} = 1 - \sum_{m=1}^{M-1} \alpha_i^{(m)}$	Satisfied	$\text{Cov}(e_{i,\alpha}, e_{i,\beta}) = -0.1\imath_M$	Violated
DGP3	Reset $\alpha_i^{(M)} = 1 - \sum_{m=1}^{M-1} \alpha_i^{(m)}$	Satisfied	$\alpha_i = \alpha + (\imath_M \otimes \tilde{X}_{iT})\phi_1 + e_{i,\alpha}$; $\beta_i = \beta + \check{X}_{iT}\phi_2 + e_{i,\beta}$	Violated
DGP4	$\alpha_i^{(M)}$ is unrestricted	Violated	$\text{Cov}(e_{i,\alpha}, e_{i,\beta}) = 0$	Satisfied
DGP5	$\alpha_i^{(M)}$ is unrestricted	Violated	$\text{Cov}(e_{i,\alpha}, e_{i,\beta}) = -0.1\imath_M$	Violated
DGP6	$\alpha_i^{(M)}$ is unrestricted	Violated	$\alpha_i = \alpha + (\imath_M \otimes \tilde{X}_{iT})\phi_1 + e_{i,\alpha}$; $\beta_i = \beta + \check{X}_{iT}\phi_2 + e_{i,\beta}$	Violated

Note: $\tilde{X}_{iT} = T^{-1}\sum_{t=1}^{T} X_{it}^{H} - (NT)^{-1}\sum_{j=1}^{N}\sum_{t=1}^{T} X_{jt}^{H}$, $\check{X}_{iT} = (TM)^{-1}\sum_{t=1}^{T}\sum_{m=1}^{M} x_{it}^{(m)} - (NMT)^{-1}\sum_{j=1}^{N}\sum_{t=1}^{T}\sum_{m=1}^{M} x_{jt}^{(m)}$.

4.2 | Simulation Results

Table 2 summarizes the simulation results for four estimators with unrestricted weights for $N = 50$. The mean bias results indicate that the MG estimator delivers the smallest bias when the normalization restriction is satisfied (DGP1-DGP3). Even when the generalized Mundlak assumption is valid, as in DGP1, the MG estimator remains less biased than the CRE estimator. When the normalization restriction fails, the MG estimator is only mildly biased under a single source of heterogeneity but exhibits pronounced bias when both types of heterogeneity are present.

The bias of the CRE estimator arises from two sources. Under the normalization restriction, misspecification of the generalized Mundlak device and nonzero correlation between $(e_{i,\alpha}, e_{i,\beta})$ contribute similarly to the bias. When the restriction is relaxed, results from DGP5–DGP6 indicate that cross-equation correlations generate greater bias than Mundlak misspecification. As expected, OLS remains severely biased in most settings. GLS and MG exhibit similar finite-sample performance in both bias and dispersion, consistent with their large-T asymptotic equivalence.

In terms of efficiency, the MG estimator exhibits uniformly smaller standard deviations than the CRE estimator across all designs in Table 2. For inference, MG generally delivers coverage rates closest to nominal levels, indicating robustness to violations of the normalization restriction. Exceptions occur in the last specifications of DGP4 and DGP5, where CRE attains more accurate coverage. Although CRE is asymptotically invariant to the normalization restriction, its finite-sample performance is sensitive to it: both bias and coverage improve as the restriction is relaxed (DGP1-DGP3 vs. DGP4-DGP6). Moreover, CRE tends to systematically over-reject the null in most designs.

In conclusion, our simulation experiments yield several key findings. First, under the normalization restriction, the MG estimator exhibits smaller bias and variance than CRE, delivering more reliable inference; even when the restriction is violated, MG remains accurate under slope heterogeneity. Second, despite its theoretical invariance, CRE's finite-sample performance is sensitive to the normalization assumption and improves when the restriction is relaxed. Third, the results from the appendix show that dictionary-based approximation performs well, and increasing polynomial lags has little effect; the MG estimator outperforms the CRE estimator in four of six designs, highlighting its robustness to approximation error. Overall, the results underscore the robustness of MG and the practical adequacy of the proposed approximation in moderate samples.

5 | Empirical Example

We revisit the relationship between temperature shocks and economic growth, a topic that has long attracted attention in both economic theory and empirical research. The idea that climate affects human behavior and productivity dates back to Montesquieu's The Spirit of Montesquieu(1750), which suggested that excessive heat renders people "sloth and dispirited". Modern empirical studies, such as Sachs and Warner (1997), Nordhaus (2006), and Dell et al. (2009, 2012), have systematically documented that temperature fluctuations influence aggregate economic performance, particularly in low-income and tropical regions.

5.1 | Empirical Motivation

While a large body of the literature documents that climate change affects economic growth, the empirical evidence remains mixed. Some studies argue that temperature shocks have persistent effects on growth (e.g., Dell et al. 2012), whereas others find mainly transitory effects on the level of output (e.g., Yang et al. 2023). This debate motivates our empirical application. Our framework differs from much of the existing work in three respects: (i) the use of high-frequency temperature data; (ii) the incorporation of heterogeneous weighting parameters; and (iii) a generalized specification that allows for heterogeneous slopes.

