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RESEARCH ARTICLE

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A discrete-choice model for large heterogeneous panels with interactive fixed effects with an application to the determinants of corporate bond issuance

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Summary

What is the effect of funding costs on the conditional probability of issuing a corporate bond? We study this question in a novel dataset covering 5610 issuances by US firms over the period from 1990 to 2014. Identification of this effect is complicated because of unobserved, common shocks such as the global financial crisis. To account for these shocks, we extend the common correlated effects estimator to settings where outcomes are discrete. Both the asymptotic properties and the small-sample behavior of this estimator are documented. We find that for non-financial firms yields are negatively related to bond issuance but that the effect is larger in the pre-crisis period.

1 | INTRODUCTION

At least since Modigliani and Miller (1958), how firms choose their capital structure has attracted much attention, and there is a large empirical and theoretical literature that explores these issues (e.g., Becker & Ivashina, 2014; Denis & Mihov, 2003; Myers, 1977; Myers & Majluf, 1984). Relative to other forms of financing such as equity and bank loans, corporate debt is an important source of funding for US corporations (Denis & Mihov, 2003) and the corporate bond market has grown rapidly over the last decade (Office of Financial Research, 2015).

In this paper, we study the effect of corporate yields on bond issuance of US firms. In contrast to earlier studies (e.g., Frank & Goyal, 2008), we adopt an incremental approach that investigates the conditional probability of issuing a corporate bond which is particularly suitable for questions related to time variation in the regressors. While previous work has documented that issuer characteristics like size, rating, profitability, leverage, equity prices, monetary policy, information asymmetry, and the supply of bank credit are important determinants of bond issuance (e.g., Adrian, Colla, & Shin, 2012; Badoer & James, 2016; Becker & Ivashina, 2014; Denis & Mihov, 2003; Gomes & Phillips, 2012; Mizen & Tsoukas, 2013), there is not much evidence yet on the effect of yields on bond issuance.

Answering the question of how funding costs in corporate bond markets affect issuance decisions sheds light on a particular transmission mechanism of monetary policy: by means of conventional and unconventional monetary policy tools, the central bank can affect the interest rates firms face in corporate bond markets. Bond issuance, on the other hand, tends to be related to corporate investment and thus aggregate demand (Farrant, Inkinen, Rutkowska, & Theodoridis, 2013).

We study the effect of yields on bond issuance using a novel dataset that includes bond issuances by US firms between 1990 and 2015 on a monthly frequency. During that period, we observe 5,610 issuances with an average size of approximately 300 million USD made by 1,004 different firms. We find that for non-financial firms yields are negatively related to bond issuance but that the effect is larger in the pre-crisis period. In contrast, there is no significant effect of yields on corporate bond issuance for financial firms. Splitting the data by the credit rating of the issuer reveals that the negative relationship between yields and corporate bond issuance is driven by firms with a low credit rating. These results are robust to applying different sample selection criteria, to including additional regressors, and to using corporate spreads instead of yields as the primary regressor.

To identify the parameters of interest, it is important to control for unobserved, common shocks that are frequently encountered in these types of datasets. In our empirical application, the unobserved factors can represent a new regulatory landscape, changes in investor behavior such as search for yield, automated trading, or policies that aim at deepening corporate bond markets, for example. Andrews (2005) shows that common shocks create problems for inference if data are available for a single cross-sectional unit and the model is estimated by least squares or instrumental variable methods. But the increased availability of panel data where both the time series and cross-sectional dimensions are large offers new opportunities for controlling for these unobserved shocks. Bai (2009) and Pesaran (2006) are examples of panel data estimators robust to common shocks.

This paper contributes to this literature by developing an estimator for large heterogeneous panels with cross-sectional dependence in a framework where outcomes are discrete. The proposed estimator belongs to the class of common correlated effects (CCE) estimators that approximate the unobserved factors with cross-sectional averages of both the regressors and the response variable (Pesaran, 2006). But this approach is complicated in nonlinear models, where it is difficult to use averages of response variables without making strong assumptions. This paper adapts the CCE estimation methodology to discrete-choice models under the assumption that the unobserved factors are contained in the span of the observed factors and the cross-sectional averages of the regressors.

We present a large-sample distribution theory for our estimation procedures for the setting where both the time dimension T and the cross-sectional dimension N are large. We first show that the estimator of the individual-specific coefficients is consistent and asymptotically normal. An important part of the asymptotic theory is uniform consistency of the preliminary estimator, which we establish under moment conditions. Based on the asymptotic properties of the estimators of the individual-specific coefficients, we derive the consistency and asymptotic normality for the mean group estimator, which is defined as the average of the individual-specific estimators. Inference regarding the mean group effect follows straightforwardly: We show that the asymptotic variance of the mean group estimator can be estimated by the covariance matrix of the individual-specific coefficient estimates. This covariance estimator is similar to the estimator obtained in linear regression models (Pesaran, 2006).

By means of a simulation study, we document that for a wide range of factor structures the mean group estimator is comparable in terms of root mean square error (RMSE) and bias to an infeasible estimator that counterfactually assumes that the common factors are known. In addition, the mean group estimator has good empirical power, size, and coverage probabilities.

Our paper is related to Fernandez-Val and Weidner (2016) and Chen, Fernandez-Val, and Weidner (2014), who propose alternative estimators for large, nonlinear panels with fixed effects. Fernandez-Val and Weidner (2016) study nonlinear panel data models with additive fixed effects. They characterize the bias that arises due to the incidental parameter problem (Neyman & Scott, 1948) and provide analytical and jackknife corrections to remove this bias. In contrast to this paper, they assume that the slope coefficients are homogeneous and that the fixed effects enter additively. Chen et al. (2014) is probably the paper closest to ours. They also propose an estimator for nonlinear panel data models with interactive fixed effects. But while the contribution we make is along the lines of simplicity and applicability and indeed the application, their focus is on developing a comprehensive asymptotic theory for a wide range of nonlinear panel data models. In contrast, we are only concerned with binary-choice models, which are popular among applied economists. One advantage of our approach is that our estimator can be computed by simply averaging regression coefficients from probit models estimated for each individual unit. In contrast, Chen et al.'s estimator is computed iteratively in a two-step procedure, which makes it more difficult to implement in practice.

Our paper is also related to the literature on common correlated effects estimation. That literature was pioneered by Pesaran (2006), who first proposed to approximate the unobserved factors by cross-sectional averages. Since then, a growing literature has extended the CCE approach in various ways: Pesaran and Tosetti (2011) combine the factor approach with spatial models by assuming that the disturbances net of the common factors follow a spatial process (see also Chudik, Pesaran, & Tosetti, 2011). Kapetanios, Pesaran, and Yamagata (2011) show that the CCE estimator is consistent even if the unobserved factors are non-stationary. Chudik and Pesaran (2015) extend the CCE estimator to dynamic panels. Baltagi, Feng, and Kao (2015) develop a CCE estimator for data with structural breaks. Harding and Lamarche (2014) propose a quantile CCE estimator for homogeneous panel data with endogenous regressors, and Boneva, Linton, and Vogt (2016) develop a quantile CCE estimator for heterogeneous panels. The contribution of this paper is to extend the CCE approach to discrete outcomes.

The remainder of this paper is organized as follows. The econometric model is presented in Section 2, and Section 3 describes the estimation methodology and discusses related estimators for nonlinear panel data. Section 4 develops the asymptotic theory. Section 5 reports the results of a simulation study and Section 6 applies our estimator to investigate how yields affect the decision to issue a corporate bond. Section 7 concludes.

