Searching the Factor Zoo

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Abstract

Hundreds of factors have been proposed to explain asset returns during the past two decades. In this paper, we develop a Bayesian approach to explore the space of possible linear factor models in this "factor zoo". We conduct an extensive rearch for promising models using 83 candidate factors and individual-stock return data. Our results show that (i) only a handful of factors matter to explain individual stocks; (ii) the only factor that is consistently selected over time is the market factor; and (iii) other factors which are occasionally selected are not those in widely used multi-factor models.

Keywords: Factor selection, Bayesian variable selection, Seemingly Unrelated Regressions

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1. Introduction

Which factors should enter a linear factor model, and what kind of fundamental, pervasive, non-diversifiable risks do they represent? This is a fundamental question in asset pricing both to academics and practitioners. As more data have become available, and computational costs have decreased, the number of proposed factors to explain asset returns has increased significantly, particularly since the early 2000s. For example, Harvey *et al.* (2016) document more than three hundred factors that have been proposed in the literature[2], most within the last two decades, a situation which Cochrane (2011) has dubbed "a zoo of new factors".

However, it is doubtful that all of these factors really matter in asset pricing; it is more likely that some of them are redundant, or proxies for the same fundamental risk, whilst many (or even most) may just be products of data mining[3]. The huge number of factors that have been identified in empirical studies is a challenge for both practitioners and academics, in particular, considering that earlier empirical studies suggested five to six factors[4], and that most prominent and widely used models proposed by Fama & French (1993) (henceforth, FF3), Carhart (1997), Pastor & Stambaugh (2003), Chen & Zhang (2010) (henceforth, CZ), Hou *et al.* (2015b) (henceforth, HXZ) and Fama & French (2015) (henceforth, FF5) all have five or less factors. Some recent studies, *e.g.* Harvey & Liu (2016), Green *et al.* (2017), Yan & Zheng (2017), DeMiguel *et al.* (2017), Feng *et al.* (2017) and Gu *et al.* (2018), have investigated large numbers of factors proposed in the literature in order to identify which factors provide independent information about average stock returns. This is not a simple issue because many factors are correlated, and an assessment about which set of factors matters must be done jointly and ideally not depend on the order in which factors are tested.

In this study, we develop a Bayesian approach to explore the space of possible linear factor models, considering many candidate factors jointly for thousands of individual stocks, in order to identify the most promising models to explain asset returns. We propose an estimation method for the posterior probabilities of models, *i.e.* sets of factors, rather than separately testing each factor with re-

[2]See also McLean & Pontiff (2016), Hou *et al.* (2015a), Kewei *et al.* (2017) and Green *et al.* (2017), which summarize hundreds of factors proposed in the literature.

[3]See Chordia *et al.* (2017) and Kewei *et al.* (2017).

[4]Roll & Ross (1980), Chen *et al.* (1986), Connor & Korajczyk (1988), and Lehmann & Modest (1988).

spect to pre-specified models such as the Fama-French five factor model. With so many candidate factors within the factor "zoo", the number of possible models is enormous, making model comparison a challenging task. For example, the total number of models is over 1 billion with 30 factors, because the number of possible models with K factors is 2^K. We develop a novel method that evaluates the space of all possible models, which would be computationally prohibitive in the conventional framework even for moderate number of factors.

Our Bayesian variable selection method explores the model space using the returns on all assets simultaneously. For the K candidate factors, we define a vector $\boldsymbol{\gamma} = (\gamma_1, \ldots, \gamma_K)'$ of dummy variables γ_j to represent whether the $j - th$ predictor should be included in the model, and make inference on its posterior distribution. The introduction of $\boldsymbol{\gamma}$ makes it possible to explore the entire space of possible models, even with a large number of factors, when it becomes infeasible to conduct an exhaustive search. Our contribution in terms of methodology can be summarized as follows. First, we propose a simple non-hierarchical approach where the prior distribution of the regression coefficients (the factor sensitivities or βs in a multi-factor asset pricing model) is independent from that of the γ_js, therefore extending the model proposed by Kuo & Mallick (1998) to the multivariate seemingly unrelated regressions (SUR) model. Second, we derive a sequential algorithm to estimate the regression coefficients (factor sensitivities) of each response variable (each asset) using the Gibbs sampler[5]. This provides an efficient way to estimate the model even for larger numbers of test assets and factors, which allows the application of the method to individual stocks, instead of portfolios[6].

Our Bayesian approach overcomes the multiple comparison problem raised by Harvey *et al.* (2016), as it allows us to simultaneously assess the most promising models within the space of all possible models, instead of statistical inference based on a "single" test, and therefore, all individual signals are evaluated together as (argued) in Sullivan *et al.* (1999, 2001). The Bayesian framework differs from the frequentist perspective of Harvey *et al.* (2016), who propose a t-statistic greater than 3 for any new factor. Our approach can be applied to thousands of individual assets together with hundreds of potential factors, and thus does not require a reduction in the dimension of the test assets by forming portfolios (Lo &

[5]See Kim & Nelson (1999) for a review of Gibbs sampling estimation in Econometric models.

[6]In terms of methodology, our approach is mostly related to the literature on variable selection in multivariate regression models, of which the SUR model is a special case, see Brown *et al.* (1998), Smith & Kohn (2000), Hall *et al.* (2002), Wang (2010), Ando (2011), Ouysse & Kohn (2010), and Puelz *et al.* (2017).

Mackinlay, 1990; Ferson *et al.* , 1999; Berk, 2000). The complex cross-sectional dependencies can be considered in this framework, as all possible combinations of factors are evaluated. Multi-collinearity problems, which become serious when the number of independent variables increases, can be avoided because our approach selects the best possible models from the posterior probability of $\boldsymbol{\gamma}$.[7]

In the empirical tests, we consider a set of 83 candidate asset pricing factors. In addition to the market factor (excess market return), we compute 82 tradable factors by sorting stocks into value-weighted decile portfolios based on various firm characteristics and variables that have been proposed in the literature, and calculating the return difference between the top and bottom decile portfolios. We apply our Bayesian variable selection methodology to all available stocks in different sub-sample periods from 1980 to 2016. We also test various portfolios formed on firm characteristics as well as sectors.

Our empirical results using individual stocks suggest that only a small number of factors (5 to 6) are important to explain the individual stock returns. We find that factor selection (in terms of posterior probabilities) varies significantly over time, and the only factor that is consistently selected in different sub-sample periods is the market excess return. Moreover, the other factors that appear to be important during certain periods are not those that have been widely used in the literature, i.e, factors such as those in the FF3, FF5, CZ and HXZ models, but include factors based on short-term reversal, change in 6-month momentum, earnings announcement return, change in the number of analysts covering stocks, industry concentration, unexpected quarterly earnings, and industry-adjusted size. These results are robust to different specifications of the priors about the factor sensitivities.

In comparison with some recent studies, our results show a smaller number of relevant factors. For example, Green *et al.* (2017) use a set of 94 firm characteristics in Fama-MacBeth regressions and show that 12 characteristics are important to explain stock returns over the period 1985-2014[8]. Barillas & Shanken (2017)

[7]Although Green *et al.* (2017) and Feng *et al.* (2017) evaluate the effects of the multi-collinearity problem carefully, this problem does not disappear in the conventional regression with a large number of independent variables that are possibly cross-correlated. As Gu *et al.* (2018) note, "...regressions and portfolio sorts are ill-suited to handle the large numbers of predictor variables that the literature has accumulated over five decades.".

[8]The 12 characteristics identified in the study are book-to-market, cash, change in the number of analysts, earnings announcement return, one-month momentum, change in six-month momentum, number of consecutive quarters with earnings higher than the same quarter a year ago, annual

develop a Bayesian approach to compare asset pricing models and find evidence supporting a six-factor model including the market return, investment, profitability, size, book-to-market, and momentum factors, but their set of candidate factors is much smaller. Other recent studies with a large number of candidate factors, such as Harvey *et al.* (2016) and Feng *et al.* (2017), have also found that the market factor is the most important one, with a possible role for profitability and investment. DeMiguel *et al.* (2017) develop a parametric portfolio approach to identify which factors matter when investors optimize a mean-variance criterion, with or without transaction costs. Their results suggest that in the absence of transaction costs, 5 factors matter, while with transaction costs, this number increases to 15, which they interpret as related to a reduction in transaction costs due to netting effects when multiple factors are combined.

The main difference from these results lies in how these factors are selected. The factors in our study are selected from a larger set of factors, using an approach that considers all factors simultaneously. Therefore, our results do not suffer from the multiple comparison problem (Harvey *et al.* , 2016). On the other hand, most other studies in the literature identify additional factors relative to arbitrary sets of factors, or even without considering other possible factors. When the entire set of factors is searched for the best model, a set of a smaller number of factors is required.

Our Bayesian variable selection method can be an alternative to traditional asset pricing tests such as the Fama & MacBeth (1973) procedure or the Gibbons *et al.* (1989) test. These tests suffer from problems that reduce their power by grouping individual stocks into portfolios, which introduces biases if the variable(s) used to sort stocks into portfolios is related to the factors in the model. In contrast, our procedure considers many factors simultaneously and can naturally be applied when the number of assets is larger than the number of time-series observations.

Our work also differs markedly from previous studies that apply a Bayesian approach to select asset pricing factors, such as Ericsson & Karlsson (2003), Ouysse & Kohn (2010), Puelz *et al.* (2017) and Barillas & Shanken (2017). These studies have focused on a smaller number of candidate factors, with a relatively small number of portfolios as test assets. Although the Bayesian approach pro-

R&D to market cap, return volatility, share turnover, volatility of share turnover, and zero trading days. We also find that this number reduces to only 2 (industry-adjusted change in employees and number of earnings increases) since 2003, with the returns to hedge portfolios that attempt to exploit this predictability becoming insignificant.

posed by Barillas & Shanken (2017) is designed to test individual asset pricing models, the number of candidate factors is limited due to its computational burden. In contrast, our methodology allows us to explore a larger model space with many possible factors, using thousands of individual stocks simultaneously, therefore bypassing the problem of using as test assets portfolios that may be related to the factors by construction. In fact, when we apply our methodology to different sets of portfolios formed on various firm characteristics, we find a very strong dependence between the portfolio formation criteria and the posterior probability of factors. For example, when portfolios are formed on firm characteristics, models with the factors formed on these characteristics are selected with high posterior probability[9].

The rest of this paper is organized as follows. Our Bayesian variable selection model and its estimation method are discussed in Section 2, and the explanation of the data set and factor construction follows in Section 3. Section 4 provides the main empirical results of the paper, as well as robustness tests and comparison with previous studies. Section 5 concludes. The Appendix shows the detailed explanation of the variable selection model and its estimation, the full list of firm characteristics and their associated references used in this study.

2. Methodology

Consider N assets and K predictor variables (factors) over T periods. The factor model is a multivariate linear regression with N equations:

$$\mathbf{r}_i = \mathbf{X}\boldsymbol{\beta}_i + \mathbf{e}_i, \qquad i = 1, \ldots, N \tag{1}$$

where, for each asset i, $\mathbf{r}_i$ is the $T \times 1$ vector of excess returns, $\mathbf{X}$ is the matrix of factors with dimension $T \times K$, $\boldsymbol{\beta}_i = (\beta_{i,1}, \ldots, \beta_{i,K})'$ is a vector of unknown regression coefficients (factor sensitivities), and $\mathbf{e}_i$ is a $T \times 1$ vector of disturbances[10]. If the error terms are contemporaneously cross-correlated, the system of regressions

[9]This is related to the concerns expressed by Lo & Mackinlay (1990), Ferson *et al.* (1999), Berk (2000), Roll (1977) and Lewellen *et al.* (2010) in the context of bias in asset pricing tests using portfolios related to the factors. A similar conclusion is reached by Harvey & Liu (2016). They argue that dispersion in portfolios is largely driven by a few portfolios that are dominated by small stocks, which leads asset pricing tests to identify factors that can explain these extreme portfolios.

[10]To avoid ambiguity, throughout this article we use the subscripts i and j for assets and predictor variables, respectively.

above is a special case of the Seemingly Unrelated Regressions (SUR) model, where the predictor variables are the same for all equations[11].