The use of high-frequency temperature data offer at least three key advantages. First, annual averages can be a poor proxy for economically relevant exposure. Many important shocks are concentrated in short periods, such as heat waves, cold spells, or unusually high temperatures in specific months. As a result, two years with similar annual mean temperatures may reflect very different realized exposures. This distinction is particularly important when damages are nonlinear—as in studies using temperature bins or degree-day measures—because annual averaging can smooth over extremes and attenuate the

TABLE 2 | Part A simulation results with $N = 50, T = 10$.

Model specification		Mean bias				SD				Coverage rate			
		OLS	GLS	MG	CRE	OLS	GLS	MG	CRE	OLS	GLS	MG	CRE
DGP1	$\phi_1 = 0, \phi_2 = 0$	−0.001	−0.001	−0.001	0.031	0.153	0.137	0.137	0.169	0.942	0.932	0.947	0.943
	$\phi_1 = 0, \phi_2 = 0.1$	0.181	−0.001	−0.001	0.005	0.163	0.137	0.137	0.185	0.830	0.952	0.966	0.924
	$\phi_1 = 0.1\iota_M, \phi_2 = 0$	0.021	−0.001	−0.001	−0.373	0.201	0.137	0.137	0.552	0.907	0.933	0.947	0.435
	$\phi_1 = 0.1\iota_M, \phi_2 = 0.1$	0.206	−0.001	−0.001	−0.483	0.227	0.137	0.137	0.423	0.811	0.952	0.966	0.350
DGP2	$\phi_1 = 0, \phi_2 = 0$	−0.002	−0.002	−0.002	0.032	0.153	0.138	0.138	0.166	0.936	0.938	0.958	0.937
	$\phi_1 = 0, \phi_2 = 0.1$	0.180	−0.001	−0.002	0.006	0.162	0.138	0.138	0.184	0.828	0.963	0.972	0.930
	$\phi_1 = 0.1\iota_M, \phi_2 = 0$	0.021	−0.001	−0.002	−0.350	0.202	0.138	0.138	0.557	0.898	0.937	0.958	0.444
	$\phi_1 = 0.1\iota_M, \phi_2 = 0.1$	0.205	−0.001	−0.002	−0.524	0.228	0.138	0.138	0.430	0.816	0.964	0.972	0.302
DGP3	$\phi_1 = 0, \phi_2 = 0$	−0.001	−0.001	−0.001	0.031	0.153	0.137	0.137	0.169	0.942	0.932	0.947	0.943
	$\phi_1 = 0, \phi_2 = 0.1$	0.028	−0.001	−0.001	0.033	0.154	0.137	0.137	0.172	0.940	0.931	0.949	0.939
	$\phi_1 = 0.1\iota_M, \phi_2 = 0$	−0.001	−0.001	−0.001	0.029	0.153	0.137	0.137	0.177	0.944	0.933	0.947	0.936
	$\phi_1 = 0.1\iota_M, \phi_2 = 0.1$	0.028	−0.001	−0.001	0.029	0.154	0.137	0.137	0.182	0.940	0.931	0.949	0.933
DGP4	$\phi_1 = 0, \phi_2 = 0$	0.017	0.008	0.008	−0.042	0.458	0.416	0.416	0.614	0.942	0.942	0.951	0.796
	$\phi_1 = 0, \phi_2 = 0.1$	0.201	0.006	0.006	−0.126	0.559	0.431	0.431	0.692	0.934	0.945	0.954	0.717
	$\phi_1 = 0.1\iota_M, \phi_2 = 0$	2.985	−0.001	−0.001	−0.029	1.765	0.996	0.996	1.110	0.670	0.986	0.991	0.934
	$\phi_1 = 0.1\iota_M, \phi_2 = 0.1$	6.465	2.548	2.548	0.011	2.613	1.261	1.261	1.032	0.117	0.700	0.763	0.938
DGP5	$\phi_1 = 0, \phi_2 = 0$	−0.383	−0.391	−0.391	−0.418	0.442	0.400	0.400	0.520	0.812	0.779	0.807	0.690
	$\phi_1 = 0, \phi_2 = 0.1$	−0.199	−0.393	−0.393	−0.481	0.539	0.415	0.415	0.570	0.911	0.800	0.823	0.616
	$\phi_1 = 0.1\iota_M, \phi_2 = 0$	2.583	−0.397	−0.397	−0.291	1.718	0.986	0.986	0.986	0.764	0.971	0.976	0.955
	$\phi_1 = 0.1\iota_M, \phi_2 = 0.1$	6.062	2.153	2.152	−0.262	2.560	1.243	1.243	0.921	0.162	0.805	0.851	0.954
DGP6	$\phi_1 = 0, \phi_2 = 0$	0.017	0.008	0.008	−0.042	0.458	0.416	0.416	0.614	0.942	0.942	0.951	0.796
	$\phi_1 = 0, \phi_2 = 0.1$	0.047	0.008	0.008	−0.050	0.471	0.416	0.416	0.633	0.945	0.944	0.951	0.788
	$\phi_1 = 0.1\iota_M, \phi_2 = 0$	0.494	0.005	0.005	−0.026	0.558	0.440	0.440	0.671	0.901	0.955	0.961	0.800
	$\phi_1 = 0.1\iota_M, \phi_2 = 0.1$	0.599	0.073	0.073	−0.016	0.575	0.442	0.442	0.691	0.870	0.959	0.967	0.794

Note: Part A sets $M = 4$ and uses unrestricted weighting parameters.

estimated relationship (Ferrara and Guérin 2018). Monthly data help address this issue by aligning the climate regressor more closely with the timing and intensity of the temperature conditions actually faced by firms and households.