2 | ECONOMETRIC MODEL

This section describes the econometric framework. We observe a sample of panel data $\{(Y_{it}, X_{it}, d_t) : i = 1, \dots, N, t = 1, \dots, T\}$, where i denotes the ith unit and t is the time point of observation. To keep the notation simple, we assume that the panel is balanced. The data are assumed to come from the model

$$Y_{it}^* = \alpha_i^\intercal d_t + \beta_i^\intercal X_{it} + e_{it}, \quad i = 1, \dots, N, t = 1, \dots, T, \tag{1}$$

where X_{it} is a $K_x \times 1$ vector of individual-specific regressors that are assumed to be strictly exogenous and stationary and d_t is a $K_d \times 1$ vector of observed common factors that do not vary across individual units. Here, Y_{it}^* is a latent variable that is related to the observed response variable Y_{it} via the indicator function $I(.)$:

$$Y_{it} = I(Y_{it}^*). \tag{2}$$

That is, Y_{it} is unity if $Y_{it}^* > 0$ and zero otherwise. This paper is concerned with inference for the heterogeneous coefficients β_i and their mean. This is complicated by cross-sectional dependence, which is modeled by assuming that the disturbances exhibit the factor structure

$$e_{it} = \kappa_i^\intercal f_t + \epsilon_{it}, \tag{3}$$

where f_t is a $K_f \times 1$ vector of unobserved common factors and κ_i is a $K_f \times 1$ vector of factor loadings. The disturbances ϵ_{it} are i.i.d. conditional on the factors and have a known symmetric density ϕ and distribution function Φ (perhaps but not necessarily the normal distribution with zero mean and unit variance). We may write

$$\Pr(Y_{it} = 1 | X_{it}, d_t, f_t) = 1 - \Phi\left(-\alpha_i^\intercal d_t - \beta_i^\intercal X_{it} - \kappa_i^\intercal f_t\right) = \Phi\left(\alpha_i^\intercal d_t + \beta_i^\intercal X_{it} + \kappa_i^\intercal f_t\right). \tag{4}$$

In many panel data applications, the unobserved common factors f_t are correlated with both the response variable and the regressors, introducing a certain type of endogeneity. To allow for this possibility, the individual-specific regressors are assumed to follow the model

$$X_{it} = A_i^\intercal d_t + K_i^\intercal f_t + u_{it}, \tag{5}$$

where A_i is a coefficient matrix of dimension $K_d \times K_x$, K_i is a $K_f \times K_x$ matrix of factor loadings, and u_{it} have a zero mean and are i.i.d. conditional on the common factors.

We make the following assumptions, which are maintained throughout the paper:

(A1) *Random coefficient model.* The coefficients $\vartheta_i = (\alpha_i^\intercal, \beta_i^\intercal, \kappa_i^\intercal, \text{vec} \quad (A_i)^\intercal, \text{vec} \quad (K_i)^\intercal)^\intercal$ are generated by

$$\vartheta_i = \vartheta_0 + \eta_i, \tag{6}$$

where η_i ~i.i.d.$(0, \Sigma)$ and is distributed independently of $\kappa_j, K_j, \epsilon_{jt}, u_{jt}, d_t, f_t$ for all i, j, t, $\|\vartheta_0\| \leqslant C < \infty$.

(A2) *Common factors.* The $(K_f + K_d) \times 1$ vector of common factors $g_t = (f_t^\intercal, d_t^\intercal)^\intercal$ is assumed to be bounded and covariance stationary with absolute summable covariances, and distributed independently of the disturbances ϵ_{it} and u_{is}, for all i, t, s.

(A3) *Factor loadings.* The factor loadings κ_i and K_i are i.i.d. across i, and distributed independently of the disturbances ϵ_{jt} and u_{jt} and the common factors f_t and d_t, for all i, j, t with finite means and variances.

(A4) The function Φ is three times differentiable.

3 | ESTIMATION

3.1 | A common correlated effects estimator for discrete choice panels

The econometric model (Equations 1–5) depends on the unobserved factors f_t, which makes estimation difficult. One approach to control for unobserved factors is to approximate them by cross-sectional averages of the regressors and the response variable (Pesaran, 2006).[1] But in nonlinear panel data models, it is difficult to use averages of response variables without making strong assumptions. Instead, we approximate the unobserved factors by cross-sectional averages of the regressors. This approach is valid if the unobserved factors are contained in the span of the observed factors and the cross-sectional averages of the regressors. This assumption is more restrictive compared to the linear set-up in Pesaran, where also the dependent variable can be used to approximate the unobserved factors.

[1] In the case of microeconometric panels, where individual-specific unobserved characteristics like ability are likely to be correlated with the regressors, the indices t and i can be interchanged and time series averages can be used to approximate the unobserved loadings.

Let $h_{0t} = A_0^{\intercal} d_t + K_0^{\intercal} f_t$ and $\bar{h}_t = \bar{A}^{\intercal} d_t + \bar{K}^{\intercal} f_t$ be vectors in $\mathbb{R}^{K_x}$, where we use A_0 and K_0 to denote the population means of A_i and K_i and $\bar{A} = N^{-1}\sum_{i=1}^{N} A_i$ and $\bar{K} = N^{-1}\sum_{i=1}^{N} K_i$ to denote their sample counterparts. These quantities will be used to rewrite the likelihood function. Then, under the assumption that for large N the $K_f \times K_x$ matrix $\bar{K}$ is of full rank:

$$\operatorname{rank}(\bar{K}) = K_f \leqslant K_x, \tag{7}$$

we have $f_t = (\bar{K}\bar{K}^{\intercal})^{-1}\bar{K}\bar{h}_t - (\bar{K}\bar{K}^{\intercal})^{-1}\bar{K}\bar{A}^{\intercal} d_t$. We also have for all t, N

$$\Pr(Y_{it} = 1 | d_t, X_{it}, f_t) = \Pr(Y_{it} = 1 | d_t, X_{it}, \bar{h}_t) = \Phi\left(\bar{\alpha}_i^{\intercal} d_t + \beta_i^{\intercal} X_{it} + \bar{\kappa}_i^{\intercal} \bar{h}_t\right), \tag{8}$$

where $\bar{\alpha}_i = \alpha_i + \tilde{K}^{\intercal}\kappa_i$ and $\bar{\kappa}_i = \tilde{K}^{\intercal}\kappa_i$ with $\tilde{K} = (\bar{K}\bar{K}^{\intercal})^{-1}\bar{K}$. The true individual-specific coefficients and their population means are denoted by $\theta_{0i} = (\bar{\alpha}_{0i}^{\intercal}, \beta_{0i}^{\intercal}, \bar{\kappa}_{0i}^{\intercal})^{\intercal}$, $\theta_0 = (\bar{\alpha}_0^{\intercal}, \beta_0^{\intercal}, \bar{\kappa}_0^{\intercal})^{\intercal} \in \mathbb{R}^{K_d + 2K_x}$.

Letting p denote the generic conditional distribution, we may define the infeasible objective function:

$$Q_T^i(\theta) = \frac{1}{T}\sum_{t=1}^{T} q_t^i(\theta, \bar{h}_t) \tag{9}$$

$$= -\frac{1}{T}\sum_{t=1}^{T} \log p(Y_{it} | d_t, X_{it}, \bar{h}_t, \theta) \tag{10}$$

$$= -\frac{1}{T}\sum_{t=1}^{T} [Y_{it} \log \Phi(\theta^{\intercal} z_{it}) + (1 - Y_{it}) \log(1 - \Phi(\theta^{\intercal} z_{it}))],$$

where $z_{it} = (d_t^{\intercal}, X_{it}^{\intercal}, \bar{h}_t^{\intercal})^{\intercal}$ and $\theta \in \mathbb{R}^{K_d + 2K_x}$; this requires knowledge of $\bar{h}_t$. Let $\tilde{\theta}_i = (\bar{\alpha}_i^{\intercal}, \tilde{\beta}_i^{\intercal}, \bar{\kappa}_i^{\intercal})^{\intercal} \in \mathbb{R}^{K_d + 2K_x}$ be defined as the (infeasible) minimizer of $Q_T^i(\theta)$ with respect to $\theta \in \Theta$. The quantity $\bar{h}_t$ is no more observable than f_t, but it has a direct analogue or approximator, $\bar{X}_t = N^{-1}\sum_{i=1}^{N} X_{it}$. Define the $K_x \times 1$ vector $\hat{h}_t \equiv \bar{X}_t = \bar{A}^{\intercal} d_t + \bar{K}^{\intercal} f_t + \bar{u}_t$, where we switch notation to emphasize the connection with $\bar{h}_t$ and h_{0t} and to understand $\bar{h}_t$ as a large-dimensional nuisance parameter that is replaced by the sample quantity $\hat{h}_t$. Then define the feasible objective function

$$\hat{Q}_T^i(\theta) = \frac{1}{T}\sum_{t=1}^{T} q_t^i(\theta, \hat{h}_t)$$

$$= -\frac{1}{T}\sum_{t=1}^{T} \log p(Y_{it} | d_t, X_{it}, \hat{h}_t, \theta) \tag{11}$$

$$= -\frac{1}{T}\sum_{t=1}^{T} \left[Y_{it} \log \Phi\left(\theta^{\intercal} \hat{z}_{it}\right) + (1 - Y_{it}) \log(1 - \Phi(\theta^{\intercal} \hat{z}_{it}))\right],$$

where $\hat{z}_{it} = z_{it} = (d_t^{\intercal}, X_{it}^{\intercal}, \hat{h}_t^{\intercal})^{\intercal}$. The estimator $\hat{\theta}_i = (\bar{\alpha}_i^{\intercal}, \hat{\beta}_i^{\intercal}, \bar{\kappa}_i^{\intercal})^{\intercal} \in \mathbb{R}^{K_d + 2K_x}$ is defined as the minimizer of $\hat{Q}_T^i(\theta)$ with respect to $\theta \in \Theta$. In practice, standard numerical algorithms can be used to find the optimum, since after substituting for $\hat{h}_t$ this amounts to estimation of a parametric binary-choice model with a known link function.