The system can be stacked in a single equation $\tilde{\mathbf{r}} = \tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}} + \tilde{\mathbf{e}}$ in the following way:

$$\begin{bmatrix} \mathbf{r}_1 \\ \mathbf{r}_2 \\ \vdots \\ \mathbf{r}_N \end{bmatrix} = \begin{bmatrix} \mathbf{X} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{X} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{X} \end{bmatrix} \begin{bmatrix} \boldsymbol{\beta}_1 \\ \boldsymbol{\beta}_2 \\ \vdots \\ \boldsymbol{\beta}_N \end{bmatrix} + \begin{bmatrix} \mathbf{e}_1 \\ \mathbf{e}_2 \\ \vdots \\ \mathbf{e}_N \end{bmatrix}, \tag{2}$$

where $\tilde{\mathbf{e}} = (\mathbf{e}_1' \quad \mathbf{e}_2' \quad \dots \quad \mathbf{e}_N')'$, and $\mathbb{E}(\tilde{\mathbf{e}}\tilde{\mathbf{e}}') = \boldsymbol{\Omega} = \boldsymbol{\Sigma} \otimes \mathbf{I_T}$.

Bayesian inference in the SUR model can be carried out in a relatively straightforward manner, see for example Giles (2003). Since our variable selection procedure relys on a Markov Chain Monte Carlo (MCMC) approach using the Gibbs sampler, we start by reviewing the Bayesian estimation of the SUR. Suppose $\tilde{\mathbf{e}} \sim N(\mathbf{0}, \boldsymbol{\Sigma} \otimes \mathbf{I_T})$ and the following prior distributions for $\tilde{\boldsymbol{\beta}}$ and $\boldsymbol{\Sigma}$:

$$\tilde{\boldsymbol{\beta}} \sim N(\mathbf{b}_0, \mathbf{B}_0) \tag{3}$$
$$\boldsymbol{\Sigma} \sim IW(\nu_0, \boldsymbol{\Phi}_0), \tag{4}$$

where $IW(\nu_0, \boldsymbol{\Phi}_0)$ denotes the inverted-Wishart distribution with ν_0 degrees of freedom and parameter matrix $\boldsymbol{\Phi}_0$. With these choices, the conditional posterior distributions required to estimate the SUR model using the Gibbs sampler are those summarized in the following lemmas[12]:

Lemma 1. *In the SUR model* (2) *and under the prior distributions for* $\tilde{\boldsymbol{\beta}}$ *and* $\boldsymbol{\Sigma}$ *given by* (3) *and* (4)*, respectively, the conditional distributions of* $\tilde{\boldsymbol{\beta}}$ *and* $\boldsymbol{\Sigma}$ *are as follows:*

$$\tilde{\boldsymbol{\beta}}|\boldsymbol{\Sigma}, \mathbf{r} \sim N(\mathbf{b}_1, \mathbf{B}_1) \tag{5}$$
$$\boldsymbol{\Sigma}|\tilde{\boldsymbol{\beta}}, \mathbf{r} \sim IW(\nu_1, \boldsymbol{\Phi}_1), \tag{6}$$

[11]The SUR model, introduced by Zellner (1962), consists of N regression equations, each with T observations, which are linked solely through the covariance structure of error terms at each observation, *i.e.* errors are contemporaneously correlated but not autocorrelated.

[12]The full derivation of all the conditional distributions required for the Gibbs sampler estimation is provided in Appendix A.

with

$$\begin{aligned}
\mathbf{b}_1 &= (\mathbf{B}_0^{-1} + \tilde{\mathbf{X}}'\mathbf{\Omega}^{-1}\tilde{\mathbf{X}})^{-1}(\mathbf{B}_0\mathbf{b}_0 + \tilde{\mathbf{X}}'\mathbf{\Omega}^{-1}\tilde{\mathbf{r}}) \\
\mathbf{B}_1 &= (\mathbf{B}_0^{-1} + \tilde{\mathbf{X}}'\mathbf{\Omega}^{-1}\tilde{\mathbf{X}})^{-1} \\
\nu_1 &= \nu_0 + T, \quad \mathbf{\Phi}_1 = \mathbf{\Phi}_0 + \mathbf{S},
\end{aligned}$$

where $\mathbf{S}$ *is the matrix of cross-products of the residuals, that is, if* $\mathbf{E} = [\mathbf{e}_1 \ldots \mathbf{e}_N]$, *then* $\mathbf{S} = \mathbf{E}'\mathbf{E}$.

Lemma 2. *In the SUR model* (2)*, if we denote by* $\tilde{\boldsymbol{\beta}}_{-i}$ *the full vector* $\tilde{\boldsymbol{\beta}}$ *excluding* $\boldsymbol{\beta}_i$*, and assume the priors*

$$\boldsymbol{\beta}_i|\tilde{\boldsymbol{\beta}}_{-i}, \mathbf{\Sigma} \sim N(\mathbf{b}_{0,i}, \mathbf{B}_{0,i}), \quad i = 1, \ldots, N, \tag{7}$$

then $\boldsymbol{\beta}$ *can be generated equation-by-equation, using*

$$\boldsymbol{\beta}_i|\tilde{\boldsymbol{\beta}}_{-i}, \mathbf{\Sigma}, \mathbf{r} \sim N(\mathbf{b}_{1,i}, \mathbf{B}_{1,i}), \quad i = 1, \ldots, N, \tag{8}$$

with

$$\begin{aligned}
\mathbf{b}_{1,i} &= (\mathbf{B}_{0,i}^{-1} + \sigma^{ii}\mathbf{X}'\mathbf{X})^{-1}(\mathbf{B}_{0,i}\mathbf{b}_{0,i} + \sigma^{ii}\mathbf{X}'\mathbf{r}_i^*) \\
\mathbf{B}_{1,i} &= (\mathbf{B}_{0,i}^{-1} + \sigma^{ii}\mathbf{X}'\mathbf{X})^{-1} \\
\mathbf{r}_i^* &= \mathbf{r}_i - (\sigma^{ii})^{-1}\mathbf{A}_{-i}(\tilde{\mathbf{r}}_{-i} - \tilde{\mathbf{X}}_{-i}\tilde{\boldsymbol{\beta}}_{-i}),
\end{aligned}$$

where σ^{ii} *denotes the* (i, i) *element of* $\mathbf{\Sigma}^{-1}$ *and* $\mathbf{A}_{-i}$ *is a* $T \times (N-1)T$ *matrix which defines a partition of* $\mathbf{\Omega}^{-1}$ *with the terms corresponding to the* $i - th$ *equation removed.*

Lemmas 1 and 2 provide two ways to estimate the SUR model. In the first approach (Lemma 1), the full vector $\boldsymbol{\beta}$ in the stacked SUR model (2) is simulated using (5) at each iteration of the Gibbs sampler. This may be computationally prohibitive if the number of equations is large, since it requires multiplication and inversion of large matrices. For example, $\tilde{\mathbf{X}}$ has dimension $NT \times NK$ and $\mathbf{\Omega}^{-1}$ has dimension $NT \times NT$. The second approach (Lemma 2) is to sequentially generate each $\boldsymbol{\beta}_i$ conditionally on the remaining $\boldsymbol{\beta}_j$, $j \neq i$ and $\mathbf{\Sigma}$ using (8). Note that in the second approach, the conditional posteriors depend only on the smaller matrices $\mathbf{X}$ and $\mathbf{\Sigma}$. In the Gibbs sampler, each $\boldsymbol{\beta}_i$ can be generated in random order at each iteration.

2.1. Bayesian Variable Selection in the SUR Model

There is a vast literature focusing on Bayesian variable selection in linear models with a single response variable, see for example George & McCulloch (1993, 1997); Kuo & Mallick (1998); Dellaportas *et al.* (1999); Hans *et al.* (2007); Clyde & George (2004); O'Hara & Sillanpää (2009). For a single regression equation, Bayesian variable selection is typically done by first introducing a vector $\boldsymbol{\gamma} = (\gamma_1, \ldots, \gamma_K)'$ of dummy variables, where if $\gamma_j = 1$, the $j-th$ predictor is included in the model, and conducting inference on the posterior distribution of $\boldsymbol{\gamma}$. Since the vector of K dummy variables indicates 2^K possible models, comparison of all possible models becomes computationally infeasible for even moderate numbers of regressors and MCMC methods are frequently used for a fast way to obtain consistent estimates of model probabilities.

Variable selection in the multivariate regression models (of which the SUR model is a special case) has been the subject of a number of studies, mostly focusing on generalizations of the hierarchical Bayesian model of George & McCulloch (1993)[13], which defines the distribution of $\boldsymbol{\beta}$ conditionally on $\boldsymbol{\gamma}$. This is done by specifying a "slab and spike" mixture distribution which places a spiked prior on zero for $\beta_j|\gamma_j = 0$ and a slab or flat prior on $\beta_j|\gamma_j = 1$. One disadvantage of this approach is that it often requires data-dependent tuning of the hyper-parameters.

In this study, we assume *a priori* independence between β_j and γ_j and extend the univariate regression model proposed by Kuo & Mallick (1998) to the case of the SUR model with common regressors. Let $\mathbf{X}_\gamma$ represent the matrix $\mathbf{X}$ where each column has been multiplied by the corresponding γ_j. Then we can write the model with variable selection as $\mathbf{r}_i = \mathbf{X}_\gamma \boldsymbol{\beta}_i + \mathbf{e}_i, i = 1, \ldots, N$, and stack the N equations as follows:

$$\tilde{\mathbf{r}} = \tilde{\mathbf{X}}_\gamma \tilde{\boldsymbol{\beta}} + \tilde{\mathbf{e}}, \tag{9}$$

[13]One of the first examples of this approach is Brown *et al.* (1998). Smith & Kohn (2000) introduced a Bayesian hierarchical model which considers variable selection by explicitly allowing the possibility that some coefficients are equal to zero. Hall *et al.* (2002) consider a hierarchical Bayesian model related to Smith & Kohn (2000) to choose style factors in models for global stock returns. Wang (2010) also follows the hierarchical setup of George & McCulloch (1993), considering structured covariance matrices within the context of normal graphical models. Ando (2011) proposes a Direct Monte Carlo method estimation for a hierarchical model related to Smith & Kohn (2000). Ouysse & Kohn (2010) apply a model related to Brown *et al.* (1998) to simultaneously make inferences on asset pricing factors and estimate factor risk premia. Puelz *et al.* (2017) consider the case of treating the variables as random, and propose strategies for model summarization.

where $\tilde{\mathbf{X}}_\gamma$ is defined analogously as before. Equivalently, we define a new variable $\boldsymbol{\theta}_i = \boldsymbol{\beta}_i \odot \boldsymbol{\gamma}$, where $\odot$ represents element-wise multiplication. The system can then be represented by $\tilde{\mathbf{r}} = \tilde{\mathbf{X}}\tilde{\boldsymbol{\theta}} + \tilde{\mathbf{e}}$. Analysis of the posterior distribution of $\tilde{\boldsymbol{\theta}}$ would be useful to understand which variables are important for each equation.

To derive the conditional distributions required for the Gibbs sampler, we need to specify the prior distribution for $\boldsymbol{\gamma}$. We follow Kuo & Mallick (1998) and set independent priors as $\gamma_j \sim B(1, \pi_j)$, $j = 1, \ldots, K$. Therefore, the prior distribution of $\boldsymbol{\gamma}$ is given by

$$f(\boldsymbol{\gamma}) = \prod_{j=1}^{K} \pi_j^{\gamma_j}(1 - \pi_j)^{1-\gamma_j}. \tag{10}$$

Note that, conditional on a known value of $\boldsymbol{\gamma}$, the model reduces to a SUR with the corresponding predictors for which $\gamma_j = 1$. Therefore, using the same prior distributions for $\tilde{\boldsymbol{\beta}}$ and $\boldsymbol{\Sigma}$ in equations (3) and (4), the conditional distributions for $\tilde{\boldsymbol{\beta}}$ and $\boldsymbol{\Sigma}$ are those given in equations (5) and (6), with $\tilde{\mathbf{X}}$ replaced by $\tilde{\mathbf{X}}_\gamma$. Alternatively, for large panels we can use the prior (7) and generate $\boldsymbol{\beta}$ equation-by-equation. The conditional marginal densities required for the Gibbs sampler are provided in the following propositions, proved in Appendix B.