Second, the effect of temperature fluctuation can depend on when the shock occurs within the year. In agriculture, exposure is more consequential during planting and growing periods (Letta et al. 2022). In outdoor or non-climate-controlled activities, labor productivity may be more sensitive during hotter months (LoPalo 2023). Energy demand likewise varies across seasons. Treating all months as equally important is therefore restrictive. Our framework allows monthly observations to enter the annual climate index with heterogeneous weights, so that periods of greater economic relevance exert a larger influence on measured annual exposure.

Third, whether within-year temperature shocks have persistent effects on growth is a distinct question. Using higher-frequency data does not, by itself, imply long-run growth effects. Any persistence must operate through dynamic mechanisms that transmit temporary shocks into future output. For example, extreme temperatures may depress current investment or slow capital accumulation, so that the impact of a shock extends beyond the contemporaneous period (Dell et al. 2012; Acevedo et al. 2020). They may also influence risk, uncertainty, and adaptation decisions in ways that shape longer-run development paths (Galor and Özak 2016). In addition, repeated or severe exposure can affect health, learning, and other components of human capital, with consequences that persist beyond the initial shock (Ireland et al. 2023). Monthly data primarily improve the measurement of short-run shocks, thereby facilitating tests of whether their effects dissipate over time or propagate into future growth.

We also allow the climate variables to have heterogeneous effects across countries. Countries differ not only in income, sectoral structure, and adaptive capacity but also in their baseline climate conditions. The same positive temperature shock can be far more harmful in a country that is already hot than in one with a milder climate. In this sense, heterogeneity may arise directly from the climatic variables themselves. On the other hand, the differences in non-climate factors can also shape vulnerability. Weak institutions, limited market integration, inadequate infrastructure, and adverse demographic structures can also hinder adaptation to climate shocks.

TABLE 3 | Summary statistics of temperature.

	Monthly temperature (°C)		Change of temperature (°C)	
Month	**Mean**	**SD**	**Mean**	**SD**
January	15.25	11.84	0.14	1.77
February	15.96	11.58	0.50	1.88
March	17.59	10.24	1.23	1.71
April	19.48	8.47	0.81	1.09
May	21.10	6.95	0.79	1.30
June	22.14	6.12	0.87	1.13
July	22.70	5.72	1.26	1.31
August	22.67	5.57	0.99	1.21
September	21.64	6.14	1.00	0.95
October	20.00	7.64	0.73	1.47
November	17.85	9.46	0.27	1.38
December	15.96	11.05	0.41	1.26

Note: This table summarizes the monthly temperature of 230 countries/regions during 1960–2017. Change of temperature is the change between the end period and beginning period.

5.2 | Data and Descriptive Statistics

This paper uses climate data from *Terrestrial Air Temperature and precipitation: 1900–2017 Gridded Monthly Time Series, Version 5.01* (Willmott and Matsuura 2018). The dataset provides monthly average temperatures and precipitation data with a resolution of 0.5*0.5 degrees, from which we can aggregate to country/region level using the Global Rural-Urban Mapping Project. We follow the same procedure as Dell et al. (2012) to construct the Climate Panel dataset except that we keep these weather variables at a quarterly/monthly frequency. The economic data used in our application are drawn from the World Development Indicators (WDI) provided by the World Bank Databank (World Bank 2025).

Table 3 reports monthly temperature statistics for 230 countries/regions from 1960 to 2017, capturing both mean levels and changes over time. The monthly frequency is important because economic effects of temperature are highly seasonal: agriculture depends on planting and harvest conditions, and energy demand fluctuates with heating in colder months and cooling in hotter months. Moreover, the data reveal that winter months exhibit greater volatility, while summer months show higher but more stable averages, implying that climate change generates asymmetric seasonal shocks rather than uniform annual effects.

To examine heterogeneity in the effects of temperature on economic growth, we classify countries and regions along three dimensions. First, "poor" and "rich" are defined as dummy variables for countries with below- and above-median GDP per capita in 1995.[3] Second, we define an agricultural (non-agricultural) indicator based on the 1995 agricultural GDP share, with countries above (below) the median classified as agricultural (non-agricultural) economies. Finally, we group countries by baseline climate using average temperatures in the 1950s, classifying those above the median as "hot" and the rest as "cool".