The mean group estimator is defined as

$$\hat{\theta} = \frac{1}{N}\sum_{i=1}^{N} \hat{\theta}_i. \tag{12}$$

We will have a particular interest in the subvector $\hat{\beta}$. Define also the infeasible mean group estimator $\tilde{\theta} = \sum_{i=1}^{N} \tilde{\theta}_i / N$.

3.2 | Comparison with related estimators for nonlinear panels

This section compares our methodology to alternative estimators for large, nonlinear panels with fixed effects (Charbonneau, 2014; Chen et al., 2014; Fernandez-Val & Weidner, 2016; Sun, 2016).

Fernandez-Val and Weidner (2016) study nonlinear panel data models with individual and time fixed effects. Compared to our paper, they assume that the fixed effects enter the model additively and that the slope coefficients are homogeneous. Thus their model can be obtained as a special case of the model in Equations 1–3 if $\beta_i = \beta$, $\kappa_i = \kappa$ and $d_t = 1$. While the assumption of slope homogeneity is probably too strong in many applications it has the advantage that faster convergence rates can be obtained. The contribution of Fernandez-Val and Weidner is to characterize the bias that arises due to the incidental parameter problem (Neyman & Scott, 1948) and to provide analytical and jackknife bias corrections.

Charbonneau (2014) and Sun (2016) also study nonlinear panel data models with additive fixed effects and homogeneous slopes. Charbonneau develops a conditional maximum likelihood approach to estimate discrete-choice panel data models with fixed effects that is analogous to the difference-in-differences estimator used in linear panel data models. Sun's estimator is obtained by maximizing a modified objective function that is not affected by the incidental parameter problem.

Finally, Chen et al. (2014) is probably the paper closest to ours.[2] They also propose an estimator for nonlinear panel data models with interactive fixed effects. But while the contribution we make is along the lines of simplicity and applicability and, indeed, the application, their focus is on developing a comprehensive asymptotic theory for a wide range of nonlinear panel data models. In particular, they provide analytical and jackknife corrections for panel data models with interactive fixed effects to eliminate the incidental parameter bias. From a practitioner's point of view, ease of implementation is one advantage of our approach: our estimator is obtained by simply averaging regression coefficients from probit models estimated for each individual unit, whereas Chen et al.'s estimator is computed iteratively in a two-step procedure. Another important difference to our paper is that Chen et al. assume that the slope coefficients are homogeneous so their model is nested in the model in Equations 1–3 if $\beta_i = \beta$ and $d_t = 1$.

4 | ASYMPTOTIC THEORY

This section characterizes the large-sample properties of both the estimators of the individual-specific coefficients and the mean group estimator in discrete-choice panels with interactive fixed effects.

Notation. We stack $\hat{h}_t$,$\bar{h}_t$, and h_{0t} to form the $TK_x \times 1$ vectors: $\hat{h}=(\bar{X}_{1,1}, \dots, \bar{X}_{K_x,1}, \bar{X}_{1,2}, \dots, \bar{X}_{K_x,2}, \dots, \bar{X}_{1,T}, \dots, \bar{X}_{K_x,T})^\intercal$, $\bar{h}=(\bar{h}_{1,1}, \dots, \bar{h}_{K_x,1}, \bar{h}_{1,2}, \dots, \bar{h}_{K_x,2}, \bar{h}_{1,T}, \dots, \bar{h}_{K_x,T})^\intercal$, and $h_0=(h^0_{1,1}, \dots, h^0_{K_x,1}, h^0_{1,2}, \dots, h^0_{K_x,2}, h^0_{1,T}, \dots, h^0_{K_x,T})^\intercal$. These vectors can be embedded within the sequence space $\mathcal{H}$, whose metric is $d(h,g) = \sup_{i\geqslant 1}|h_i - g_i|$, in which case we write $\bar{h} = (h^0_{1,1}, \dots, h^0_{K_x,1}, h^0_{1,2}, \dots, h^0_{K_x,2}, h^0_{1,T}, \dots, h^0_{K_x,T}, 0, \dots)$, and likewise $\hat{h}$, and let $\|h\|_{\mathcal{H}} = d(h,0)$. We use Θ to denote the finite-dimensional parameter set for θ_i (where the dependence on i is suppressed) and $\mathcal{H}$ for the infinite-dimensional parameter set of sequences $\{h_t\}_{t=1}^{\infty}$.

4.1 | Asymptotic theory for the estimators of the individual-specific coefficients

This section shows that the estimators of the individual-specific coefficients $\hat{\theta}_i$ are consistent and have the same asymptotic distribution as the infeasible estimator $\tilde{\theta}_i$, which assumes that the unobserved common factors f_t are known. Observe that the vector $\hat{\theta}_i$ contains both the coefficients of interest $\hat{\beta}_i$ and the auxiliary coefficients on the known factors d_t and the cross-sectional averages $\bar{X}_t$, which play the role of nuisance parameters. For notational simplicity, the asymptotic theory is presented for $\hat{\theta}_i$, from which one can obtain the theory for the parameter of interest $\hat{\beta}_i$. Note that the general framework allows for triangular arrays of random variables, which we notationally suppress for simplicity.

Define

$$Q^i(\theta) = EQ^i_T(\theta), \tag{13}$$

where θ_{0i} is the unique minimum of $Q^i(\theta)$ over Θ.

An important condition to derive the asymptotic properties of $\widehat{\theta}_i$ is the uniform consistency of $\hat{h}_t$. We make the following assumptions:

(B1) $E(|u^j_{it}|^k) \leqslant C < \infty$, for some $k \geqslant 6$, where u^j_{it} denotes the jth element in the $K_x \times 1$ vector u_{it}.
(B2) $T, N \to \infty$ such that $T/N \to 0$.

Assumption B1 is required for the trimming argument we make to employ Bernstein's exponential inequality. In condition (B2) we require that the cross-sectional dimension be large relative to the time series dimension.

The following lemma gives an upper bound on the uniform convergence rate of $\hat{h}_t - \bar{h}_t$.[3]

Lemma 1. *Suppose that assumptions (B1)–(B2) hold. Then*

$$\|\hat{h} - \bar{h}\|_{\mathcal{H}} = O_p\left(\frac{\log T}{\sqrt{N}}\right). \tag{14}$$

[2] A related paper is Chen (2014).
[3] All proofs are relegated to the Supporting Information Appendix.

We next show that the estimators of the individual-specific coefficients are consistent. Towards this objective, we make the following assumptions:

(C1) The parameter space Θ is compact and $\theta_{i0} \in \Theta$.
(C2) $\hat{\theta}_i \in \Theta$ and $\widehat{Q}^i_T(\hat{\theta}_i) = \inf_{\theta \in \Theta} \widehat{Q}^i_T(\theta)$.
(C3) $\tilde{\theta}_i - \theta_{0i} \xrightarrow{p} 0$ for each fixed i, where $\tilde{\theta}_i = \arg\min_{\theta \in \Theta} Q^i_T(\theta)$ and $Q^i_T(\theta)$ is defined in Equation 10.
(C4) For $\delta_T \to 0$:

$$\sup_{||h-\bar{h}||_{\mathcal{H}} \leqslant \delta_T} \sup_{\theta \in \Theta} \frac{1}{T} \sum_{t=1}^{T} \left| q^i_t(\theta, h_t) - q^i_t(\theta, \bar{h}_t) \right| = o_p(1).$$

Compactness of the parameter space (C1) can be dropped in situations where the log-likelihood function is globally concave. Assumption C2 defines the estimator and can be weakened to $\widehat{Q}^i_T(\hat{\theta}_i) = \inf_{\theta_i \in \Theta} \widehat{Q}^i_T(\theta_i) + o_p(1)$ (Pakes & Pollard, 1989). Consistency of the infeasible estimator $\tilde{\theta}_i$ (Assumption C3), follows from standard arguments for extremum estimators (e.g., Newey & McFadden, 1994; Wald, 1949). Assumption C4 ensures that the feasible criterion function approximates the infeasible one uniformly well over the parameter space.

Theorem 1. *Suppose that Assumptions B1–B2 and C1–C4 hold. Then, as $(T, N) \to \infty$ jointly, $\hat{\theta}_i - \theta_{0i} \xrightarrow{p} 0$ for each fixed i.*

We next derive the asymptotic distribution of the individual-specific estimators $\hat{\theta}_i$. In addition, we make the following assumptions.