Proposition 1. *In the SUR model with variable selection* (9)*, under the prior distributions for* $\tilde{\boldsymbol{\beta}}$*,* $\boldsymbol{\Sigma}$*, and* $\boldsymbol{\gamma}$ *given by* (3)*,* (4) *and* (10)*, respectively, the following conditional distributions obtain:*

$$\begin{aligned} \tilde{\boldsymbol{\beta}}|\boldsymbol{\gamma}, \boldsymbol{\Sigma}, \mathbf{r} &\sim N(\mathbf{b}_1, \mathbf{B}_1) && (11)\\ \boldsymbol{\Sigma}|\boldsymbol{\gamma}, \tilde{\boldsymbol{\beta}}, \mathbf{r} &\sim IW(\nu_1, \boldsymbol{\Phi}_1), && (12)\\ P(\gamma_j = 1|\boldsymbol{\gamma}_{-j}, \tilde{\boldsymbol{\beta}}, \boldsymbol{\Sigma}, \tilde{\mathbf{r}}) &= \left(1 + \frac{1-\pi_j}{\pi_j}\exp(-0.5\,\mathrm{Tr}(\boldsymbol{\Sigma}^{-1}(\mathbf{S}_\gamma^1 - \mathbf{S}_\gamma^0))\right)^{-1}, && (13) \end{aligned}$$

where

$$\begin{aligned} \mathbf{b}_1 &= (\mathbf{B}_0^{-1} + \tilde{\mathbf{X}}_\gamma'\boldsymbol{\Omega}^{-1}\tilde{\mathbf{X}}_\gamma)^{-1}(\mathbf{B}_0\mathbf{b}_0 + \tilde{\mathbf{X}}_\gamma'\boldsymbol{\Omega}^{-1}\tilde{\mathbf{r}})\\ \mathbf{B}_1 &= (\mathbf{B}_0^{-1} + \tilde{\mathbf{X}}_\gamma'\boldsymbol{\Omega}^{-1}\tilde{\mathbf{X}}_\gamma)^{-1}\\ \nu_1 &= \nu_0 + T, \quad \boldsymbol{\Phi}_1 = \boldsymbol{\Phi}_0 + \mathbf{S}, \end{aligned}$$

and $\mathbf{S}_\gamma^1$ *and* $\mathbf{S}_\gamma^0$ *represent the matrices of residuals when* $\gamma_j = 1$ *and* $\gamma_j = 0$*, respectively.*

Proposition 2. *In the SUR model with variable selection* (9)*, under the prior* (7)*, we can alternatively generate $\boldsymbol{\beta}$ equation-by-equation, using*

$$\boldsymbol{\beta}_i|\tilde{\boldsymbol{\beta}}_{-i}, \boldsymbol{\gamma}, \boldsymbol{\Sigma}, \tilde{\mathbf{r}} \sim N(\mathbf{b}_{1,i}, \mathbf{B}_{1,i}), \quad i = 1, \ldots, N,$$

with

$$\begin{aligned} \mathbf{b}_{1,i} &= (\mathbf{B}_{0,i}^{-1} + \sigma^{ii}\mathbf{X}_\gamma'\mathbf{X}_\gamma)^{-1}(\mathbf{B}_{0,i}\mathbf{b}_{0,i} + \sigma^{ii}\mathbf{X}_\gamma'\mathbf{r}_i^*) \\ \mathbf{B}_{1,i} &= (\mathbf{B}_{0,i}^{-1} + \sigma^{ii}\mathbf{X}_\gamma'\mathbf{X}_\gamma)^{-1} \\ \mathbf{r}_i^* &= \mathbf{r}_i - (\sigma^{ii})^{-1}\mathbf{A}_{-i}(\tilde{\mathbf{r}}_{-i} - \tilde{\mathbf{X}}_{\gamma,-i}\tilde{\boldsymbol{\beta}}_{-i}), \end{aligned}$$

where σ^{ii} denotes the (i,i) element of $\boldsymbol{\Sigma}^{-1}$ and $\mathbf{A}_{-i}$ is a $T \times (N-1)T$ matrix which defines a partition of $\boldsymbol{\Omega}^{-1}$ with the terms corresponding to the $i-th$ equation removed.

Using the conditional distributions above, we can simulate each variable using the Gibbs sampler, with the option of using the sequential generation for the $\boldsymbol{\beta}_i$s for large panels. Each γ_j can be generated, preferably in random order, using (13)[14].

2.2. Prior Distributions

The most important prior distribution is the one for $\tilde{\boldsymbol{\beta}}$. As discussed by O'Hara & Sillanpää (2009), the MCMC algorithm might not mix well in the $\boldsymbol{\gamma}$ space if the prior for $\tilde{\boldsymbol{\beta}}$ is too vague. The reason for this is that, when a particular $\gamma_j = 0$, the $\beta_{ij}, i = 1, \ldots, N$ are sampled from the full prior conditional distribution. In this case, it may be difficult for the model to transition between $\gamma_j = 0$ and $\gamma_j = 1$, since the generated β_{ij} will be unlikely to be in the region where θ_{ij} has higher posterior probability.

We propose a few choices for the priors on $\tilde{\boldsymbol{\beta}}$. The first is $\tilde{\boldsymbol{\beta}} \sim N(\mathbf{0}, c\mathbf{I})$. This choice reflects a complete lack of knowledge about the predictors, both in terms of which predictors should enter the model as well as regarding the dependence structure of the regression coefficients. A second possibility is to use an empirical Bayes prior, *i.e.* center each $\boldsymbol{\beta}_i$ around their OLS or maximum likelihood estimate: $\boldsymbol{\beta}_i \sim N((\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{r}_i, c\sigma_i^2(\mathbf{X}'\mathbf{X})^{-1})$. These priors can be made less informative by

[14]An alternative approach would be to apply a Metropolis-within-Gibbs step of the type suggested by Brown *et al.* (2002), see also George & McCulloch (1997) .

increasing c[15]. Note that the first component of each β_i is for the alpha of each regression. The intercept is included as a factor because there is no guarantee that the factors we test in this study can fully explain individual stock returns.

The standard choice for the prior of $\mathbf{\Sigma}$ is to set $\nu_0 = N$ and $\mathbf{\Phi}_0 = \mathbf{I}$. Another possibility is to choose the parameters so that the prior variance is equivalent to a given number, which may come from our knowledge of the problem. For the prior of π_j, the prior probability that predictor j is included in the model, we choose an equal probability of $\frac{1}{2}$ for all factors. This prior reflects the lack of knowledge about the inclusion of the predictors, and implies that any model has an equal prior probability of $\frac{1}{2^K}$. Prior information regarding predictors that the researcher believe should be included in the model can be incorporated by letting $\pi_j = 1$. For example, if we want to reflect a prior belief that the market factor should always be included, we can set the corresponding π_j equal to 1.

2.3. Comparison with other variable selection models

The method we propose has two main differences compared to other approaches. The first one is that we do not follow the hierarchical structure as in Brown *et al.* (1998); Smith & Kohn (2000); Ouysse & Kohn (2010); Wang (2010); Ando (2011); Puelz *et al.* (2017). Our non-hierarchical structure results in a simple method for variable selection in SUR models, with the advantage that it does not require complex tuning of the hyper-parameters.

It is possible to make inference about which variables matter for each asset (equation) by summarizing the posterior distribution of $\boldsymbol{\theta}_i = \boldsymbol{\beta}_i \odot \boldsymbol{\gamma}$. Thus, by focusing on finding a single set of predictors for the N equations, we identify common pricing factors in the multi-factor models. Other studies such as Wang (2010) and Puelz *et al.* (2017) propose methods that can identify different sets of predictors for each equation. However, a common set of factors should price all assets, even if some factor loadings may not be significant for some assets.

[15] We have performed a simulation study to analyze the impact of the choice of the prior for $\boldsymbol{\beta}$ on variable selection, varying the number of cross-sections (N) as well as the number of time series observations (T). The results of this simulation, which are reported in Appendix D, suggest that our methodology is able to identify the correct variables under either prior, but when T and N are large, a larger value of c is required. In our robustness tests, we have not noticed significant changes when different priors or values of c are used.

3. Data and Factor Construction

3.1. Factor Returns and Their Statistical Properties

We start by compiling data on 82 firm characteristics that have been tested by Green *et al.* (2017)[16], by combining data from CRSP and Compustat for the sample period from January 1980 to December 2016, a total of 37 years (444 months). We exclude firm characteristics that have too many missing values or whose deciles are not meaningful[17]. Factor returns are calculated by the difference between the value-weighted returns on the highest and lowest decile portfolios[18]. We use all available U.S. common stocks from the CRSP and Compustat databases for the calculation of factor returns. In addition to these 82 factors, we also consider the excess market return[19] and the intercept, and thus the total number of factors is 84. Due to differences in data availability, different factors are available for different sub-sample periods.

Table 1 reports basic descriptive statistics for the factors used in this study. For each factor, we calculate and report statistics using all the available stocks. We also report Dependent False Discovery Rate (DFDR) p-values using the method of Benjamini & Yekutieli (2001), which takes into account the fact that multiple tests are being run simultaneously. The factors with a DFDR p-value less than 0.05 are shown in bold, and the corresponding t-statistic includes an asterisk.

The average returns on the factors based on well-known characteristics such as mve (market cap), bm (book-to-market ratio) and mom12m (12-month momentum) are in line with numbers reported on the literature. Despite the differences in the factor return calculation and the sample period, the average factor returns are

[16]We thank Jeremiah Green for making his SAS code available online. As in (Green *et al.* , 2017, pg. 4398), characteristics are constructed at each month t using annual accounting data from month $t-1$, if the firm's fiscal year ended at least six months before the end of month $t-1$. For characteristics that use quarterly accounting data, we assume that data are available at $t-1$ if the fiscal quarter ended at least four months before the end of month $t-1$.

[17]The excluded characteristics are convind (convertible debt indicator), divi (dividend initiation), divo (dividend omission), dy (dividend yield), ipo (new equity issue), nincr (number of earnings increases), rd (R&D increase), rd_mve (R&D to market capitalization), rd_sale (R&D to sales), secured (secured debt), securedind (secured debt indicator) and sin (Sin stocks). The exclusion of these 12 firm characteristics, however, does not affect our main results because the intercept is not selected for the explanation of individual stocks.

[18]We apply the same procedure for all characteristics, and thus average return difference may be positive (*e.g.* book-to-market ratio) or negative (*e.g.* market value of equity).

[19]The excess market return is taken from Kenneth French's data library.

similar to those of Green *et al.* (2017). It is noteworthy that only 6 of the 83 factors are significant when the DFDR p-values are considered, despite the fact that 27 factors have t-statistics higher than 2.0 in absolute value, reflecting the much higher burden of significance when multiple testing is taken into account. These factors are acc (working capital accruals), chcsho (change in shares outstanding), chinv (change in inventory), invest (capital expenditures and inventory), nanalyst (number of analysts covering stock), and sfe (scaled earnings forecast). On the other hand, some characteristics which are significant in their univariate regressions are not significant in multiple testing, although most have large t-statistics. This is the case of agr (asset growth, t-stat = -2.9), chatoia (industry-adjusted change in turnover, t-stat = 2.85), ear (earnings announcement return, t-stat = 2.93), egr (growth in common shareholder equity, t-stat = -2.84), grcapx (growth in capital expenditures, t-stat -2.70), grltnoa (growth in long term net operating assets, -3.20), pchsalepchnvt (change in sales - change in inventory, t-stat = 1.58), and sue (unexpected quarterly earnings, t-stat = 2.57).

[Table 1 about here.]