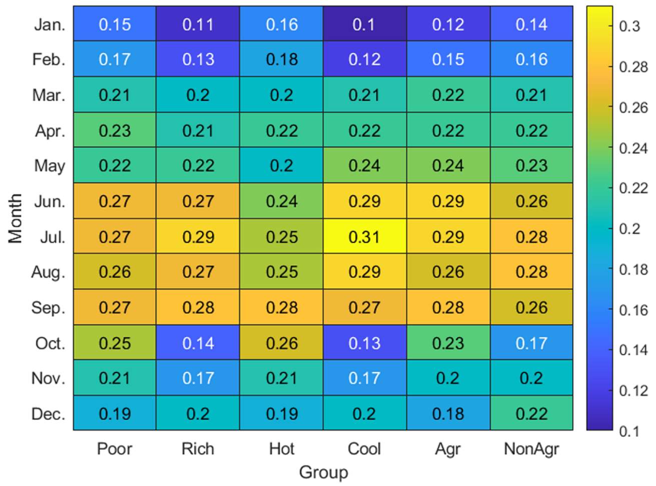

FIGURE 1 | Simple correlations of GDP per capita and temperature.

We also compute the simple correlations between monthly temperature and GDP per capita across countries to assess heterogeneity in the temperature-growth relationship. As shown in Figure 1, the correlation between January temperature and GDP per capita is the weakest among all months, indicating that a simple averaging scheme may obscure meaningful variation and introduce bias. Moreover, the month exhibiting the strongest correlation differs across country groups, highlighting substantial heterogeneity in the relevant weighting of temperature. Although simple correlation estimates are subject to obvious limitations, the observed pattern nonetheless supports our approach, which permits flexible, data-driven weighting rather than imposing uniform weights across months and countries.

5.3 | Growth Model and Econometric Specification

To better motivate the empirical relevance of our econometric framework, we consider the following growth model. The aggregate output of country i at time t is determined by

$$GDP_{it} = e^{\psi_i T_{it}} A_{it} L_{it} \tag{19}$$

$$\Delta A_{it} / A_{it} = c_i + \theta_i T_{it} \tag{20}$$

Equation (19) specifies that the aggregate output of country i at time t is determined by its productivity A_{it}, population L_{it}, and the level effect of temperature T_{it}. Equation (20) characterizes the growth effect of temperature, captured by θ_i, operating through the productivity channel.

The above model generalizes the framework proposed by Bond et al. (2010). Our key modification is to allow both ψ_i and θ_i to vary across countries, thereby accommodating heterogeneous responses to climate shocks. The original model of Bond et al. (2010) only admits heterogeneity through additive fixed terms c_i. Allowing slope heterogeneity provides a more realistic characterization of countries' adaptation capacities, reflecting differences in technology, infrastructure, and climate resilience.

We obtain the estimating equation by taking logarithms on both sides of Equation (19) and differencing across two consecutive periods. Combining this with Equation (20) yields

$$g_{it} = c_i + (\psi_i + \theta_i)T_{it} - \psi_i T_{it-1}, \tag{21}$$

where g_{it} is the growth rate of the output per capita (in percentage terms). The level effect ψ_i can be identified as the negative coefficient in the lagged temperature variable, while the growth effect θ_i corresponds to the sum of the parameters in the contemporaneous and lagged temperature variables.

Our econometric model is completed by specifying the aggregation process of the temperature variables as follows:

$$T_{it} = \sum_{t=1}^{M} \alpha_i^{(m)} T_{it}^{(m)}, \tag{22}$$

where the annual climate variable T_{it} is constructed as a linear combination of the high-frequency variable $T_{it}^{(m)}$, with $M = 4$ for quarterly data and $M = 12$ for monthly data. As discussed earlier, most existing studies assume a homogeneous flat weighting scheme $\alpha_i^{(m)} = 1/M$ when aggregating high-frequency weather variables into annual measures. Yang et al. (2023) propose a data-driven approach to aggregate quarterly data, but their framework allows for no heterogeneity beyond standard additive individual effects. In contrast, our model explicitly accounts for heterogeneity both in the aggregation of high-frequency variables and in the response to the aggregated variables.

Since precipitation may also affect economic output, we incorporate precipitation variables, Q_{it}, as an additional climate factor. Consistent with the rationale discussed above, we introduce country-specific weighting parameters, $\pi_i^{(m)}$, in constructing the annual precipitation measure. The level and growth effect parameters of precipitation are denoted by ζ_i and ξ_i, respectively, which are directly analogous to ψ_i and θ_i. Define $\tau_i = \psi_i + \theta_i$ and $\delta_i = \zeta_i + \xi_i$. Combining Equations (21) and (22) gives our empirical estimating equation:

$$\begin{aligned} g_{it} = c_i &+ \tau_i \sum_{t=1}^{M} \alpha_i^{(m)} T_{it}^{(m)} \\ &- \psi_i \sum_{t=1}^{M} \alpha_i^{(m)} T_{it-1}^{(m)} + \delta_i \sum_{t=1}^{M} \pi_i^{(m)} Q_{it}^{(m)} \\ &- \zeta_i \sum_{t=1}^{M} \pi_i^{(m)} Q_{it-1}^{(m)} + u_{it} \end{aligned} \tag{23}$$

Following Dell et al. (2012), we begin with Equation (23) without including any lagged terms and test the null hypothesis that temperature has no overall effect on economic output,

$$H_0^1(\text{no lags}) : E(\tau_i) = E(\psi_i + \theta_i) = 0.$$

Failure to reject H_0^1 would imply the absence of both level and growth effects.