(D1) As $N, T \to \infty$.

$$\sqrt{T}\left(\tilde{\theta}_i - \theta_{0i}\right) \xrightarrow{d} N(0, V_i(\theta_{i0}, h_0)),$$

where

$$V_i = M_i(\theta_{0i}, h_0)^{-1} J_i(\theta_{i0}, h_0) M_i(\theta_{0i}, h_0)^{-1^{\intercal}},$$

$$\lim \text{var} \left(\sqrt{T} \frac{\partial Q^i_T}{\partial \theta}(\theta_{i0}) \right) = J_i(\theta_{i0}, h_0),$$

$$M_i = M_i(\theta_{i0}, h_0) = p \lim \frac{\partial^2 Q^i_T(\theta_{i0})}{\partial \theta \partial \theta^{\intercal}},$$

and the $(K_d + 2K_x) \times (K_d + 2K_x)$ matrix M_i has full rank.

(D2) For some sequence $\delta_T = o(1)$

$$\sup_{\|h-\bar{h}\|_{\mathcal{H}} < \delta_T} \sup_{\|\theta-\theta_{0i}\| \leqslant \delta_T} \frac{1}{T} \sum_{t=1}^{T} \left\| \frac{\partial^2 q^i_t(\theta, h_t)}{\partial \theta \partial h^{\intercal}} - E\left(\frac{\partial^2 q^i_t(\theta, h_t)}{\partial \theta \partial h^{\intercal}} \right) \right\| = o_P(1),$$

$$\sup_{\|h-\bar{h}\|_{\mathcal{H}} < \delta_T} \sup_{\|\theta-\theta_{0i}\| \leqslant \delta_T} \frac{1}{T} \sum_{t=1}^{T} \left\| \frac{\partial^2 q^i_t(\theta, h_t)}{\partial \theta \partial \theta^{\intercal}} - E\left(\frac{\partial^2 q^i_t(\theta, h_t)}{\partial \theta \partial \theta^{\intercal}} \right) \right\| = o_P(1).$$

(D3) $T, N \to \infty$ such that $\frac{T(\log T)^2}{N} \to 0$.

Assumption D1 follows from standard arguments for extremum estimators (e.g., Newey & McFadden, 1994; Wald, 1949). In particular, we have

$$\frac{\partial Q^i_T}{\partial \theta}(\theta_{i0}) = -\frac{1}{T} \sum_{t=1}^{T} \frac{Y_{it} - \Phi_{it0}}{\Phi_{it0}(1 - \Phi_{it0})} \phi_{it0} z_{it} \equiv \frac{1}{T} \sum_{t=1}^{T} v_{it}, \tag{15}$$

which is a sample average with zero mean that is i.i.d. conditional on the factors. Here, Φ_{it0}, ϕ_{it0} denote the c.d.f. and density function evaluated at the true parameter values $\theta_{0i} = (\bar{\alpha}^{\intercal}_{0i}, \beta^{\intercal}_{0i}, \bar{\kappa}^{\intercal}_{0i})^{\intercal}$. Under our assumptions, $J_i = E[v_{it} v^{\intercal}_{it}]$. Assumption D2 is a uniform convergence condition on the Hessian in a shrinking neighborhood of the true parameters θ_{i0} and h_0 and it can be replaced by a more primitive Uniform Law of Large Numbers (ULLN) Andrews (1993). The restriction on the relative size of T and N in Assumption D3 ensures that the estimated preliminary functions $\hat{h}$ do not affect the asymptotic distribution. Theorem 2 summarizes the asymptotic normality result for the individual-specific estimators $\hat{\theta}_i$.

Theorem 2. *Suppose that Assumptions B1–B2, C1–C4, and D1-D3 hold. Then, as $(T,N) \to \infty$ jointly,*

$$\sqrt{T}(\hat{\theta}_i - \theta_{0i}) \xrightarrow{d} N(0, V_i)$$

for each fixed i.

Consistent standard errors may be obtained from the estimator

$$\hat{V}_i = \left[\frac{\partial^2 \hat{Q}_T^i(\hat{\theta}_i)}{\partial\theta\partial\theta^\intercal}\right]^{-1} \left[\frac{1}{T}\sum_{t=1}^{T} \hat{v}_{it}\hat{v}_{it}^\intercal\right] \left[\frac{\partial^2 \hat{Q}_T^i(\hat{\theta}_i)}{\partial\theta\partial\theta^\intercal}\right]^{-1},$$

$$\hat{v}_{it} = \frac{Y_{it} - \hat{\Phi}_{it}}{\hat{\Phi}_{it}(1-\hat{\Phi}_{it})}\hat{\phi}_{it}\hat{z}_{it},$$

where $\hat{\Phi}_{it}, \hat{\phi}_{it}$ denote the c.d.f. and density function evaluated at the estimated parameter values.

4.2 | Asymptotic theory for the mean group estimator

In this section, we investigate the asymptotic properties of the mean group estimator $\hat{\beta} = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_i$, which is a subset of the parameter estimates contained in $\hat{\theta}$. Consistency of $\hat{\theta}$ follows by similar arguments as in the case of the individual-specific estimators $\hat{\theta}_i$. We shall assume that the infeasible counterpart $\tilde{\theta} = \frac{1}{N}\sum_{i=1}^{N}\tilde{\theta}_i$ is consistent and asymptotically normal at rate $\sqrt{N}$. This can be established using for example the arguments of Chen, Jacho-Chavez, and Linton (2016), henceforth CJL, who consider averaging of estimators in a different context. In their framework, there is no heterogeneity, that is, $\theta_{0i} = \theta_0$ for all i. Furthermore, they emphasize the case where the information about θ_0 is decreasing with i, which is natural for that class of problems. In our case, there is no reason to impose this structure. On the other hand, we have a simpler weighting scheme (equal weighting) than they did, so we would not require their conditions: A1, A*1, B (4.7), B3(a) and B4. We also assume a smooth objective function, so we would not require their conditions A3, A*3, B1, B2, and B3(b). We shall not repeat their conditions here but just assume the required properties of the infeasible estimators.

We shall show that the feasible estimator approximates the infeasible one, and we need some additional conditions.

(C3*) $\tilde{\theta} - \theta_0 \xrightarrow{p} 0$.

(C5*) For $\delta_T \to 0$:

$$\max_{1\leqslant i\leqslant N} \sup_{\|h-\bar{h}\|_{\mathcal{H}}\leqslant\delta_T} \sup_{\theta\in\Theta} \frac{1}{T}\sum_{t=1}^{T}\left|q_t^i(\theta, h_t) - q_t^i(\theta, \bar{h}_t)\right| = o_p(1).$$

Theorem 3. *Suppose that assumptions B1–B2, C1, C2, C3*, C4, and C5* hold. Then, as $(T,N) \to \infty$ jointly, $\hat{\theta} - \theta_0 \xrightarrow{p} 0$.*

To show that the mean group estimator is asymptotically normal, we assume that $\tilde{\theta}_i$ are uniformly consistent and asymptotically normal.

(E1) Suppose $T, N \to \infty$ such that $T^2/N(\log N)^4 \to \infty$.

(E2) Suppose that for some matrix Ω

$$\sqrt{N}(\tilde{\theta} - \theta_0) \xrightarrow{d} N(0, \Omega),$$

where $\Omega_\beta = \Sigma_\beta$, where Σ_β denotes the submatrix of Σ corresponding to β.

(E3) Suppose that

$$\max_{1\leqslant i\leqslant N}\left\|\tilde{\theta}_i - \theta_{i0}\right\| = O_P\left(\frac{\log N}{\sqrt{T}}\right).$$

(E4) The random variables below are stochastically bounded (for $r = 1, \dots, p$):

$$\frac{1}{2NT}\sum_{t=1}^{T}\sum_{i=1}^{N}\left\|M_i^{-1}\right\| \sup_{\|h-\bar{h}\|_{\mathcal{H}}<\delta_T}\left\|\frac{\partial^3 q_t^i}{\partial\theta_r\partial h\partial h}(\theta_{0i}, h_t)\right\|,$$

$$\frac{1}{2NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left\|M_i^{-1}\right\| \sup_{\|h-\bar{h}\|_{\mathcal{H}}<\delta_T} \sup_{\|\theta-\theta_{0i}\|\leqslant\delta_T}\left\|\frac{\partial^3 q_t^i(\theta, h_t)}{\partial\theta_r\partial\theta\partial\theta^\intercal}\right\|^2,$$

$$\max_{1\leqslant i\leqslant N}\sup_{\|\theta-\theta_{0i}\|\leqslant\delta_T}\sup_{\|h-\bar{h}\|_{\mathcal{H}}<\delta_T}\left\|\frac{1}{T}\sum_{t=1}^{T}\frac{\partial^2 q_t^i(\theta,h_t)}{\partial\theta\partial\theta^\intercal}\right\|.$$

Assumptions E are similar to Assumptions D, which have been imposed to establish asymptotic normality of the individual-specific estimators. Condition E3 can be established in the same way as in Lemma 1, swapping the roles of N and T. Conditions D3 and E1 are satisfied by many sequences, for example $N = T^{3/2}$.