Table 2 reports statistics of the absolute pairwise correlations between the factors for the period during which all 83 factors (except the intercept) are available, a total of 114 months from July 2007 to December 2016. There are 3403 total pairwise correlations. The median absolute correlation is 0.179, and 90% of all absolute correlations are below 0.498. We also report the 10 largest absolute correlations. Some factors are highly correlated, and 4 correlations are higher than 0.90. Figure 1 plots the distribution of the absolute correlations. The high correlation between some factors could cause multi-collinearity problems in conventional regressions, despite a weaker cross-correlations between individual firm characteristics as in Green *et al.* (2017). This is issue is not a problem in our Bayesian framework, as models with highly correlated factors will not have high posterior probabilities.

[Table 2 about here.]

[Figure 1 about here.]

3.2. Test Assets

The Bayesian variable selection method is applied to thousands of common stocks listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and NASDAQ. We exclude financial stocks (Standard Industrial

Classification code from 6000 to 6999) because their accounting practices and variables are not comparable with those of the other sectors. We also exclude a large number of microcap stocks whose market size is less than the bottom 20th percentile of market cap of NYSE stocks as well as penny stocks whose prices are less than US$1 at the beginning of test periods. If these stocks were included, our results could be overly affected by market microstructure biases and thin trading of these stocks whose value is less than 3 percent of the total market value. For robustness purposes, we later investigate factor selection using microcap stocks only.

When considering individual stocks over long sample periods, there is a serious survivorship bias. Therefore, we consider shorter sub-sample periods to minimize the survivorship bias and also capture time variation in factor selection. When deciding the length of the sub-sample periods, we need to consider a trade-off between precision (using more data to conduct inference on factor selection) and the potential for survivorship bias. We also face a natural limit given the large number of candidate factors *i.e.* the number of months in each sub-sample period should be larger than that of factors.

To balance these concerns, we have used two different approaches. First, we divide our sample period into three sub-sample periods of 144 (January 1980 to December 1991), 144 (January 1992 to December 2003) and 156 (January 2004 to December 2016) months and apply the Bayesian variable selection method using all available factors in each sub-sample period[20]. This approach allows us to study a larger set of candidate factors, with some reduction in survivorship bias. The second approach consists of 5 shorter sub-sample periods, with the first 4 containing 90 months each, and the last containing 84 months. For these shorter sub-sample periods (not larger than 90 monthly observations), we restrict the number of candidate factors to 55 including the market excess return and the intercept. These are the factors that are significant in any of the regressions in Green *et al.* (2017).

To compare our results with those of previous studies and to assess the performance of our method, we also consider an extensive set of portfolios formed by sorting stocks according to different criteria[21]. First, we apply the Bayesian

[20]These two break points are chosen considering the importance of research on firm characteristics (e.g., Fama & French (1992) and Jegadeesh & Titman (1993)) and the structural breaks in the performance of firm characteristics in cross-sectional asset returns (Green *et al.* , 2017).

[21]Testing portfolios is motivated by the dependence we observe between the portfolio formation criteria and the selected factors. Lewellen, Nagel and Shanken (2007) argue that it is problematic

variable selection method to different sets of portfolios formed on univariate and bivariate sorts, as well as industry classification. Data on these portfolios are obtained from Kenneth French's data library[22] and the total number of individual portfolios considered is over 300[23]. We then consider applying the methodology to a much larger set of portfolios, consisting of all available decile portfolios used to create the candidate factors, as described in Section 3.1, as well as the 49 industry portfolios, resulting in 751 portfolios with data for the whole sample period. This could lead to different results as all portfolios are considered simultaneously.

4. Selection of Asset Pricing Factors

We first discuss our main empirical findings using individual stocks, followed by the results using portfolios. These results have been obtained using an empirical Bayes prior for the factor sensitivities, *i.e.* we center each $\boldsymbol{\beta}_i$ around their OLS estimate by setting $\boldsymbol{\beta}_i \sim N((\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{r}_i, c\sigma_i^2(\mathbf{X}'\mathbf{X})^{-1})$, with $c = 1$. We consider an equal prior probability for each factor: $\pi_j = \pi = 0.5$. The results for individual stocks are based on 10,000 iterations of the MCMC algorithm, while those for portfolios are based on 50,000 iterations. At the end of this section we test the robustness of our results with respect to these choices.

4.1. Individual Stocks as Test Assets

We apply our Bayesian variable selection methodology to individual stocks for various sub-sample periods using all available factors in the sub-sample periods in Section 3.2. These results are free from the biases inherent in using portfolios formed on characteristics which may be related to the factors we study, as discussed by Lo & Mackinlay (1990), Ferson *et al.* (1999), Berk (2000), Lewellen *et al.* (2010) and others.

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to use portfolios formed on firm characteristics to test asset pricing models, because these portfolios will have a tight factor structure by construction. In this case, the idiosyncratic component of the model will be very small, and the factors will appear to be statistically significant cross-sectionally.

[22] `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

[23] The univariate sort portfolios considered are those formed on size, book-to-market, operating profitability, investment, earnings-to-price, cashflow-to-price, dividend yield, momentum, short-term reversal, long-term reversal, beta, variance and residual variance. The bivariate sort portfolios include size and book-to-market, size and operating profitability, size and investing, book-to-market and operating profitability, book-to-market and investment, and operating profitability and investment. The industry portfolios comprise 49 industries.

4.1.1. Results using three sub-sample periods and the full set of factors

The results for the three sub-sample periods are reported in Table 3. The total number of non-microcap stocks in each period are 807, 893 and 967, respectively, while the number of candidate factors are 75, 81 and 83, respectively.

[Table 3 about here.]

For all sub-sample periods, models with less than 5 factors are generally selected by our Bayesian variable selection procedure. This is quite surprising, as the number of possible models is enormous, varying from 2^{75} in the first sub-sample period to 2^{81} in the last sub-sample period. However, we do not find that a single model (a set of factors) or factors other than the market return are consistently selected across sub-sample periods. Additionally, among the large number of candidate factors, only 13 factors are ever selected over the three sub-sample periods. These factors are mkt (the market return), aeavol (abnormal earnings announcement volume), chmom (change in 6-month momentum), chanalyst (change in number of analysts covering stock), ear (earnings announcement return), ep (earnings-to-price), herf (industry sales concentration), mom1m (1-month momentum), ms (Mohanram (2005a)'s financial statement score), pctacc (percent accruals), saleinv (sales to inventory), tb (tax income to book income), and the intercept. When only factors whose marginal posterior probabilities are above 0.5 in any of the sub-sample periods are counted, we have only four factors: mkt, chmom, herf, and mom1m.

During the first sub-sample period, from January 1980 to December 1991, there is a substantial amount of model uncertainty, as the posterior probability of the best model is quite low. The best model includes the market factor and chmom (change in 6-month momentum), with a posterior probability of 0.24. Other models include either mom1m (1-month momentum) and/or ms (Mohanram (2005a)'s financial statement score). Lower probability models include other factors formed on ep (earnings-to-price) or tb (tax income to book income). The only factors that have marginal posterior probabilities higher than 0.5 (our prior) during this period are the market factor and chmom (change in 6-month momentum).

In the second sub-sample period, which comprises the period from January 1992 to December 2003, model uncertainty is much lower, with the best model including only the market factor with a high posterior probability of 0.64. The second best model includes aeavol (abnormal earnings announcement volume) or pctacc (percent accruals), the latter with very low posterior probability.

Finally, in the last sub-sample period, from January 2004 to December 2016, two models appear with similar posterior probabilities. The best model, with posterior probability 0.24, includes the intercept and 3 factors. In addition to the market return, this model includes herf (industry sales concentration) and mom1m (1-month momentum). The second best model, with posterior probability 0.20, drops the intercept and includes chanalyst (change in number of analysts covering stock). We note that many models include the intercept, which suggests that the models with 83 factors may not explain the individual stock returns during this period.

A few interesting points can be raised from these results. First, factor selection varies substantially over time, with no specific model dominating the others. The only factor which is consistently selected across all sub-sample periods is the excess market return. The other factor that is selected in more than one sub-sample period is mom1m (1-month momentum), which is included in the best models in the first and last sub-sample periods. All other factors matter only during one sub-sample period. Second, the models with high posterior probabilities do not include the popular factors (other than the market return) that have been proposed in the literature, *e.g.* those in the FF3, FF5, CZ or HXZ models. The additional factors that are selected by our Bayesian variable selection method are related to other anomalies or characteristics such as short-term reversal, momentum, earnings announcement volume, change in the number of analysts covering stocks, and industry concentration. Third, the total number of factors selected in these models over all sub-sample periods is small relative to the total number of candidate factors. Only 13 factors (out of more than 80) are ever selected by the variable selection methodology, and from these, only 4 factors have marginal posterior probabilities higher than 0.5 in any of the sub-sample periods.

4.1.2. Results using five sub-sample periods and the reduced set of factors

The selection of the intercept during the last sub-sample period in the previous subsection suggests that even models with as many as 7 factors do not fully explain individual stock returns, as the intercept is often included. Moreover, the large numbers of models in the first and third sub-sample periods indicate model uncertainty during these periods. In this subsection we explore the possibility that these results arise because of the relatively long sub-sample periods, *i.e.* 12 years. When the true model is time-varying, a linear regression model over a long period requires a larger number of factors or even does not explain asset returns (Jagannathan and Wang, 1996).

Five shorter sub-sample periods are used to test individual stocks: January 1980 to June 1987, July 1987 to December 1994, January 1995 to June 2002, July 2002 to December 2009, and January 2010 to December 2016. The number of stocks varies from 1,014 in the first sub-sample period to 1,225 in the last sub-sample period. By selecting factors that are significant in any of the regressions in Green *et al.* (2017), the numbers of factors we test for these five sub-sample periods range from 44 to 49. The results are reported in Table 4.

[Table 4 about here.]

The results are similar to those of the three longer sub-sample periods with the full set of candidate factors in Table 3. No single model or factor is consistently selected across sub-sample periods except for the excess market return. However, a few important differences from the shorter sub-sample periods can be summarized as follows. First, model uncertainty decreases for the shorter periods. At most 4 factors are selected in all five sub-sample periods, compared with up to 7 factors in Table 3, and only 10 factors (out of almost 50) are selected by the Bayesian variable selection methodology. These are: mkt (market excess return), aeavol (abnormal earnings announcement volume), bm (book-to-market), chmom (change in 6-month momentum), ear (earnings announcement return), mom1m (1-month momentum), mve_ia (industry adjusted size), pchsale_pchrect (change in sales - change in A/R), pctacc (percent accruals), and sue (unexpected quarterly earnings). From these, only 6 have marginal posterior probabilities higher than 0.5 (mkt, chmom, ear, mom1m, mve_ia, and sue). Second, despite the smaller numbers of factors, the intercept is not selected in any of the sub-sample periods, showing that these 10 factors are enough to explain individual stocks. Therefore, model mis-specification is less likely with the shorter sub-sample periods.

Starting in Panel A, a single model is selected during the first sub-sample period; the model includes the mkt (market excess return) and chmom (change in 6-month momentum) factors. Panel B shows that, during the period from July 1987 to December 1994, ear (earnings announcement return) and mom1m (1-month momentum) factors need to be added on top of these two factors. Model uncertainty is still very low, with only two models having non-zero posterior probabilities. The next three sub-sample periods show higher model uncertainty, and different factors are included in the best models. In the period from January 1995 to June 2002 (Panel C), the best model includes only the market return, with a posterior probability of 0.44. The next best models require either pctacc (percent accruals), mom1m (1-month momentum), or aevol (abnormal earnings announcement volume), although with much lower posterior probabilities. During the period from July 2002 to December 2009 (Panel D), the best model includes the market return and sue (unexpected quarterly earnings), with a posterior probability of 0.44. The next best models include bm (book-to-market) or pchsale_pchrect (change in sales - change in A/R) with lower posterior probabilities. Finally, in the last period, from January 2010 to December 2016, we see more model uncertainty regarding the best model, as the posterior probabilities of the three best models are quite similar (0.36, 0.28, and 0.24). The best models include, in addition to the market return, mom1m (1-month momentum), mve_ia (industry-adjusted market value of equity), sue (unexpected quarterly earnings) or a combination thereof.