A large body of empirical research has focused on the heterogeneous effects of temperature fluctuations. Such heterogeneity is typically captured in standard panel data frameworks through the inclusion of dummy variables, such as those indicating poor countries, hot regions, or agricultural economies. These time-invariant dummy variables cannot be directly incorporated into our MG approach due to obvious identification issues. We provide an explicit treatment of such dummy variables within the MG estimation framework. Let D_i denote a generic dummy variable, and define our parameter of interest as $\Delta(D) \equiv E(\tau_i | D_i = 1) - E(\tau_i | D_i = 0)$.[4] The second goal of this empirical analysis is to uncover the heterogeneous effects of temperature across different subgroups defined by D_i,

$$H_0^2 : \Delta(D) \equiv E(\tau_i | D_i = 1) - E(\tau_i | D_i = 0) = 0.$$

Finally, we extend Equation (23) by incorporating additional lagged terms to assess the cumulative effects, equivalently, the growth effects of temperature on economic growth,

$$H_0^3(\text{with lags}) : E(\theta_i) = E(\tau_i - \psi_i) = 0.$$

In principle, richer lag structures can be incorporated into Equation (23) without affecting identification of the growth effect θ_i (see Dell et al. 2012). For brevity, we proceed directly to the empirical analysis, which includes additional lagged climate variables without explicitly presenting the extended specification.

In this application, the slope parameter is interpreted as the average effect of temperature on economic growth, which naturally implies that the weights assigned to quarters or months sum to one for each country. This normalization makes the MG approach particularly suitable for our purpose. Moreover, our simulation results indicate that the MG estimator generally delivers more accurate inference than the CRE estimator. Accordingly, we use the proposed MG estimation method to estimate the empirical model described above.

The MG approach does not accommodate aggregate time fixed effects, which are often important in empirical applications. To address this limitation, we incorporate time trends into the model. This strategy removes systematic, smooth temporal variation while leaving nonlinear or shock-driven components—such as common shocks—as potential omitted factors. Thus, identification relies on the assumption that remaining common shocks are either limited or not systematically correlated with weather fluctuations. Although less flexible than full time fixed effects, linear (or quadratic) trends are appropriate in our setting given the gradual evolution of climate variables, and they enable us to identify the economic effects of deviations from underlying trends.

5.4 | Estimation Results

The empirical contribution of using our new methodology is threefold. First, we document a larger temperature-induced growth gap between poor and rich countries. Second, we find stronger adverse effects of warming in already hot countries. Third, we uncover little evidence of persistent long-run growth effects in poor countries. Detailed discussions are provided in the following subsections.

TABLE 4 | Estimation of the overall effects.

	MG (with t)		MG (with t and t^2)		FE	
	Temperature	**Precipitation**	**Temperature**	**Precipitation**	**Temperature**	**Precipitation**
Sample with quarterly Data						
Full sample	−0.135 (0.291)	−0.003 (0.022)	−0.304 (0.270)	−0.014 (0.022)	0.126 (0.243)	−0.002 (0.005)
Poor (P)	−0.942* (0.492)	−0.019 (0.041)	−1.083** (0.446)	−0.035 (0.042)	−0.352 (0.348)	−0.000 (0.006)
Rich (R)	1.240*** (0.417)	−0.018 (0.035)	0.765* (0.412)	−0.028 (0.031)	0.372 (0.290)	−0.008 (0.007)
Hot (H)	−0.846* (0.483)	−0.033 (0.043)	−1.074** (0.430)	−0.061 (0.044)	−0.197 (0.329)	−0.002 (0.006)
Cool (C)	1.113** (0.437)	−0.004 (0.033)	0.729* (0.430)	−0.002 (0.029)	0.291 (0.290)	−0.007 (0.008)
Agriculture (AG)	−0.142 (0.572)	−0.051 (0.045)	−0.446 (0.539)	−0.064 (0.045)	0.560 (0.421)	−0.003 (0.006)
Non-agriculture (NAG)	0.277 (0.309)	0.032 (0.032)	−0.147 (0.328)	0.021 (0.028)	−0.253 (0.211)	0.001 (0.007)
Sample with monthly Data						
Full sample	0.107 (0.380)	−0.028 (0.026)	−0.007 (0.342)	−0.034 (0.027)	0.172 (0.244)	−0.002 (0.005)
Poor (P)	−0.918* (0.548)	−0.029 (0.034)	−0.817 (0.503)	−0.046 (0.035)	−0.314 (0.346)	−0.002 (0.006)
Rich (R)	1.490** (0.600)	−0.094* (0.051)	0.970* (0.548)	−0.099* (0.052)	0.431 (0.304)	−0.009 (0.007)
Hot (H)	−0.962* (0.530)	−0.023 (0.039)	−1.040** (0.478)	−0.046 (0.040)	−0.162 (0.328)	−0.003 (0.006)
Cool (C)	1.498** (0.612)	−0.099** (0.046)	1.163** (0.556)	−0.099** (0.048)	0.381 (0.304)	−0.007 (0.008)
Agriculture (AG)	−0.188 (0.616)	−0.084 (0.052)	−0.261 (0.599)	−0.106** (0.053)	0.583 (0.418)	−0.004 (0.006)
Non-agriculture (NAG)	0.436 (0.515)	−0.011 (0.037)	0.002 (0.463)	−0.020 (0.038)	−0.160 (0.216)	−0.001 (0.007)

Note: Standard errors of the FE estimators are clustered at the country level. ∗ denotes significance at the 10% level, ∗∗ at the 5% level and ∗∗∗ at the 1% level.