Theorem 4 contains the asymptotic normality result for the mean group estimator.

Theorem 4. *Suppose that assumptions B1–B2, C1, C2, C3*, C4, and C5*, D1–D3, and E1–E4 hold. Then, as* $(T,N)\to\infty$ *jointly:*

$$\sqrt{N}(\hat{\beta}-\beta_0)\xrightarrow{d}N(0,\Sigma_\beta).$$

Observe that the asymptotic variance of the mean group estimator is equal to that of the random coefficients (Assumption A1). In practice, Σ_β can be consistently estimated by

$$\hat{\Sigma}_\beta=\frac{1}{N-1}\sum_{i=1}^{N}(\hat{\beta}_i-\hat{\beta})(\hat{\beta}_i-\hat{\beta})^\intercal. \tag{16}$$

The estimator $\hat{\Sigma}_\beta$ is identical to the one obtained in OLS and quantile regression settings (Boneva et al., 2016; Pesaran, 2006).

5 | SMALL-SAMPLE EXPERIMENTS

To complement the asymptotic results above, this section studies the small-sample properties of the *CCE mean group estimator* and compares them to the following set of alternative estimators:

1. The *infeasible mean group estimator*, which counterfactually assumes that the unknown factors can be observed.
2. The *naive mean group estimator*, which does not account for unobserved common factors.
3. The *linear probability mean group estimator*, which replaces the probit model with a linear probability model.

The small-sample performance of these estimators is evaluated in five experiments that cover a wide range of factor structures than can be encountered in economic and financial panel datasets:[4]

Experiment 1. The data-generating process (DGP) is

$$Y_{it}^*=\alpha_i+\beta_{1i}X_{1it}+\beta_{2i}X_{2it}+\kappa_{1i}f_{1t}+\kappa_{2i}f_{2t}+\epsilon_{it},\quad Y_{it}=I(Y_{it}^*), \tag{17}$$

$$X_{jit}=a_{ji}+k_{ji1}f_{1t}+k_{ji2}f_{2t}+u_{jit},\quad j=1,2, \tag{18}$$

$$\epsilon_{it}\sim\text{n.i.d.}(0,1),u_{jit}\sim\text{n.i.d.}(0,1),\quad j=1,2, \tag{19}$$

where the factors are generated by[5]

$$f_{lt}=\rho_f f_{lt-1}+v_{lft},\quad t=-50,\dots,T,\quad l=1,2, \tag{20}$$

$$v_{lft}\sim\text{n.i.d.}(\mu_f(1-\rho_f),1-\rho_f^2),\quad \rho_f=0.5,\quad \mu_f=0.5,\quad l=1,2. \tag{21}$$

The coefficients α_i and a_{ji} are held fixed across replications and are initially generated as: $\alpha_i\sim n.i.d.(-0.5,0.1)$, $a_{ji}\sim n.i.d.(0.5,0.1), j=1,2$. The remaining coefficients are drawn independently across replications according to $\beta_{1i}=0.5+\eta_{1i}$, $\eta_{1i}\sim n.i.d.(0,0.02)$,$\beta_{2i}=-0.5+\eta_{2i}$,$\eta_{2i}\sim n.i.d.(0,0.02)$, $\kappa_{ij}\sim n.i.d.(0.5,0.1)$, $k_{ji1}\sim n.i.d.(0.5,0.1)$ and $k_{ji2}\sim n.i.d.(0.5,0.1), j=1,2,$.

---

[4]When estimating binary-choice models, one occasionally encounters the problem of quasi-complete separation. Quasi-complete separation occurs when the dependent variable separates the independent variables to a certain degree. In that case, the maximum likelihood estimator does not exist and attempting to compute it usually results in an upward-biased estimate. To mitigate this problem in the Monte Carlo experiments, we use the bias reduction method of Firth (1993). Asymptotically, this estimator is equivalent to maximum likelihood to first order.

[5]The DGP for the factors (Equation 20) does not satisfy Assumption A2 because the factors are not bounded. However, this does not affect the asymptotic theory because under normality, as assumed here, the penalty term in the uniform rate (Lemma 1) is $\sqrt{\log(T)}$, which is smaller than the current penalty of $\log(T)$.

Experiment 2 is identical to Experiment 1 except that $\beta_{1i} = 0.5, \beta_{2i} = -0.5$ for all i. There is no slope heterogeneity.

Experiment 3 is identical to Experiment 1 except that $k_{ji2} \sim$ n.i.d.$(0, 0.1)$. The rank condition (Equation 7) is not satisfied.

Experiment 4 is identical to Experiment 1 except that

$$Y_{it}^* = \alpha_i + \beta_i X_{it} + \kappa_{1i} f_{1t} + \kappa_{2i} f_{2t} + \kappa_{3i} f_{3t} + \epsilon_{it}, \quad Y_{it} = I(Y_{it}^*), \tag{22}$$

where κ_{3i} and f_{3t} are generated as κ_{1i} and f_{1t}. In this experiment, there are more unknown factors than proxies, which illustrates another failure of the rank condition (Equation 7).

Experiment 5 is identical to Experiment 1 except that $k_{ji2} = 0$ for all i, j and $\kappa_{2i} = 0$ for all i. There are more regressors than unobserved factors.

5.1 | Coefficient estimates

To assess the small-sample performance of the different estimators, we compute the maximal bias and RMSE for β_1, which are defined as

$$\text{RMSE}_\beta = \left(\sqrt{\frac{1}{R} \sum_{r=1}^{R} (\hat{\beta}_{1r} - \beta_1)^2} \right),$$

$$\text{Bias}_\beta = \left(\beta_1 - \frac{1}{R} \sum_{r=1}^{R} \hat{\beta}_{1r} \right),$$

where R is the number of replications and $\hat{\beta}_{1r}$ is the estimate of β_1 from replication r.

Table 1 reports the RMSE and bias in Experiment 1.[6] Results for Experiments 2–5 are reported in the Supporting Information Appendix. The naive estimator has poor small-sample properties in all experimental settings. This result is not surprising because this estimator omits the unobserved common factors that play an important role in the DGP. In contrast, the CCE mean group estimator is comparable to the infeasible estimator in terms of RMSE even if the coefficients are homogeneous or if there are more regressors than unobserved factors. If the rank condition is not satisfied, the performance of the CCE mean group estimator deteriorates.

We also report empirical sizes, power and coverage probabilities. Power is computed under the alternative $\beta_1 = 0.45$, and the variance of $\hat{\beta}_1$ is calculated using the formula in Equation 16. While the naive estimator has distorted empirical sizes across all experiments, the empirical sizes of the CCE mean group estimator are close to the nominal size of 5% except if the rank condition fails. The CCE mean group estimator also has good power, and coverage probabilities are close to the nominal level of 95% provided that the rank condition holds.

5.2 | Marginal effects

Applied research usually reports marginal effects rather than coefficient estimates when estimating discrete-choice models. Unlike coefficient estimates, marginal effects can be used to assess the economic significance of the results, which is important in informing debates about economic policy. For the probit model, the average marginal effect for β_{1i} is defined as

$$\text{ME}_{1i} = \beta_{1i} \frac{1}{T} \sum_{t=1}^{T} \phi\left(\bar{\alpha}_i^\intercal d_t + \beta_i^\intercal X_{it} + \bar{\kappa}_i^\intercal \bar{h}_t\right).$$

Bias and RMSE for the mean group marginal effect $\sum_{i=1}^{N} ME_{1i}/N$ are computed as for the coefficient estimates in Section 5.1. The distribution of the marginal effects follows from delta method applied to

$$\widehat{\text{ME}}_{1i} = \hat{\beta}_{1i} \frac{1}{T} \sum_{t=1}^{T} \phi\left(\hat{\alpha}_i^\intercal d_t + \hat{\beta}_i^\intercal X_{it} + \hat{\kappa}_i^\intercal \hat{h}_t\right).$$

[6]The linear probability estimator is excluded in this section because the coefficients represent marginal effects and are thus are not comparable to the other estimates.