The only factor for which we find consistent evidence across all sub-sample periods is the excess market return. Other factors which are selected in some sub-sample periods, such as chmom (change in 6-month momentum), sue (unexpected quarterly earnings) and mom1m (1-month momentum), are not those in models such as FF5 and HXZ. Exceptions are the inclusion of bm (book-to-market) in Panel D (although with low posterior probability) and a size factor (mve_ie) in Panel E. As in our previous results in Table 3, the additional factors are related to short-term reversal, earnings announcement returns, surprise earnings, etc.

4.1.3. Which factors explain the returns on microcap stocks?

Many previous studies report that microcap stocks perform differently mainly due to their illiquidity (Baker & Wurgler, 2006; Stambaugh *et al.* , 2012; Antoniou *et al.* , 2015). In this subsection, we apply our methodology to the set of microcap stocks in each sub-sample period, to investigate which factors matter to explain their returns. We report results using the three and five subsample periods used for non-microcap stocks.

The results using three sub-sample periods are reported in Table 5. There are some differences compared with the results obtained with non-microcap stocks, reported in Table 3). First, fewer factors are selected to explain microcaps; second, the only factor other than the market return to be selected with high probability is ear (earnings announcement return), during the second sub-sample period (1992-2003). The chmom (change in 6-month momentum) and mom1m (1-month momentum) factors, which appear to be important to explain the returns on non-microcaps, are not relevant to explain microcaps.

[Table 5 about here.]

When the five sub-sample periods are used (Table 6), we find some similarities in the selected factors over different sub-sample periods, compared with non-microcap stocks (Table 4). For example, chmom (change in 6-month momentum) is selected for both groups of stocks during the first sub-sample period and ear (earnings announcement return) is selected in the second sub-sample period. One interesting result is that, during the period January 1995 to June 2002 (Panel C), the two highest posterior probability models for microcaps do not include the market return factor. The two best models, which together represent a posterior probability of 0.88, include aeavol (abnormal earnings announcement volume) and chanalyst (change in number of analysts covering stock). A possible explanation is that the microcap universe during the period of the high-tech bubble of the 1990s includes a large number of small technology stocks whose prices were extremely sensitive to these variables during this unusual period, and not very sensitive to overall market movements, as many investors were captivated by the possibility of finding the next "hot" technology stock (during the build-up of the bubble) or concerned about any news regarding their technology stocks during the bursting of the bubble.

[Table 6 about here.]

In summary, smaller numbers of factors are selected to explain microcap compared with non-microcap stocks, and these factors are again not those in popular models. Overall, only 6 factors are ever selected in any of the periods: mkt (market excess return), aeavol (abnormal earnings announcement volume), chmom (change in 6-month momentum), ear (earnings announcement return), pchsale_pchrect (change in sales - change in A/R) and sue (unexpected quarterly earnings). From these, only 3 have a marginal posterior probability higher than 0.5: mkt, aeavol, and ear.

4.2. Portfolios as Test Assets

For portfolios of stocks, we test the whole sample period from 1980 to 2016 because there is no survivorship bias. The best model for each set of portfolios and the associated posterior probabilities are reported in Table 7. Several interesting results are reported as follows.

First, when portfolios are formed on firm characteristics, factors related to these characteristics are included in the best models. For example, the best model to explain portfolios formed on size includes mve_ia (industry-adjusted size); for portfolios formed on book-to-market, the bm factor is included; for portfolios formed on operating profitability, roic (return on invested capital), which is highly correlated with the factor formed on roe (return on equity), is included, and so on. This pattern also holds for portfolios formed on bivariate sorts. For example, the 25 Fama-French portfolios formed on size and book-to-market require a size factor (mve_ia) and lev (leverage, which has almost 0.70 correlation with the bm factor).

The pattern of dependence between the variable used for portfolio formation and the selected factors reflects the concerns expressed by Lo & Mackinlay (1990), Ferson *et al.* (1999), Berk (2000), Roll (1977) and Lewellen *et al.* (2010). The selected models appear to be incorrectly promising because none of the high posterior probability models include the intercept even for the long testing period, i.e, 444 monthly data.

Second, model uncertainty increases for the portfolios and varies significantly across the different sets of factors. The posterior probabilities of the best models varies from 0.10 for the portfolios formed on long-term reversal to 0.57 for the portfolios formed on operating profitability. For the double-sorted portfolios, the posterior probabilities of the best models are close to 0.2. Even for the portfolios formed on characteristics related to widely used factor models, the best models also include factors other then the firm characteristics that are used to form portfolios, for example, Fama & French (2015), Hou *et al.* (2015a), and others.

The model uncertainty indicates that sorting stocks using one or two firm characteristics does not completely remove the effects of other firm characteristics. For example, the returns of portfolios formed on the book-to-market ratios are explained by idiosyncratic volatility and leverage. If firm characteristics are not correlated, then portfolios formed on one firm characteristic should not be explained by factors formed on other firm characteristics. The model uncertainty confirms the problems raised by Fama & French (2008), *i.e.* forming portfolios based on one or more firm characteristics does not guarantee that these portfolios are not affected by other firm characteristics although sorts of returns on firm characteristics give use a simple picture of how average returns vary across these firm characteristics.

Third, once again, the one most important factor is invariably the market factor. In untabulated results, we calculate the average posterior probability of all factors across all sets of portfolios, and find that the only factor with an average posterior probability higher than 0.5 is the excess market return, which is consistent with the results we obtained using individual stocks.

One set of portfolios for which the results may not be as biased is the set of industry portfolios. We find that the results for the 49 industry portfolios support a five-factor model with the market factor, beta, illiquidity, leverage and organizational capital. Organizational capital represents selling, general and administrative expenses which is a distinct factor that can only be found in the sector portfolios[24].

[24] See Eisfeldt & Papanikolaou (2013).

Overall, these results show data mining when portfolios formed on firm characteristics are used to test pricing factors, a typical approach followed in many previous studies. As an additional test, we apply the Bayesian variable selection method to a larger set of portfolios, *i.e.* 751 portfolios consisting of all available decile portfolios that are used to create the candidate factors as described in Section 3.1 as well as the 49 industry portfolios. The best model (refer to line "Decile Portfolios + Industries " of Table 7) is a 9-factor model including the 5 factors required for the industry portfolios, with the addition of factors formed on chinv (change in inventory), depr (depreciation), mom12m (12-month momentum), ms (Mohanram (2005a)'s score), and tang (Debt capacity/firm tangibility). This model, however, has a relatively low posterior probability of 0.20.

In summary, we interpret the evidence in this section as strongly supportive of the case to use individual stocks instead of portfolios formed on firm characteristics.

[Table 7 about here.]

4.3. Robustness of Results

One potential concern with the Bayesian approach is that the results might be sensitive to the choice of the prior distributions. The main results reported so far have been obtained using an empirical Bayes prior for the factor sensitivities $\tilde{\boldsymbol{\beta}}$, *i.e.* we centered each $\boldsymbol{\beta}_i$ around their OLS estimate: $\boldsymbol{\beta}_i \sim N((\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{r}_i, c\sigma_i^2(\mathbf{X}'\mathbf{X})^{-1})$, using $c = 1$. In this section, we investigate whether our results are sensitive to this prior specification. The first test we conduct is to make the empirical Bayes prior less informative, by using $c = 5$ instead of $c = 1$. We then change the form of the prior and use a prior centered on zeros: $\tilde{\boldsymbol{\beta}} \sim N(\mathbf{0}, c\mathbf{I})$, where again we consider the cases $c = 1$ and $c = 5$. The prior centered on zeros reflects a complete lack of knowledge regarding the factor sensitivities. Overall, we find small differences in factor selection in all our robustness tests. The tables are included in Appendix C.

For individual stocks, we report robustness results for non-microcap stocks using the three sub-sample periods[25]. Table C.1 reports the results using the empirical Bayes prior with $c = 5$. The results are almost identical to the ones obtained with $c = 1$, reported previously in Table 3. The results using the prior centered on zeros with $c = 1$ and $c = 5$ are reported in Tables C.2 and C.3, respectively. The

[25]The results using five sub-sample periods and the results for microcap stocks do not change our conclusions and are available from the authors upon request.

differences are negligible compared with the results in Table 3 and do not change any of our conclusions.

We repeat the robustness exercise using portfolios as test assets. Table C.4 reports results for the same sets of portfolios reported in Table 7, but using the empirical Bayes prior with $c = 5$. The results are largely similar, although in most cases, the best model includes fewer factors compared to the results obtained with $c = 1$. Model uncertainty decreases in the sense that the best models have higher posterior probabilities. This reflects the fact that, as the priors of the regression coefficients become more diffuse, fewer factors are selected, increasing model probabilities. In a few cases, some factors are dropped and others are included, but similar patterns still hold, *i.e.* factors related to the characteristics used for portfolio formation remain in the model.

Tables C.5 and C.6 report the results using the prior centered on zeros, with $c = 1$ and $c = 5$, respectively. There is substantially less model uncertainty under these priors, and for several of the portfolios based on univariate sorts, the best models include only the market factor. Nevertheless, the same pattern of dependence between portfolio formation criteria and factor selection is present, especially for the portfolios formed on bivariate sorts. The results with industry portfolio and the extended set of 751 portfolios are also quite similar.

Overall, we conclude that our results are not sensitive to the prior specification, particularly for individual stocks, where we find virtually identical results.

4.4. Comparison with Other Studies

Although there have been several studies that apply a Bayesian approach to asset pricing, comparison is challenging due to the differences in data, both in terms of factors as well as test assets. The most important difference/contribution from previous studies that use a Bayesian variable selection procedure to identify asset pricing factors (Ericsson & Karlsson (2003), Ouysse & Kohn (2010), Puelz *et al.* (2017)), is that we apply our method to thousands of individual stocks rather than portfolios. Another relevant difference is the tradable factors based on cross-sectional return patterns reported in the literature. Studies such as Ericsson & Karlsson (2003) and Ouysse & Kohn (2010) test macroeconomic factors. Our set of candidate factors is also much larger.

Our tests using a large collection of portfolios reveal a strong pattern of dependence between the portfolio formation criteria and the selected factors, confirming skepticism in interpreting results of studies when the candidate factors are tested using portfolios that are related to these factors. Our results using a set of 49 industry portfolios (which are not directly formed based on sorting accounting or return characteristics) suggest a model which includes, in addition to the market factor, factors related to beta, illiquidity, leverage, and organizational capital. In comparison, *e.g.* Ericsson & Karlsson (2003)'s results using 10 industry portfolios support the Carhart model with the addition of macroeconomic factors (credit risk spread and industrial production). For portfolios formed on size and book-to-market ratio, our results are comparable to Puelz *et al.* (2017) and Ericsson & Karlsson (2003), but not surprisingly they favor model which include factors correlated with size and book-to-market, with the addition of illiquidity in our case.

Recently, Barillas & Shanken (2017) developed a Bayesian asset pricing test which can be calculated in closed form and, in principle, be used to test all possible models using a set of candidate factors. However, as argued before, their test is not feasible when the number of factors increases more than 25 or 30. In their empirical tests, the authors consider only 10 factors, *i.e.* the factors in FF5, HXZ, as well as a different version of HML proposed by Asness & Frazzini (2013) and momentum. Their tests, conducted on the factors themselves and on sets of portfolios formed on either size and momentum or book-to-market and investment, support a six-factor model with the market return, the HXZ versions of investment (IA) and profitability (ROE), the FF5 version of size (SMB), the modified HML factor from Asness & Frazzini (2013), and the momentum factor. These results are not unexpected, as the portfolios are related to the factors.

Since we build tradable factors based on the characteristics studied by Green *et al.* (2017), it is interesting to compare our results with theirs. They identify 9 characteristics for non-microcap stocks[26]. The only commonalities are earnings announcement return and 1-month momentum, while we also find that change in 6-month momentum, market value of equity, and unexpected quarterly earnings are important factors, for some periods. When they include microcaps, 3 additional characteristics (book-to-market, change in 6-month momentum, and zero trading days) are also significant. There are similarities with our results, as we find that change in the number of analysts, earnings announcement, and change in 6-month momentum are important factors to explain microcap stocks. However, our results suggest that these factors are not consistently selected in different subsample periods. Also, similarly to Green *et al.* (2017), we find that the factors

[26]These are cash, change in the number of analysts, earnings announcement return, one-month momentum, the number of consecutive quarters with an increase in earnings over the same quarter a year ago, annual R&D to market cap, return volatility, share turnover, and volatility of share turnover.

from prominent models such as FF and HXZ are not relevant to explain individual stocks.