5.4.1 | Estimation of the Overall Effects

We begin by testing, using quarterly and monthly data, the null that weather variables have no effect on economic growth—H_0^1 : $E(\tau_i) = 0$—through either level or growth channels. We first consider a parsimonious specification that excludes dynamic responses to temperature and precipitation by setting all lag coefficients to zero. Estimates are presented for subsamples defined by the dummy variables in Section 5.2, with MG estimates reported under both linear and quadratic time trends. For comparison, we also report results from the fixed effects estimator, which imposes parameter homogeneity with flexible weighting schemes.

The top panel of Table 4 reports results based on quarterly data. At the aggregate level, the effect of temperature on growth is statistically insignificant. Clear heterogeneity emerges across subsamples. For poor countries, a 1°C increase reduces annual growth by about 0.92 percentage points, a large and significant effect. By contrast, rich countries show a positive association, which weakens and loses significance with quadratic time trends. Climatic conditions reinforce this pattern: hotter countries experience negative and significant effects, while cooler countries tend to benefit, though estimates become less precise under more flexible trends. By economic structure, agriculture-dependent countries exhibit negative but insignificant temperature coefficients.

Moving from quarterly to monthly data yields several new findings. First, the previously negative effect of temperature on poor countries becomes statistically insignificant once quadratic time trends are included. Second, the absolute magnitudes of temperature effects increase: adverse effects in hot countries and beneficial effects in cool countries are both larger at the monthly frequency. Finally, precipitation has a negative and significant effect on growth in cool countries; a 1 mm increase is associated with about a 0.1 percentage point decline in growth.

Traditional fixed effects models in both cases largely yield statistically insignificant estimates and, in some instances, coefficients with implausible signs. Comparing the MG estimator based on high-frequency data with its low-frequency counterpart, as well as with the conventional fixed effects estimator, the results in Table 4 highlight the importance of incorporating high-frequency information and explicitly allowing for cross-country heterogeneity within the panel MIDAS framework.

Overall, Table 4 shows substantial heterogeneity in temperature effects across country groups. A 1°C increase is associated with sizable output losses—close to 1 percentage point of annual growth—in vulnerable economies, especially those that are poor or already hot. By contrast, richer and cooler countries tend to experience positive but less precisely estimated effects. Precipitation, in contrast, shows no systematic relationship with output across most subsamples, with few coefficients statistically significant.

5.4.2 | Estimation of the Heterogeneous Effects

This subsection tests our second hypothesis, $H_0^2 : \Delta(D) = 0$. Building on Tables 4 and 5 reports the differential effects of temperature and precipitation across subsamples. These estimates are directly comparable to those in Dell et al. (2012) and Yang et al. (2023), thereby facilitating a clear assessment of how our findings relate to the existing literature.

TABLE 5 | Estimation of heterogeneous effects across groups.

	MG (with t)		MG (with t and t^2)		FE	
	Temperature	**Precipitation**	**Temperature**	**Precipitation**	**Temperature**	**Precipitation**
Sample with quarterly data						
Difference P vs R	-2.182^{***} (0.645)	−0.001 (0.054)	-1.848^{***} (0.607)	−0.007 (0.052)	-0.724^{*} (0.414)	0.007 (0.009)
Difference H vs C	-1.958^{***} (0.651)	−0.029 (0.054)	-1.803^{***} (0.608)	−0.059 (0.052)	−0.487 (0.399)	0.005 (0.010)
Difference AG vs NAG	−0.418 (0.650)	−0.084 (0.055)	−0.298 (0.631)	−0.086 (0.053)	0.813^{*} (0.419)	−0.004 (0.009)
Sample with monthly data						
Difference P vs R	-2.407^{***} (0.813)	0.065 (0.061)	-1.786^{**} (0.744)	0.053 (0.063)	-0.745^{*} (0.417)	0.007 (0.009)
Difference H vs C	-2.461^{***} (0.810)	0.075 (0.061)	-2.203^{***} (0.734)	0.053 (0.063)	−0.543 (0.402)	0.004 (0.010)
Difference AG vs NAG	−0.625 (0.803)	−0.073 (0.064)	−0.263 (0.757)	−0.086 (0.065)	0.743^{*} (0.417)	−0.003 (0.009)

Note: Standard errors of the FE estimators are clustered at the country level. $*$ denotes significance at the 10% level, $**$ at the 5% level and $***$ at the 1% level.

For the quarterly specifications, consistent with the literature, we find that poor countries are significantly more vulnerable to temperature increases than rich countries. Dell et al. (2012) report that a 1°C increase is associated with a 1.6 percentage point growth differential between poor and rich countries. Relative to our MG estimates (1.85–2.18), this appears to understate the true cross-country differential. A further contribution of our results is that higher temperatures have substantially larger adverse effects in hot regions than in cooler ones. Relative to cool countries, a 1°C increase reduces growth in hot countries by about 1.8-1.9 percentage points. In contrast, Dell et al. (2012) and Yang et al. (2023) find these differences to be statistically insignificant. These comparisons highlight the importance of heterogeneous weighting schemes and slope coefficients within the panel MIDAS framework.