TABLE 1 Small-sample properties of the mean group estimator $\hat{\beta}$: Experiment 1

T/N	Bias (×1,000)				RMSE (×1,000)				Power				Size				Coverage probability			
	50	100	200	300	50	100	200	300	50	100	200	300	50	100	200	300	50	100	200	300
Infeasible estimator																				
50	1.676	2.908	3.371	2.844	35.62	25.18	18.34	14.58	0.272	0.5315	0.861	0.9575	0.049	0.045	0.0485	0.041	0.951	0.955	0.9515	0.959
100	0.0632	0.2128	0.924	0.5095	23.58	16.51	11.62	9.573	0.5345	0.865	0.9935	0.9995	0.0495	0.0435	0.044	0.049	0.9505	0.9565	0.956	0.951
200	0.2336	0.1127	0.3904	0.1257	16.04	11.43	8.042	6.663	0.8625	0.9885	1	1	0.0425	0.0475	0.0455	0.05	0.9575	0.9525	0.9545	0.95
300	−0.2732	0.2284	−0.1364	0.1139	12.86	9.158	6.408	5.36	0.9625	1	1	1	0.0365	0.044	0.0385	0.0455	0.9635	0.956	0.9615	0.9545
CCEMG estimator																				
50	−2.455	−0.5866	0.8046	0.2931	35.76	24.87	17.81	14.27	0.2325	0.489	0.8205	0.944	0.0535	0.0475	0.0465	0.0465	0.9465	0.9525	0.9535	0.9535
100	−4.728	−3.246	−1.891	−2.265	23.74	16.66	11.71	9.757	0.455	0.817	0.9895	0.9995	0.0535	0.049	0.055	0.0515	0.9465	0.951	0.945	0.9485
200	−4.495	−3.553	−2.543	−2.615	16.82	12.01	8.341	7.076	0.781	0.9775	1	1	0.052	0.0545	0.055	0.064	0.948	0.9455	0.945	0.936
300	−4.948	−3.335	−3.039	−2.615	13.8	9.753	7.147	5.906	0.9275	0.9985	1	1	0.048	0.056	0.061	0.0705	0.952	0.944	0.939	0.9295
Naive estimator																				
50	157.4	158.2	159	158	161.4	160.7	160.8	159.6	1	1	1	1	0.9985	1	1	1	0.0015	0	0	0
100	157.3	157.7	158.6	157.6	159.1	158.8	159.4	158.3	1	1	1	1	1	1	1	1	0	0	0	0
200	158.3	158	157.9	158.1	159.1	158.6	158.3	158.5	1	1	1	1	1	1	1	1	0	0	0	0
300	158.3	158.2	158.1	158.2	158.9	158.6	158.4	158.5	1	1	1	1	1	1	1	1	0	0	0	0

Note. The DGP is defined in Equations 17–21. The nominal size is 5% and power is computed under the alternative $\beta_1 = 0.45$. The number of replications is set to 2,000.

TABLE 2 Small-sample properties of the marginal effect $\widehat{ME}$: Experiment 1

T/N	Bias (×1,000)				RMSE (×1,000)			
	50	100	200	300	50	100	200	300
Infeasible estimator								
50	−5.054	−4.752	−4.586	−4.698	10.18	7.812	6.416	5.882
100	−2.632	−2.574	−2.403	−2.51	6.78	5.057	3.893	3.567
200	−1.25	−1.287	−1.205	−1.272	4.519	3.349	2.489	2.207
300	−0.9353	−0.8084	−0.9129	−0.8394	3.644	2.638	1.979	1.692
CCEMG estimator								
50	−5.014	−4.837	−4.592	−4.755	10.23	7.86	6.4	5.908
100	−2.718	−2.618	−2.42	−2.574	6.796	5.062	3.908	3.606
200	−1.31	−1.359	−1.238	−1.307	4.629	3.406	2.5	2.213
300	−0.9738	−0.8487	−0.9373	−0.8654	3.698	2.669	2.016	1.695
Naive estimator								
50	58.31	58.46	58.67	58.5	59.12	59	59.1	58.87
100	62.33	62.42	62.66	62.36	62.69	62.66	62.86	62.53
200	64.51	64.39	64.35	64.45	64.69	64.52	64.44	64.53
300	65.11	65.07	65.03	65.08	65.22	65.15	65.1	65.14
Linear probability estimator								
50	4.978	5.199	5.416	5.286	10.6	8.368	7.164	6.474
100	2.539	2.651	2.867	2.696	6.955	5.221	4.281	3.773
200	1.383	1.346	1.453	1.368	4.776	3.474	2.665	2.3
300	0.8393	0.9552	0.8512	0.937	3.749	2.761	2.025	1.769

Note. The mean group estimator of the average marginal effect is reported. The DGP is defined in Equations 17–21. The number of replications is set to 2,000.

Table 2 reports RMSE and bias for marginal effects in Experiment 1. Results for Experiments 2–5 are reported in the Supporting Information Appendix. Marginal effects computed from the CCE mean group estimates have similar bias and RMSE when compared to the infeasible marginal effects and outperform naive marginal effects that do not account for unobserved common factors. These conclusions hold even if the rank condition is not satisfied, as in Experiments 3 and 4.[7] The linear probability model augmented with cross-sectional averages has good small-sample properties, too.[8]

Overall, the Monte Carlo evidence indicates that the CCE mean group estimator has good small-sample properties compared to the infeasible estimator. These conclusions are robust to the case where coefficients are homogeneous and there are more regressors than unobserved factors. The performance of the CCE mean group estimator deteriorates, however, if the rank condition fails.

6 | THE EFFECT OF CORPORATE BOND YIELDS ON BOND ISSUANCE BY US FIRMS

At least since Modigliani and Miller (1958), the capital structure of firms has attracted much attention, and there is a large empirical and theoretical literature that explores why it matters (e.g., Brealey, Myers, & Allen, 2008; Myers, 1977). For example, the mix of debt and equity is relevant in the presence of the bankruptcy costs or asymmetric information (Frank & Goyal, 2008; Myers & Majluf, 1984).

Relative to equity and bank loans, debt financing is an important source of external funds for US corporations (Denis & Mihov, 2003). Debt financing can take the form of bank loans, other loans, or public debt. The focus here is on public debt: the corporate bond market has grown rapidly over the last decade when the stock of corporate bonds doubled (Office of Financial Research, 2015).

There is a large literature discussing the relative merits of bond finance (ICMA, (2013); Langfield & Pagano, (2015); and references therein). Compared to equity, bonds provide a more stable source of funding as investors often hold bonds until maturity, which reduces turnover in secondary markets. Relative to bank loans, bond financing is less exposed to financial cycles, giving issuers access to funding even when banks deleverage or even default. For example, during financial crises, market-based

[7]This is also observed in Fernandez-Val and Weidner (2016), for example, who show that the robustness of the marginal effects is due to their convergence rate.
[8]The linear probability model performs worse if the marginal effects at the average are computed instead of the average marginal effects. These results are available from the author on request.

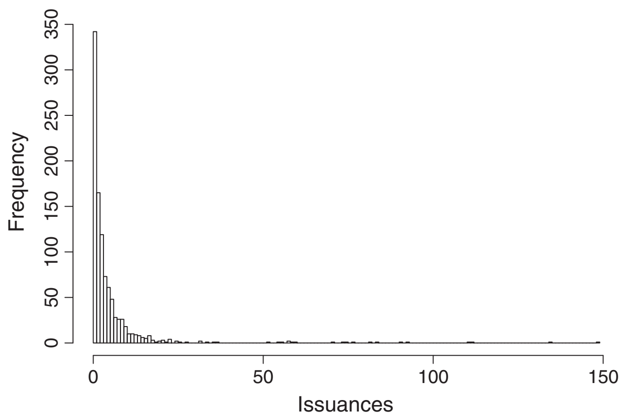

FIGURE 1 Histogram for the number of issuances by firm. Data sources: Bloomberg, Datastream, and own calculations

funding substituted for the decline in bank-based finance (Becker & Ivashina, 2014), thereby contributing to finance trade and investment activities of firms, and consumption expenditure and mortgages of households (Farrant et al., 2013; ICMA, 2013).

In this section, we use our estimator to study the effect of corporate bond yields on the decision of US firms to issue a bond. In contrast to earlier studies (Frank & Goyal, 2008), however, we adopt an incremental approach that investigates the conditional probability of issuing a corporate bond, which is particularly suitable for questions related to time variation in the regressors.

Answering the question of how funding costs in corporate bond markets affect issuance decisions sheds light on a particular transmission mechanism of monetary policy: by means of conventional and unconventional monetary policy tools, the central bank can affect the interest rates firms face in corporate bond markets. Bond issuance, on the other hand, is often related to corporate investment and thus aggregate demand (Farrant et al., 2013).