DeMiguel *et al.* (2017) also build factors based on the dataset of characteristics of Green *et al.* (2017). Their approach combines a LASSO factor selection stage with a subsequent bootstrap technique to determine which factors are significant in portfolio optimization when factors are added to a benchmark (market) portfolio. When no transaction costs are considered, they find that five characteristics are significant at the 5% level: unexpected quarterly earnings (sue), return volatility (retvol), asset growth (agr), 1-month momentum (mom1m), and gross profitability (gma). In contrast, only sue and mom1m are significant in our approach, and only during some periods. When they allow for transaction costs, 15 factors become significant, and the only factors among those which are significant in our approach is sue and industry sales concentration (herf). Thus the factors that appear significant in terms of portfolio optimization are quite different from those in our linear factor model approach.

Our work is also related to recent studies that test factors using procedures to directly account for data mining issues. For example, using a multiple testing framework based on a bootstrapping procedure with individual stocks, Harvey & Liu (2016) test a set of 14 factors that includes many of the ones in our study, and find evidence that the most important factor is, by far, the market return, with only a small role for the profitability factor. We note that, while Harvey & Liu (2016)'s approach and set of factors is quite different from ours, their conclusion regarding the importance of the market return for individual stocks is mirrored in our results.

5. Conclusion

The asset pricing literature has proposed hundreds of factors to explain asset returns, most within the last two decades. It is unlikely that so many factors matter to determine security prices; rather, some are likely to be redundant, while others (or even most) may be product of data mining. In this paper we propose a Bayesian variable selection methodology to explore the most promising factor models, given a set of candidate factors and a set of assets. The proposed methodology builds on the literature on Bayesian variable selection in multivariate regression models and provides a computationally feasible means of exploring model selection in large panels of data.

We apply the methodology to identify the most relevant factors to explain returns on individual stocks, as well as on an extensive set of portfolios. We consider a large set of 83 candidate factors, including 82 tradable factors based on various firm characteristics identified in the literature, as well as the market return suggested by Sharpe (1964).

Using individual stocks, we find that (i) the only factor that matters across all sub-sample periods is the market excess return; (ii) factor selection varies substantially over time, with no specific model dominating the others in the various sub-sample periods we investigate; (iii) other factors (in addition to the market return) which are selected for specific sub-sample periods are not the factors in widely used models such as the ones proposed by Fama & French (1992, 1996), Chen & Zhang (2010), Hou *et al.* (2015a) and Fama & French (2015). The additional factors that are selected in certain periods to explain individual stocks are related to other anomalies or characteristics such as short-term reversal, change in 6-month momentum, earnings announcement return, change in the number of analysts covering stocks, industry concentration, unexpected quarterly earnings, and industry-adjusted size; (iv) the total number of factors selected in these models over all sub-sample periods is small relative to the total number of candidate factors, *i.e.* only 10 factors (out of more than 80) are ever selected by the variable selection methodology, and from these, only 5 to 6 have a marginal posterior probability higher than 0.5; and (v) the factors that matter to explain microcap stocks include factors formed on change in six-month momentum, abnormal earnings announcement volume and change in number of analysts covering stock.

Our work builds on the literature on asset pricing factor selection, by showing that, despite the large number of factors that have been proposed, only a handful appear to explain the returns on individual stocks, with the market return remaining the most important factor. We leave for future research refinements of the model to allow even more efficient exploration of the model space when the numbers of factors and assets are large.

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Figure 1: **Histogram of absolute pairwise factor correlations**

The figure plots the distribution of the pairwise absolute correlations of 83 factors, including 82 factors formed on firm characteristics obtained following Green *et al.* (2017), and the market excess return.

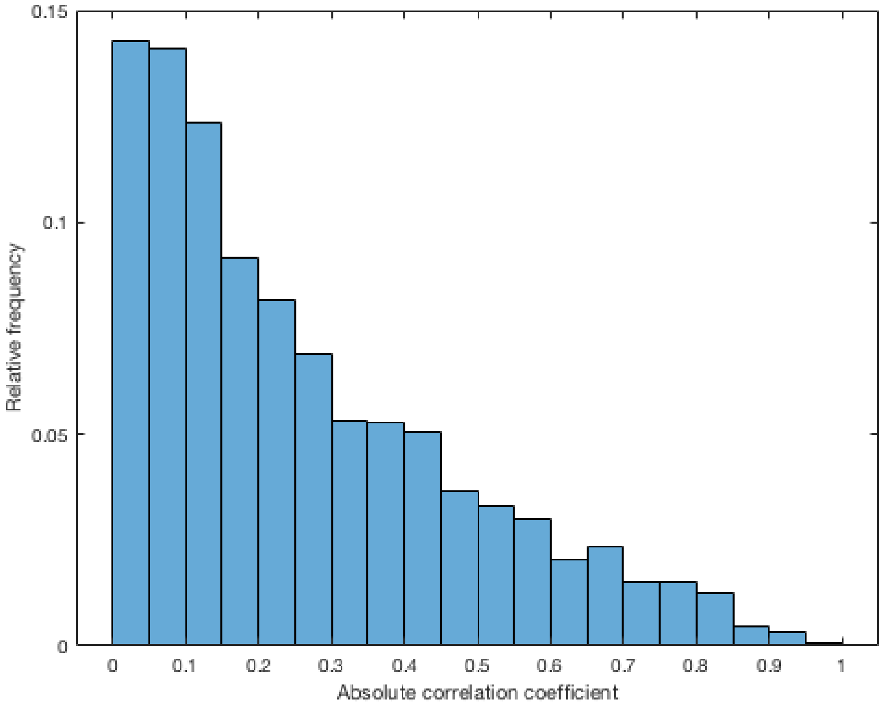

Table 1: Statistics of Candidate Factors

The 82 factors are constructed from value-weighted portfolios sorting all non-microcap stocks into deciles based on the characteristics of Green *et al.* (2017). The factor returns are calculated as the difference between the top and bottom deciles. We also report statistics for the market excess return, calculated as the excess return on the market, value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 at the beginning of month t, minus the one-month Treasury bill rate. The table reports the first date at which the factor has been calculated, the total number of months, the average monthly return, the standard deviation, and the t-statistic. An */bold line denotes a Dependent False Discovery Rate (DFDR) p-value lower than 0.05, calculated using the method of Benjamini & Yekutieli (2001).

Factor	First Date	#Months	Average Return	Standard Deviation	Tstat	Factor	First Date	#Months	Average Return	Standard Deviation	Tstat
mkt	198001	444	0.65%	4.46%	3.05	lev	198001	444	0.27%	4.47%	1.29
absacc	198001	444	0.06%	3.58%	0.33	mom12m	198001	444	0.68%	7.40%	1.93
acc	**198001**	**444**	**-0.45%**	**2.61%**	**-3.61***	mom1m	198001	444	-0.27%	5.39%	-1.06
aeavol	198001	444	0.00%	2.69%	0.00	mom36m	198001	444	-0.58%	5.22%	-2.35
age	198001	444	0.04%	4.46%	0.20	ms	198001	444	0.16%	3.25%	1.02
agr	198001	444	-0.45%	3.30%	-2.90	mve	198001	444	-0.52%	4.68%	-2.36
baspread	198001	444	-0.10%	8.25%	-0.26	mve_ia	198001	444	-0.16%	3.22%	-1.06
beta	198001	444	-0.06%	8.79%	-0.14	**nanalyst**	**200707**	**114**	**-0.91%**	**2.27%**	**-4.26***
bm	198001	444	0.44%	4.46%	2.09	operprof	198001	444	0.36%	2.98%	2.52
bm_ia	198001	444	0.29%	4.44%	1.38	orgcap	198001	444	0.58%	5.29%	2.32
cash	198001	444	0.27%	4.68%	1.23	pchcapx_ia	198001	444	-0.13%	3.80%	-0.74
cashdebt	198001	444	0.11%	3.42%	0.71	pchcurrat	198001	444	-0.22%	1.74%	-2.67
cashpr	198001	444	-0.40%	3.38%	-2.47	pchdepr	198001	444	0.16%	2.34%	1.42
cfp	198001	444	0.47%	4.90%	2.01	pchgm_pchsale	198001	444	0.20%	2.36%	1.78
cfp_ia	198001	444	-0.05%	4.27%	-0.24	pchsaleinv	198001	444	0.20%	2.34%	1.83
chatoia	198001	444	0.34%	2.52%	2.85	pchsale_pchinvt	198001	444	0.17%	2.29%	1.58
chcsho	**198001**	**444**	**-0.51%**	**3.01%**	**-3.54***	pchsale_pchrect	198001	444	0.08%	2.10%	0.77
chempia	198001	444	0.00%	2.97%	0.02	pchsale_pchxsga	198001	444	-0.14%	2.83%	-1.06
chfeps	198901	336	0.25%	3.73%	1.23	pctacc	198001	444	-0.17%	2.74%	-1.28
chinv	**198001**	**444**	**-0.57%**	**2.98%**	**-4.05***	pricedelay	198001	444	0.04%	2.59%	0.31
chmom	198001	444	-0.49%	4.64%	-2.23	ps	198001	444	0.49%	4.24%	2.42
chnanalyst	198904	333	-0.02%	2.20%	-0.20	realestate	198501	384	0.26%	4.57%	1.12
chpmia	198001	444	-0.17%	3.55%	-1.02	retvol	198001	444	-0.31%	7.78%	-0.83
chtx	198001	444	0.18%	3.15%	1.18	roaq	198001	444	0.37%	4.17%	1.87
cinvest	198001	444	0.07%	2.09%	0.66	roavol	198001	444	-0.18%	4.49%	-0.86
currat	198001	444	-0.14%	4.59%	-0.64	roeq	198001	444	0.34%	4.34%	1.63
depr	198001	444	0.06%	5.20%	0.23	roic	198001	444	0.35%	3.98%	1.84
disp	198901	336	-0.35%	5.00%	-1.30	rsup	198001	444	-0.23%	3.53%	-1.40
ear	198001	444	0.32%	2.33%	2.93	salecash	198001	444	-0.04%	4.26%	-0.20
egr	198001	444	-0.43%	3.18%	-2.84	saleinv	198001	444	0.25%	2.95%	1.80
ep	198001	444	0.29%	5.41%	1.14	salerec	198001	444	0.44%	3.51%	2.63
fgr5yr	198901	336	0.15%	6.59%	0.43	**sfe**	**198901**	**336**	**-1.06%**	**4.88%**	**-3.99***
gma	198001	444	0.17%	3.21%	1.11	sgr	198001	444	-0.15%	3.66%	-0.86
grcapx	198001	444	-0.37%	2.88%	-2.70	sp	198001	444	0.44%	4.25%	2.17
grltnoa	198001	444	-0.42%	2.76%	-3.20	stdcf	198001	444	-0.28%	4.12%	-1.42
herf	200001	204	-0.11%	4.29%	-0.38	std_dolvol	198001	444	0.24%	3.19%	1.57
hire	198001	444	-0.34%	3.33%	-2.12	std_turn	198001	444	0.00%	5.50%	0.00
idiovol	198001	444	-0.21%	7.82%	-0.56	sue	198001	444	0.41%	3.34%	2.57
ill	198001	444	0.31%	3.78%	1.70	tang	198001	444	0.17%	3.89%	0.94
indmom	199408	269	0.26%	6.80%	0.63	tb	198001	444	0.10%	2.69%	0.81
invest	**198001**	**444**	**-0.54%**	**3.08%**	**-3.68***	turn	198001	444	-0.10%	5.78%	-0.38
						zerotrade	198001	444	0.07%	5.53%	0.26

Table 2: Statistics of Factor Correlations

The table reports summary statistics of the pairwise absolute correlations of a set of 83 factors, including 82 factors on firm characteristics and the market excess return.