Turning to monthly specifications, we obtain a similar pattern, but with larger absolute effects than in the quarterly data, suggesting that low-frequency aggregation understates cross-country heterogeneity in temperature impacts. Because the panel MIDAS model with quarterly aggregation can be viewed as a restricted model based on monthly data, the latter provides a more general specification. We therefore place greater weight on the results obtained from monthly data and regard them as more reliable.

In summary, Table 5 delivers two main findings. First, consistent with the existing literature, poor countries are more vulnerable to temperature increases than rich countries. However, the magnitudes we estimate are larger than those previously reported. Second, we find that the adverse effects of temperature are significantly more pronounced in hot countries than in cooler ones. This result represents a novel contribution, as earlier studies have generally reported statistically insignificant differences along this dimension.

5.4.3 | Estimation of the Growth Effects

Finally, we turn to the estimation of growth effects or equivalently, the cumulative effects of temperature. We test our third hypothesis that $H_0^3 : E(\theta_i) = 0$, which examines whether, on average across countries, temperature has systematic impact on economic growth through its growth effect. Recall that these effects are identified as the sum of the coefficients on the contemporaneous and lagged temperature terms. Table 6 reports the results from estimating Equation (23) with no lag, one lag, three lags, and five lags, using quarterly and monthly data, respectively. Since precipitation does not appear to influence the growth rate, as suggested by the preceding results, our analysis primarily focuses on the growth effects of temperature.

The results based on quarterly data, reported in Table 6, indicate that temperature exerts only a temporary negative effect on the growth of poor countries. This finding is broadly consistent with Yang et al. (2023), but contrasts with the results of Dell et al. (2012), who document persistent medium to long-run growth effects for poor countries. Specifically, they report that a 1°C increase in temperature reduces the long run growth rate by approximately 0.98 to 1.4 percentage points. In comparison, our estimates suggest that the adverse impact in poor countries dissipates over time and does not translate into statistically significant cumulative growth losses. For rich countries, we find that higher temperatures generate a positive short-run effect on economic growth, a result that aligns with both Dell et al. (2012) and Yang et al. (2023). Moreover, a novel finding in our analysis is that rising temperatures are associated with positive growth effects in cooler countries, suggesting that baseline climate conditions play an important role in shaping the dynamic response of output to temperature shocks.

The results obtained using monthly data are largely consistent with those based on quarterly data. The main difference is that, with monthly data, the positive growth effects of rising temperature in cool countries appear to be short to medium-term rather than persistent over longer horizons. It is worth noting that the quarterly panel MIDAS specification can be viewed as a restricted version of the more general monthly panel MIDAS model. The monthly framework permits more flexible aggregation, reducing the risk of misspecification from restrictive temporal assumptions. Therefore, estimates based on monthly data are more reliable and informative about the dynamic growth effects of temperature.

The main findings of Table 6 are summarized as follows. First, under our new estimation framework, temperature exerts only short-run effects on the growth of poor countries. This result is

TABLE 6 | Estimation of the growth effects.

	MG with t				MG with t and t^2			
	No lags	**One lag**	**Three lags**	**Five lags**	**No lags**	**One lag**	**Three lags**	**Five lags**
Sample with quarterly data								
Poor (P)	−0.942* (0.492)	−0.303 (0.705)	−0.244 (1.131)	−2.297 (2.235)	−1.083** (0.446)	−0.368 (0.616)	0.538 (1.064)	−2.816 (2.379)
Rich (R)	1.240*** (0.417)	1.870*** (0.576)	2.108** (1.006)	1.652 (1.220)	0.765* (0.412)	2.017*** (0.705)	2.808** (1.200)	1.373 (1.577)
Hot (H)	−0.846* (0.483)	0.046 (0.705)	−0.288 (1.157)	−2.844 (2.284)	−1.074** (0.430)	−0.186 (0.596)	1.270 (1.207)	−2.967 (2.452)
Cool (C)	1.113** (0.437)	1.494** (0.598)	2.116** (0.981)	2.130* (1.145)	0.729* (0.430)	1.802** (0.741)	1.911* (1.000)	1.548 (1.405)
Agriculture (AG)	−0.142 (0.572)	0.987 (0.753)	1.618 (1.162)	2.239* (1.262)	−0.446 (0.539)	1.142 (0.776)	1.925 (1.248)	2.120 (1.276)
Non-Agriculture (NAG)	0.277 (0.309)	0.647 (0.398)	0.883 (0.829)	−0.480 (0.927)	−0.147 (0.328)	0.412 (0.425)	1.331 (0.946)	0.089 (1.590)
Sample with monthly data								
Poor (P)	−0.918* (0.548)	0.192 (0.596)	0.969 (0.901)	−0.058 (1.454)	−0.817 (0.503)	0.202 (0.642)	1.031 (1.060)	−0.794 (1.926)
Rich (R)	1.490** (0.600)	1.356* (0.713)	3.163*** (1.074)	1.462 (1.174)	0.970* (0.548)	1.479* (0.765)	2.057 (1.326)	0.569 (2.240)
Hot (H)	−0.962* (0.530)	0.253 (0.639)	1.867** (0.868)	1.271 (1.025)	−1.040** (0.478)	0.175 (0.683)	1.272 (1.068)	−0.659 (1.642)
Cool (C)	1.498** (0.612)	1.282* (0.659)	2.057* (1.131)	−0.137 (1.711)	1.163** (0.556)	1.512** (0.710)	1.768 (1.319)	0.407 (2.550)
Agriculture (AG)	−0.188 (0.616)	0.638 (0.734)	1.955 (1.175)	0.689 (1.741)	−0.261 (0.599)	0.828 (0.803)	2.012 (1.429)	0.890 (2.864)
Non-agriculture (NAG)	0.436 (0.515)	0.378 (0.664)	1.926** (0.771)	0.573 (1.153)	0.002 (0.463)	0.281 (0.644)	0.236 (0.891)	−1.911* (1.133)