There is already a large literature that explores the determinants of bond issuance (e.g., Adrian et al., 2012; Badoer & James, 2016; Becker & Ivashina, 2014; Denis & Mihov, 2003; Mizen & Tsoukas, 2013). These studies have documented that issuer characteristics such as size, rating, profitability, leverage, equity prices, monetary policy, and the supply of bank credit are important determinants of bond issuance. Other papers have investigated the effects of quantitative easing (Lo Duca, Nicoletti, & Vidal Martinez, 2014), asymmetric information (Gomes & Phillips, 2012) or the Basel reforms on issuance decisions of banks or non-financial corporations (Baba & Inada, 2009). However, there is not much evidence yet on the effect of yields on bond issuances, which is the contribution of this study. Additionally, previous studies have not controlled for common unobserved factors that can affect both bond issuance and its determinants.

6.1 | Data

The dataset includes bond issuances by US firms between 1990 and 2015 on a monthly frequency. The sample is restricted to bonds in US dollars, with a fixed coupon and short-run unsecured collateral. Non-bullet and callable bonds are excluded. The number of issuances is 5,610, with an average size of approximately 300 million USD made by 1004 different firms. As documented in Figure 1, the distribution of the number of issuances is highly skewed, with many firms only issuing one bond over the sample period: the average number of issuances is six but the median number of issuances is only two.

Figure 2 reports time series of the average issuer-specific yield, together with the number of bond issuances between 1990 and 2015. Issuer-specific yields are constructed as the median of the individual bond yields. The number of bond issuances increased sharply around 2003 but fell again during the financial crisis, when yields increased. The time series of the number of issuances for financial sector firms comove closely with the aggregate series.[9] Albeit only one quarter of all firms are in the financial sector, a large number of issuances can be attributed to them. The comovement between aggregate and financial sector series can be observed for average yields, too.

Figure 3 reports the cross-sectional mean, median, and dispersion of yields over time. Yields exhibit a downward trend over the sample period. In 2008, both the level and the dispersion of yields increased sharply but started to fall again in 2009, which is in part explained by the quantitative easing program of the Federal Reserve. This trend was only reversed with the "Taper Tantrum" in mid-2013, when changes in expectations about monetary policy triggered an increase in US Treasury yields with

[9]The industry classification is according to NACE, which is obtained from Bloomberg.

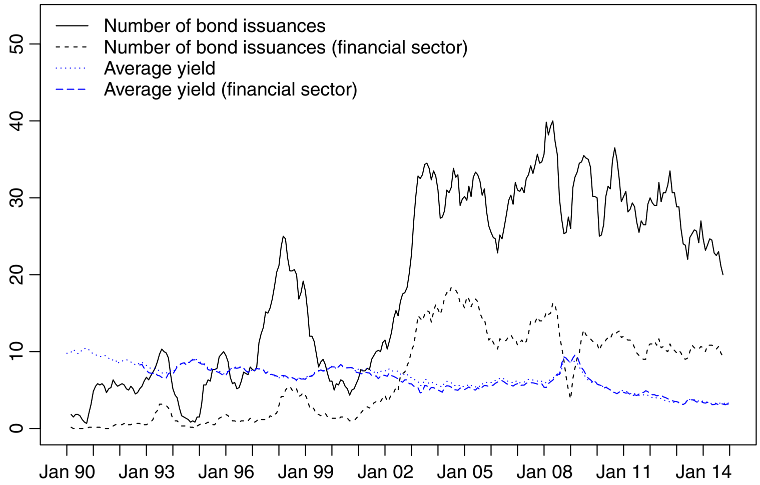

FIGURE 2 Number of bond issuances per month and cross-sectional average of issuer-specific bond yields. Number of bond issuances are computed as 6-month moving sums. Data sources: Bloomberg, Datastream, and own calculations [Colour figure can be viewed at wileyonlinelibrary.com]

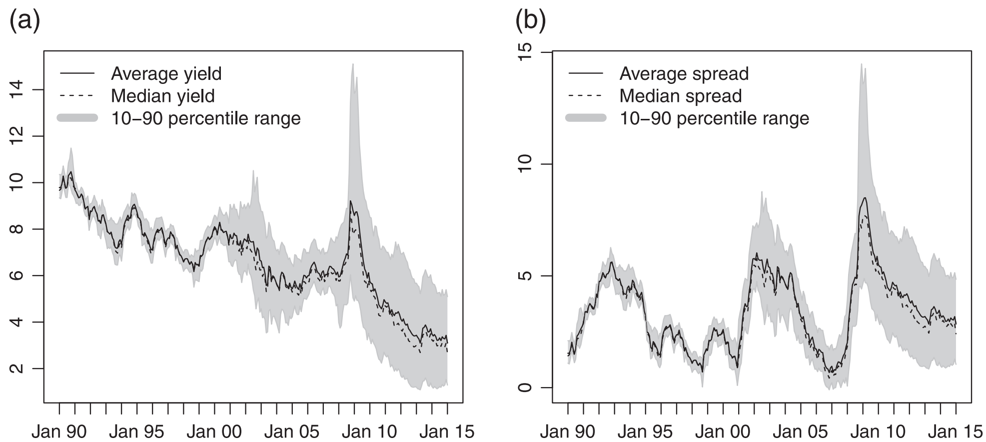

FIGURE 3 Cross-sectional distribution of issuer-specific bond yields (a) and spreads (b). Data sources: Bloomberg, Datastream, and own calculations

spillovers to USD-denominated bonds. The elevated dispersion as well as the Taper Tantrum effects are also visible in the distribution of spreads (Figure 3b).

Figure 4(a) illustrates the unconditional correlation between the cross-sectional average of yields and the number of issuances per month. For the pre-crisis period, there is a negative correlation for yields below 8%. When splitting the data by issuer rating, the pattern is less clear but conditional on a low credit rating, there is a negative relationship between the number of issuances and yields for yields higher than 5% (Figure 4b). However, these unconditional correlations could be driven by common, unobserved shocks, which will be controlled for in the regression analysis below.

6.2 | Results

To investigate the effect of yields on bond issuance by US firms, we estimate the econometric model in Equations 1–3, where Y_{it} indicates whether firm i has issued a bond in month t, and X_{it} contains the issuer's corporate bond yield and assets at the end of the previous month.[10,11] The observed common factors d_t include a constant, a measure of monetary policy, and broker–dealer leverage, which is a measure of bank credit conditions (Adrian et al., 2012). For the pre-crisis period, the stance of monetary policy is measured by the federal funds rate, and in the post-crisis period the change in Federal Reserve Holdings of Treasury

[10]Yields are winsorized at 0.5% and assets at 0.1%.

[11]Because our estimator requires estimation of a probit model for each individual cross-sectional unit, we can only include firms in the estimation that have issued bonds. We assess the robustness of our results to sample selection in Section 6.3.

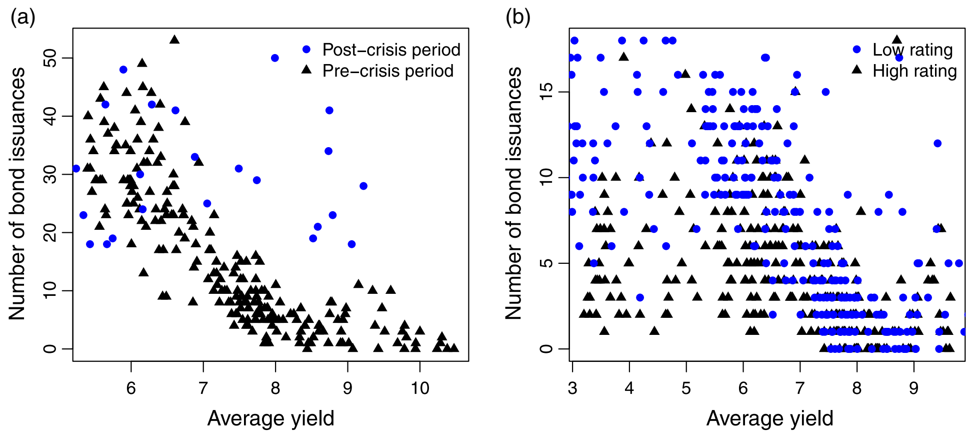

FIGURE 4 Unconditional correlations between the number of issuances per month and cross-sectional average of bond yields: (a) pre- and post crisis; (b) low and high rating. Data sources: Bloomberg, Datastream, and own calculations [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 3 The effect of yields on bond issuance for US firms in the pre-crisis period

	All	Financial	Other	All (no factors)
Coefficient estimates				
Yield	−0.162	−0.148	−0.217	−0.091
	(−1.938)	(−0.853)	(−2.156)	(−2.653)
Size	0.064	0.006	0.067	0.091
	(0.281)	(0.168)	(0.211)	(0.543)
Marginal effects				
Yield	−0.018	−0.006	−0.025	−0.013
Size	0.015	−0.003	0.021	0.021
Observations	321	62	225	321

The dependent variable is 1 if a firm issues a bond in a particular month and zero otherwise. Yield is the the firm-specific corporate bond yield and size is measured by assets/1,000. All specifications include a measure of credit supply (leverage in the broker–dealer market) and the federal funds rate as a common factor. The first column uses all firms, the second column uses financial sector firms and the third column uses all other firms (excluding mining and agriculture). The last column reports the results when the common unobserved factors are omitted. *t*-statistics are shown in parentheses.