Statistics of (absolute) correlations among candidate factors								
# Factors	**# correlations**	**Min**	**10th percentile**	**25th percentile**	**Median**	**75th percentile**	**90th percentile**	**Maximum**
83	3403	0.000	0.033	0.081	0.179	0.333	0.498	0.971
10 highest absolute correlations								
ill_mve	0.971							
turn_zerotrade	0.963							
baspread_retvol	0.960							
pchsaleinv_pchsale_pchinvt	0.934							
baspread_beta	0.895							
beta_retvol	0.880							
roaq_roeq	0.877							
cashdebt_roic	0.877							
idiovol_std_turn	0.874							
baspread_idiovol	0.869							

Table 3: Posterior model probabilities for non-microcap stocks, 3 sub-sample periods, empirical Bayes prior with $c = 1$

We apply the Bayesian variable selection method to all non-microcap stocks in each sub-sample period and report the models with the highest posterior probability. The set of candidate factors includes all available factors in each sub-sample period. The prior for the factor sensitivities is an empirical Bayes prior centered on OLS factor sensitivities, *i.e.* we set $\boldsymbol{\beta}_i \sim N((\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{r}_i, c\sigma_i^2(\mathbf{X}'\mathbf{X})^{-1})$, with $c = 1$.

Panel A. January 1980 - December 1991, # stocks = 807, # factors =75

Model	**# Factors**	**Posterior probability**
mkt, chmom	2	0.24
mkt, mom1m	2	0.16
mkt, mom1m, ms	3	0.16
mkt	1	0.08
mkt, chmom, ms	3	0.08
mkt, chmom, mom1m	3	0.08
mkt, chmom, mom1m, ms	4	0.08
mkt, ep	2	0.04
mkt, ep, ms	3	0.04
mkt, chmom, tb	3	0.04

Factors with marginal posterior probability > 0: mkt, chmom, ep, mom1m, ms, tb
Factors with marginal posterior probability > 0.5: mkt, chmom

Panel B. January 1992 - December 2003, # stocks = 893, # factors = 81

Model	**# Factors**	**Posterior probability**
mkt	1	0.64
mkt,aeavol	2	0.32
mkt,aeavol,pctacc	3	0.04

Factors with marginal posterior probability > 0: mkt, aeavol, pctacc
Factors with marginal posterior probability > 0.5: mkt

Panel C. January 2004 - December 2016, # stocks = 967, # factors = 83

Model	**# Factors**	**Posterior probability**
intercept,mkt,herf,mom1m	4	0.24
mkt,chnanalyst,herf,mom1m	4	0.2
mkt,mom1m	2	0.08
intercept,mkt,herf,mom1m,saleinv	5	0.08
intercept,mkt,chnanalyst,herf,mom1m	5	0.08
mkt,herf,mom1m	3	0.04
mkt,ear,herf,mom1m	4	0.04
mkt,chnanalyst,herf,mom1m,ms	5	0.04
mkt,chnanalyst,ear,herf,mom1m	5	0.04
intercept,mkt,herf,mom1m,ms	5	0.04
intercept,mkt,chnanalyst,herf,mom1m,saleinv	6	0.04
intercept,mkt,chnanalyst,herf,mom1m,ms	6	0.04
intercept,mkt,chnanalyst,ear,herf,mom1m,saleinv	7	0.04

Factors with marginal posterior probability > 0: intercept, mkt, chnanalyst, ear, herf, mom1m, ms, saleinv
Factors with marginal posterior probability > 0.5: intercept, mkt, herf

Table 4: Posterior model probabilities for non-microcap stocks, 5 sub-sample periods, empirical Bayes prior with $c = 1$

We apply the Bayesian variable selection method to all non-microcap stocks in each sub-sample period and report the models with the highest posterior probability. The set of candidate factors includes all significant factors in Green *et al.* (2017) in addition to the intercept and the excess market return. The prior for the factor sensitivities is an empirical Bayes prior centered on OLS factor sensitivities, *i.e.* we set $\boldsymbol{\beta}_i \sim N((\mathbf{X'X})^{-1}\mathbf{X'r}_i, c\sigma_i^2(\mathbf{X'X})^{-1})$, with $c = 1$.

Panel A. January 1980 - June 1987, # stocks = 1,014, # factors = 44

Model	**# Factors**	**Posterior probability**
mkt, chmom	2	1

Factors with marginal posterior probability > 0: mkt, chmom
Factors with marginal posterior probability > 0.5: mkt, chmom

Panel B. July 1987 - December 1994, # stocks = 1,114, # factors = 44

Model	**# Factors**	**Posterior probability**
mkt, chmom, ear, mom1m	4	0.8
mkt, chmom, ear	3	0.2

Factors with marginal posterior probability > 0: mkt, chmom, ear, mom1m
Factors with marginal posterior probability > 0.5: mkt, chmom, ear, mom1m

Panel C. January 1995 - June 2002, # stocks = 1,112, # factors = 48

Model	**# Factors**	**Posterior probability**
mkt	1	0.44
mkt, pctacc	2	0.16
mkt, mom1m	2	0.12
mkt, mom1m, pctacc	3	0.08
mkt, aeavol	2	0.08

Factors with marginal posterior probability > 0: mkt, aeavol, mom1m, pctacc
Factors with marginal posterior probability > 0.5: mkt

Panel D. July 2002 - December 2009, # stocks = 1,296, # factors = 48

Model	**# Factors**	**Posterior probability**
mkt, sue	2	0.44
mkt, bm	2	0.16
mkt, bm, sue	3	0.16
mkt	1	0.08
mkt, pchsale_pchrect	2	0.08

Factors with marginal posterior probability > 0: mkt, bm, pchsale_pchrect, sue
Factors with marginal posterior probability > 0.5: mkt, sue

Panel E. January 2010 - December 2016, # stocks = 1,225, # factors = 49

Model	**# Factors**	**Posterior probability**
mkt, mom1m, mve_ia	3	0.36
mkt, mve_ia	2	0.28
mkt, mom1m, mve_ia, sue	4	0.24
mkt, mve_ia, sue	3	0.08
mkt, mom1m, sue	3	0.04

Factors with marginal posterior probability > 0: mkt, mom1m, mve_ia, sue
Factors with marginal posterior probability > 0.5: mkt, mom1m, mve_ia

Table 5: Posterior model probabilities for microcap stocks, 3 sub-sample periods, empirical Bayes prior with $c = 1$

We apply the Bayesian variable selection method to all microcap stocks in each sub-sample period and report the models with the highest posterior probability. The set of candidate factors includes all available factors in each sub-sample period. The prior for the factor sensitivities is an empirical Bayes prior centered on OLS factor sensitivities, *i.e.* we set $\boldsymbol{\beta}_i \sim N((\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{r}_i, c\sigma_i^2(\mathbf{X}'\mathbf{X})^{-1})$, with $c = 1$.

Panel A. January 1980 - December 1991, # stocks = 580, # factors =75

Model	**# Factors**	**Posterior probability**
mkt, ear	2	1.00

Factors with marginal posterior probability > 0: mkt, ear
Factors with marginal posterior probability > 0.5: mkt, ear

Panel B. January 1992 - December 2003, # stocks = 573, # factors = 81

Model	**# Factors**	**Posterior probability**
mkt	1	0.84
mkt, aeavol	2	0.16

Factors with marginal posterior probability > 0: mkt, aeavol
Factors with marginal posterior probability > 0.5: mkt

Panel C. January 2004 - December 2016, # stocks = 794, # factors = 83

Model	**# Factors**	**Posterior probability**
mkt	1	0.92
mkt, ear	2	0.04
mkt, chnanalyst	2	0.04

Factors with marginal posterior probability > 0: mkt, aeavol, chnanalyst
Factors with marginal posterior probability > 0.5: mkt

Table 6: Posterior model probabilities for microcap stocks, 5 sub-sample periods, empirical Bayes prior with $c = 1$

We apply the Bayesian variable selection method to all microcap stocks in each sub-sample period and report the models with the highest posterior probability. The set of candidate factors includes all significant factors in Green *et al.* (2017) in addition to the intercept and the excess market return. The prior for the factor sensitivities is an empirical Bayes prior centered on OLS factor sensitivities, *i.e.* we set $\boldsymbol{\beta}_i \sim N((\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{r}_i, c\sigma_i^2(\mathbf{X}'\mathbf{X})^{-1})$, with $c = 1$.

Panel A. January 1980 - June 1987, # stocks = 868, # factors = 44

Model	**# Factors**	**Posterior probability**
mkt	1	0.44
mkt, aeavol	2	0.40
mkt, chmom	2	0.12
mkt, aeavol, chmom	3	0.04

Factors with marginal posterior probability > 0: mkt, aeavol, chmom
Factors with marginal posterior probability > 0.5: mkt

Panel B. July 1987 - December 1994, # stocks = 1,138, # factors = 44

Model	**# Factors**	**Posterior probability**
mkt, ear	2	1.00

Factors with marginal posterior probability > 0: mkt, ear
Factors with marginal posterior probability > 0.5: mkt, ear

Panel C. January 1995 - June 2002, # stocks = 1,289, # factors = 48

Model	**# Factors**	**Posterior probability**
aeavol	1	0.48
aeavol, chnanalyst	2	0.40
mkt, aeavol	2	0.04
mkt, aeavol, chnanalyst	3	0.04

Factors with marginal posterior probability > 0: mkt, aeavol, chnanalyst
Factors with marginal posterior probability > 0.5: aeavol

Panel D. July 2002 - December 2009, # stocks = 1,119, # factors = 48

Model	**# Factors**	**Posterior probability**
mkt, pchsale_pchrect	2	0.44
mkt	1	0.40
mkt, sue	2	0.12
mkt, pchsale_pchrect, sue	3	0.04

Factors with marginal posterior probability > 0: mkt, pchsale_pchrect, sue
Factors with marginal posterior probability > 0.5: mkt

Panel E. January 2010 - December 2016, # stocks = 1,058, # factors = 49

Model	**# Factors**	**Posterior probability**
mkt	1	1.00

Factors with marginal posterior probability > 0: mkt
Factors with marginal posterior probability > 0.5: mkt

Table 7: Highest posterior probability models for sets of portfolios, 1980-2016, empirical Bayes prior with $c = 1$

We apply the Bayesian variable selection methodology to sets of portfolios formed according to various criteria, for the period 1980 to 2016. The table reports the best model, *i.e.* the model with highest posterior probability, the number of factors in the model, and the posterior probability. The prior for the factor sensitivities is an empirical Bayes prior centered on OLS factor sensitivities, *i.e.* we set $\boldsymbol{\beta}_i \sim N((\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{r}_i, c\sigma_i^2(\mathbf{X}'\mathbf{X})^{-1})$, with $c = 1$.