Note: * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.

consistent with Yang et al. (2023) but contrasts with the evidence reported by Dell et al. (2012), who document persistent long-run growth impacts in poorer economies. Second, we find that rising temperatures generate only temporary negative growth effects in hot countries, while producing short-run positive effects in cool countries. Overall, we do not find statistically significant evidence supporting persistent long-run growth effects of temperature shocks. Instead, the estimated impacts appear to be transitory, suggesting that temperature primarily influences economic growth through short- to medium-term adjustment dynamics rather than permanent shifts in long-run growth trajectories.

5.4.4 | Summary of Key Findings

We conclude our empirical analysis by summarizing the main findings. First, although the full-sample estimates provide limited evidence of an average temperature effect, substantial heterogeneity emerges across country groups. Rising temperatures significantly reduce economic growth in poor and hot countries, while benefiting rich and cooler economies. Quantitatively, the implied growth gap between poor and rich countries in our estimates is larger than that reported in earlier studies. Second, we provide new evidence that the adverse effects of temperature are considerably more pronounced in hot countries than in cooler ones. This represents a novel contribution, as previous studies have generally found statistically insignificant differences along this dimension. Finally, our results indicate that temperature fluctuations do not generate persistent growth effects in poor countries, in contrast to the findings of Dell et al. (2012). Taken together, this suggests that temperature shocks primarily influence economic performance through level effects rather than through permanent changes in long-run growth rates.

6 | Conclusion

This paper develops estimation methods for heterogeneous panel data models with mixed sampling frequencies, where covariates are observed more frequently than the dependent variable. The framework accommodates two forms of heterogeneity: slope coefficients and aggregation parameters, both of which may be correlated with covariates, as is typical in empirical applications.

We first extend the MG estimator to a heterogeneous panel MIDAS framework. Under mild conditions, MG slope estimators are consistent and asymptotically normal, while aggregation weights estimates are generally biased. To address this issue, we propose a CRE approach based on a generalized Mundlak device, yielding consistent estimates of average slopes and aggregation parameters under additional functional-form assumptions. When covariates are observed at much higher frequency, we further incorporate machine learning techniques to approximate unknown weighting functions, allowing flexible aggregation structures. Simulations show that the proposed estimators perform well in finite samples.

We apply the new method to estimate the effects of temperature fluctuations on economic growth. Our empirical contribution is threefold. First, we estimate a substantially larger temperature-induced growth gap between poor and rich countries than documented in earlier research. Second, we find robust evidence that the negative effects of rising temperatures are markedly stronger in already hot countries, challenging previous studies reporting insignificant differences across climate zones. Third, in contrast with Dell et al. (2012), we find no persistent growth effects of temperature shocks in poor countries, suggesting impacts operate mainly through level effects rather than permanent changes in long-run growth rates.

Collectively, this paper provides a flexible and implementable framework for applied researchers working with mixed-frequency panel data. The proposed estimators lend themselves to a broad range of empirical applications, including macroeconomic forecasting, financial modeling, and environmental economic analysis, where accounting for heterogeneity and mixed-frequency information is essential.

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Data Availability Statement

The data that support the findings of this study are openly available in the Journal Data Archive at https://doi.org/10.15456/jae.2026127.0002917558.

Endnotes

[1]In the original paper by Swamy (1970), u_{it} can be heteroskedastic with large T. Here we mainly focus on the fixed T case so we add the homoskedastic assumption. In practice, we need to substitute these unknown covariance matrix and variance parameter with their estimators. For example, Γ can be estimated by $\frac{1}{N-1}\sum_{i=1}^{N}(\hat{\gamma}_i - \hat{\gamma}_{mg})(\hat{\gamma}_i - \hat{\gamma}_{mg})'$, where $\hat{\gamma}_i$ and $\hat{\gamma}_{mg}$ are given in equation (7). A feasible estimator of σ_u^2 would be $\frac{1}{NT-K}\sum_{i=1}^{N}(Y_i - X_i^H\hat{\gamma}_i)'(Y_i - X_i^H\hat{\gamma}_i)$.

[2]Simulation results for $N = 100$ are qualitatively similar to those for $N = 50$ and are therefore reported in the Appendix S1.

[3]We use 1995 as the baseline because most countries have data by then; results are robust to alternative base years.

[4]The corresponding estimator and its asymptotic distribution can be found in the appendix.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1.** Supporting Information.