Notes is used. In this specific empirical application, the unobserved factors can represent regulation, changes in investor behavior such as search for yield, automated trading or policies that aim at deepening corporate bond markets, for example.

For the empirical analysis, results are reported separately for the pre- and post-crisis period. In the post-crisis period, policies such as quantitative easing or credit guarantee schemes are likely to fundamentally change the incentives for firms to issue bonds relative to the pre-crisis period. In each estimation sample, the dataset is restricted to firms with at least 30 time series observations.

Columns 1–3 in Table 3 report the CCE mean group estimate of β and marginal effects for the pre-crisis period. We find that the conditional probability of issuing a bond is higher if yields are low. This effect is statistically significant when considering all firms (column 1) or firms that do not operate in the financial sector (column 3). But the marginal effects reveal that the effect of yields on issuance is small in absolute magnitude: The probability of issuing a bond decreases by 0.018 in response to a one-unit change in yields. In contrast, there is no statistically significant effect of yields on issuance for financial firms, and the effect of firm size is not statistically significant either. For comparison, column 4 reports the mean group estimates when the common factors are omitted, which differ from the CCE mean group estimates in size and statistical significance: For all firms, the marginal effect is only −0.013 compared to our baseline estimate of −0.018.

Table 4 splits the pre-crisis sample by credit rating. With the exception of financial firms where sample sizes are small, yields are negatively related to the probability of issuing a bond for low-rated firms, but this effect is economically small. In contrast, the negative relationship between yields and issuance is statistically insignificant conditional on a high credit rating.

TABLE 4 The effect of yields on bond issuance for US firms in the pre-crisis period by credit rating

	All		Financial		Other	
	High	**Low**	**High**	**Low**	**High**	**Low**
Coefficient estimates						
Yield	0.017	−0.224	−0.185	−0.026	0.033	−0.248
	(0.177)	(−2.404)	(−0.79)	(−0.175)	(0.325)	(−1.923)
Size	0.009	−0.174	0.062	0.006	0.008	−0.243
	(0.091)	(−1.065)	(1.104)	(0.298)	(0.057)	(−0.983)
Marginal effects						
Size	−0.005	−0.024	0.006	0	−0.007	−0.033
Observations	135	135	27	28	100	88

The dependent variable is 1 if a firm issues a bond in a particular month and zero otherwise. Yield is the firm-specific corporate bond yield and size is measured by assets/1,000. All specifications include a measure of credit supply (leverage in the broker–dealer market) and the federal funds rate as a common factor. Columns 1–2 use all firms, columns 3–4 use financial sector firms, and columns 5–6 use all other firms (excluding mining and agriculture). Low (high) means that the issuer has a credit rating below (above) the sample median. *t*-statistics are shown in parentheses.

TABLE 5 The effect of yields on bond issuance for US firms in the post-crisis period

	All	**Financial**	**Other**	**All (no factors)**
Coefficient estimates				
Yield	−0.043	−0.004	−0.097	0.011
	(−1.056)	(−0.074)	(−1.896)	(0.47)
Size	−0.194	−0.028	−0.245	−0.115
	(−2.62)	(−0.488)	(−2.448)	(−1.945)
Marginal effects				
Yield	−0.007	0.003	−0.015	−0.002
Size	−0.024	−0.006	−0.03	−0.015
Observations	378	72	273	378

The dependent variable is 1 if a firm issues a bond in a particular month and zero otherwise. Yield is the firm-specific corporate bond yield and size is measured by assets/1,000. All specifications include a measure of credit supply (leverage in the broker–dealer market) and the change in Federal Reserve Holdings of Treasury Notes as common factors. The first column uses all firms, the second column uses financial sector firms, and the third column uses all other firms (excluding mining and agriculture). The last column reports the results when the common unobserved factors are omitted. *t*-statistics are shown in parentheses.

The finding that higher yields are associated with less issuance activity of non-financial firms is observed in the post-crisis period, too (Table 5). As in the pre-crisis period, this result is driven by firms with a low credit rating (Table 6). In contrast to the pre-crisis period, however, size has a significant effect on issuance in some specifications: Non-financial corporations that are relatively small are more likely to issue a bond. One explanation for this finding builds on the substitution from bank loans to bonds in the post-crisis period (Farrant et al., 2013). This effect is likely to be stronger for relatively small firms that relied more heavily on bank loans prior to the financial crisis.

6.3 | Robustness

In this section, we assess the robustness of our results by including additional control variables, using the corporate spread instead of the yield as a regressor, and applying alternative sample selection criteria. The results of these robustness checks are reported in the Supporting Information Appendix.

The finding that yields are negatively related to issuance is robust to augmenting the baseline specification with a measure of liquidity computed as the share of current debt in total debt. Additionally, in the pre-crisis period, liquidity has a positive and significant effect on the conditional probability of issuing a corporate bond. Low levels of liquidity can be interpreted by investors as a signal for low creditworthiness, which discourages issuance ex ante (Mizen & Tsoukas, 2013).

TABLE 6 The effect of yields on bond issuance for US firms in the post-crisis period by credit rating

	All		Financial		Other	
	High	**Low**	**High**	**Low**	**High**	**Low**
Coefficient estimates						
Yield	0.031	−0.085	0.052	−0.045	0.016	−0.194
	(0.6)	(−1.174)	(0.599)	(−0.501)	(0.247)	(−2.043)
Size	−0.007	−0.196	−0.032	−0.045	−0.005	−0.258
	(−0.06)	(−4.37)	(−0.314)	(−1.487)	(−0.033)	(−4.317)
Marginal effects						
Yield	0.004	−0.012	0.01	−0.001	0.002	−0.027
Size	−0.004	−0.025	−0.01	−0.006	−0.003	−0.033
Observations	160	160	40	25	113	112

The dependent variable is 1 if a firm issues a bond in a particular month and zero otherwise. Yield is the firm-specific corporate bond yield and size is measured by assets/1,000. All specifications include a measure of credit supply (leverage in the broker–dealer market) and the change in Federal Reserve Holdings of Treasury Notes as common factors. Columns 1–2 use all firms, columns 3–4 use financial sector firms and columns 5–6 use all other firms (excluding mining and agriculture). Low (high) means that the issuer has a credit rating below (above) the sample median. t-statistics are shown in parentheses.

We also find a negative relationship between issuance and funding costs when replacing yields by spreads in our baseline specification. In particular, the coefficients on spreads are of similar size when compared to the baseline specification but less statistically significant in the pre-crisis period.

In our baseline results, we used firms with 30 or more time series observations over the estimation period. As documented in the Supporting Information Appendix, we find that our results are robust to using either firms with at least 20 or 40 time series observations.

Finally, we document that our results are robust to varying the sample of firms. Our baseline results use all firms that have issued at least one bond during the estimation period. In the Supporting Information Appendix we replicate our main results when the sample is restricted to firms that have issued at least two bonds over the estimation period. The results of this robustness exercise are quantitatively similar to our baseline results but statistical significance is lower in the pre-crisis period, possibly due to the much smaller sample size.

7 | CONCLUSIONS

Economic variables are affected by common shocks such as financial crises, natural disasters, technological innovation, or changes in the political or regulatory environment. These shocks tend to be difficult to measure and their impact differs across individual observations. The increased availability of panel data where both the time series and cross-sectional dimensions are large has motivated researchers to develop novel estimators that are robust to common shocks (Bai, 2009; Pesaran, 2006).

In this paper, we extend the CCE estimator of Pesaran (2006), where the unobserved factors are approximated with cross-sectional averages to discrete-choice data. In the theoretical part of the paper, we derive the asymptotic properties and assess the small-sample behavior of our estimator. In the empirical part, the methodology is applied to study the effect of yields on the conditional probability to issue a corporate bond. We find that for non-financial firms yields are negatively related to bond issuance of non-financial firms but that the effect is larger in the pre-crisis period compared to the post-crisis period. Splitting the data by the credit rating of the issuer reveals that the negative relationship between yields and corporate bond issuance is driven by firms with a low credit rating.

There are many ways in which this work can be developed further. An interesting extension of the empirical application is to examine how participation in a credit guarantee scheme affects the issuance decisions of firms. These schemes were adopted in 2008 as part of financial sector rescue packages in order to help banks retain access to funding markets (Grande, Levy, Panetta, & Zaghini, 2011). In addition, we expect that constructing a firm-specific measure of credit supply from individual loan data can reveal additional insights into how yields affect the substitution between bonds and loans.

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