Portfolio formation	**# Portfolios**	**Best model**	**# Factors**	**Probability**
Univariate Sorts				
Size	10	mkt, ill, mve_ia, std_dolvol	4	0.21
Book-to-market	10	mkt, bm, idiovol, lev	4	0.31
Operating profitability	10	mkt, roavol, roic	3	0.57
Investment	10	mkt, agr, roavol, sgr	4	0.47
Earnings-to-price	10	mkt, age, ep, lev	4	0.32
Cashflow-to-price	10	mkt, age, ep, lev	4	0.33
Dividend Yield	10	mkt, age, beta, cashpr, salecash	5	0.13
Momentum	10	mkt, age, mom12m, roavol	4	0.20
Short-term reversal	10	mkt, mom1m, std_turn	3	0.54
Long-term reversal	10	mkt, lev, mom36m, std_turn	4	0.10
Beta	10	mkt, age, beta, idiovol	4	0.29
Variance	10	mkt, retvol, salecash, stdcf	4	0.18
Residual variance	10	mkt, idiovol, retvol, stdcf	4	0.30
Bivariate Sorts				
Size and book-to-market	25	mkt, ill, lev, mve_ia, roavol, std_dolvol	6	0.20
Size and operating profitability	25	mkt, age, idiovol, ill, mve_ia, roavol, std_dolvol, std_turn, zerotrade	9	0.20
Size and investing	25	mkt, beta, ill, mve_ia, sgr, stdcf	6	0.20
Book-to-market and operating profitability	25	mkt, baspread, beta, bm, cash, lev, retvol, roavol, salecash, stdcf	10	0.20
Book-to-market and investment	25	mkt, bm, lev	3	0.20
Operating profitability and investment	25	mkt, roic, std_turn, turn	4	0.20
Other Portfolios				
Industries	49	mkt, beta, ill, lev, orgcap	5	0.40
Decile Portfolios + Industries	751	mkt,beta,chinv,depr,ill,mom12m,ms,orgcap,tang	9	0.20

Appendix A. Bayesian Estimation of the SUR Model

This section details the estimation of SUR model using the Gibbs sampler. The SUR model with common regressors can be written as

$$\mathbf{r}_i = \mathbf{X}\boldsymbol{\beta}_i + \mathbf{e}_i, \qquad i = 1, \dots, N \tag{A.1}$$

where, for each equation $i = 1, \dots, N$, $\mathbf{r}_i$ is the $T \times 1$ vector of observed responses, $\mathbf{X}$ is the matrix of regressors with dimension $T \times K$, $\boldsymbol{\beta}_i = (\beta_{i,1}, \dots, \beta_{i,K})'$ is a $K \times 1$ vector of unknown regression coefficients and $\mathbf{e_i}$ is a $T \times 1$ vector of disturbances. The system can be stacked in a single equation $\tilde{\mathbf{r}} = \tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}} + \tilde{\mathbf{e}}$ in the following way (see *e.g.* Greene (2003)):

$$\begin{bmatrix} \mathbf{r}_1 \\ \mathbf{r}_2 \\ \vdots \\ \mathbf{r}_N \end{bmatrix} = \begin{bmatrix} \mathbf{X} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{X} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{X} \end{bmatrix} \begin{bmatrix} \boldsymbol{\beta}_1 \\ \boldsymbol{\beta}_2 \\ \vdots \\ \boldsymbol{\beta}_N \end{bmatrix} + \begin{bmatrix} \mathbf{e}_1 \\ \mathbf{e}_2 \\ \vdots \\ \mathbf{e}_N \end{bmatrix} \tag{A.2}$$

Letting $\tilde{\mathbf{e}} = (\mathbf{e}_1' \quad \mathbf{e}_2' \quad \dots \quad \mathbf{e}_N')'$, the basic assumption of the SUR model is $\mathbb{E}(\tilde{\mathbf{e}}\tilde{\mathbf{e}}') = \boldsymbol{\Omega} = \boldsymbol{\Sigma} \otimes \mathbf{I_T}$. We assume $\tilde{\mathbf{e}} \sim N(\mathbf{0}, \boldsymbol{\Sigma} \otimes \mathbf{I_T})$ and the following prior distributions for $\tilde{\boldsymbol{\beta}}$ and $\boldsymbol{\Sigma}$:

$$\begin{aligned} \tilde{\boldsymbol{\beta}} &\sim N(\mathbf{b}_0, \mathbf{B}_0) \\ \boldsymbol{\Sigma} &\sim IW(\nu_0, \boldsymbol{\Phi}_0). \end{aligned} \tag{A.3}$$

Proof of Lemma 1. The likelihood for the full system of equations is given by

$$L(\tilde{\boldsymbol{\beta}}, \boldsymbol{\Sigma}|\mathbf{X}, \mathbf{r}) = (2\pi)^{-\frac{NT}{2}} |\boldsymbol{\Omega}|^{-\frac{T}{2}} \exp\left(-\frac{1}{2}(\tilde{\mathbf{r}} - \tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}})'\boldsymbol{\Omega}^{-1}(\tilde{\mathbf{r}} - \tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}})\right). \tag{A.4}$$

Let $\boldsymbol{\Omega}^{-1} = \mathbf{P}'\mathbf{P}$ and define $\tilde{\mathbf{X}}^* = \mathbf{P}\mathbf{X}$, $\tilde{\mathbf{r}}^* = \mathbf{P}\tilde{\mathbf{r}}$. Then $\tilde{\mathbf{X}}'\boldsymbol{\Omega}^{-1}\tilde{\mathbf{X}} = \tilde{\mathbf{X}}^{*\prime}\tilde{\mathbf{X}}^*$ and $\tilde{\mathbf{X}}\boldsymbol{\Omega}^{-1}\tilde{\mathbf{r}} = \tilde{\mathbf{X}}^{*\prime}\tilde{\mathbf{r}}$ and we can write

$$L(\tilde{\boldsymbol{\beta}}, \boldsymbol{\Sigma}|\mathbf{X}, \mathbf{r}) \propto \exp\left(-\frac{1}{2}(\tilde{\mathbf{r}}^* - \tilde{\mathbf{X}}^*\tilde{\boldsymbol{\beta}})'(\tilde{\mathbf{r}}^* - \tilde{\mathbf{X}}^*\tilde{\boldsymbol{\beta}})\right). \tag{A.5}$$

Distribution of $\tilde{\boldsymbol{\beta}}|\boldsymbol{\Omega}, \tilde{\mathbf{r}}$

We will use the notation $f(\cdot)$ to denote a generic probability density function, and $f(\cdot|\cdot)$ to denote a conditional density. The prior for $\tilde{\boldsymbol{\beta}}$ is given by

$$f(\tilde{\boldsymbol{\beta}}|\boldsymbol{\Omega}) \propto \exp\left(-\frac{1}{2}(\tilde{\boldsymbol{\beta}} - \mathbf{b}_0)'\mathbf{B}_0^{-1}(\tilde{\boldsymbol{\beta}} - \mathbf{b}_0)\right), \tag{A.6}$$

where $\mathbf{b}_0, \mathbf{B}_0$ are known. Therefore the posterior conditional distribution of $\tilde{\boldsymbol{\beta}}|\boldsymbol{\Omega}, \tilde{\mathbf{r}}$ is

$$f(\tilde{\boldsymbol{\beta}}|\boldsymbol{\Omega}, \mathbf{r}) \propto f(\tilde{\boldsymbol{\beta}}|\boldsymbol{\Omega})L(\tilde{\boldsymbol{\beta}}, \boldsymbol{\Sigma}|\mathbf{X}, \tilde{\mathbf{r}})$$
$$\propto \exp\left(-\frac{1}{2}(\tilde{\boldsymbol{\beta}} - \mathbf{b}_0)'\mathbf{B}_0^{-1}(\tilde{\boldsymbol{\beta}} - \mathbf{b}_0)\right)\exp\left(-\frac{1}{2}(\tilde{\mathbf{r}}^* - \tilde{\mathbf{X}}^*\tilde{\boldsymbol{\beta}})'(\tilde{\mathbf{r}}^* - \tilde{\mathbf{X}}^*\tilde{\boldsymbol{\beta}})\right).$$

Expanding the products and collecting terms on $\boldsymbol{\beta}$, we have

$$f(\tilde{\boldsymbol{\beta}}|\boldsymbol{\Omega}, \mathbf{r}) \propto \exp\left(-\frac{1}{2}\left[\tilde{\boldsymbol{\beta}}'(\mathbf{B}_0^{-1} + \tilde{\mathbf{X}}^{*\prime}\tilde{\mathbf{X}}^*)\tilde{\boldsymbol{\beta}} - 2\tilde{\boldsymbol{\beta}}'(\mathbf{B}_0^{-1}\mathbf{b}_0 + \tilde{\mathbf{X}}^{*\prime}\tilde{\mathbf{r}}^*)\right]\right).$$

Letting $\mathbf{B}_1 = (\mathbf{B}_0^{-1} + \tilde{\mathbf{X}}^{*\prime}\tilde{\mathbf{X}}^*)^{-1}$ we obtain

$$f(\tilde{\boldsymbol{\beta}}|\boldsymbol{\Omega}, \mathbf{r}) \propto \exp\left(-\frac{1}{2}\left[\tilde{\boldsymbol{\beta}}'\mathbf{B}_1^{-1}\tilde{\boldsymbol{\beta}} - 2\tilde{\boldsymbol{\beta}}'(\mathbf{B}_0^{-1}\mathbf{b}_0 + \tilde{\mathbf{X}}^{*\prime}\tilde{\mathbf{r}}^*)\right]\right).$$

Finally, completing the quadratic form and letting

$$\mathbf{b}_1 = (\mathbf{B}_0^{-1} + \tilde{\mathbf{X}}'\boldsymbol{\Omega}^{-1}\tilde{\mathbf{X}})^{-1}(\mathbf{B}_0\mathbf{b}_0 + \tilde{\mathbf{X}}'\boldsymbol{\Omega}^{-1}\tilde{\mathbf{r}}),$$

we obtain

$$f(\tilde{\boldsymbol{\beta}}|\boldsymbol{\Omega}, \mathbf{r}) \propto \exp\left(-\frac{1}{2}\left[\left(\tilde{\boldsymbol{\beta}} - \mathbf{b}_1\right)'\mathbf{B}_1^{-1}\left(\tilde{\boldsymbol{\beta}} - \mathbf{b}_1\right)\right]\right),$$

therefore recognizing that $\tilde{\boldsymbol{\beta}}|\boldsymbol{\Omega}, \mathbf{r} \sim N(\mathbf{b}_1, \mathbf{B}_1)$.

Distribution of $\boldsymbol{\Sigma}|\tilde{\boldsymbol{\beta}}, \tilde{\mathbf{r}}$

Since $\boldsymbol{\Omega} = \boldsymbol{\Sigma} \otimes \mathbf{I}_T$, it suffices to derive the conditional distribution of $\boldsymbol{\Sigma}|\tilde{\boldsymbol{\beta}}, \tilde{\mathbf{r}}$. The prior for $\boldsymbol{\Sigma}$ is an inverted Whishart distribution with parameters ν_0 and $\boldsymbol{\Phi}_0$:

$$f(\boldsymbol{\Sigma}) \propto |\boldsymbol{\Sigma}|^{-\frac{\nu_0+N+1}{2}}\exp\left(-\frac{1}{2}\operatorname{Tr}\left(\boldsymbol{\Phi}_0\boldsymbol{\Sigma}^{-1}\right)\right).$$

To derive the posterior of $\boldsymbol{\Sigma}|\tilde{\boldsymbol{\beta}}, \tilde{\mathbf{r}}$, it is convenient to write the likelihood function in a different way, by arranging the system such that, instead of stacking all T observations for each equation, we will stack the N equations for each observation. For an arbitrary observation t, let $\mathbf{r}_t = (y_{t,1}, y_{t,2}, \ldots, y_{t,N})'$ denote the $N \times 1$ vector of observed responses, $\mathbf{x}_t = (x_{t,1}, x_{t,2}, \ldots, x_{t,K})'$ denote the $K \times 1$ vector of predictors, and $\mathbf{e}_t = (e_{t,1}, e_{t,2}, \ldots, e_{t,N})'$ denote the vector of error terms. Then we can write

$$\mathbf{r}'_t = \mathbf{x}'_t \begin{bmatrix} \boldsymbol{\beta}_1 & \boldsymbol{\beta}_2 & \cdots & \boldsymbol{\beta}_N \end{bmatrix} + \mathbf{e}'_t, \qquad t = 1, \ldots, T. \tag{A.7}$$

The SUR correlation structure now can be represented conveniently as $\mathbb{E}(\mathbf{e}_t\mathbf{e}'_t) = \boldsymbol{\Sigma}$. The likelihood at each observation is $L_t = (2\pi)^{-\frac{N}{2}} |\boldsymbol{\Sigma}|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}\mathbf{e}'_t\boldsymbol{\Sigma}^{-1}\mathbf{e}_t\right)$ and the full likelihood can be written as

$$\begin{aligned} L &= \prod_{t=1}^{T} L_t = (2\pi)^{-\frac{NT}{2}} |\boldsymbol{\Sigma}|^{-\frac{T}{2}} \exp\left(-\frac{1}{2}\sum_{t=1}^{T} \mathbf{e}'_t\boldsymbol{\Sigma}^{-1}\mathbf{e}_t\right) \\ &\propto |\boldsymbol{\Sigma}|^{-\frac{T}{2}} \exp\left(-\frac{1}{2}\,\mathrm{Tr}\,(\boldsymbol{\Sigma}^{-1}\mathbf{S})\right), \end{aligned} \tag{A.8}$$

where $\mathbf{S} = \sum_{t=1}^{T} \mathbf{e}_t\mathbf{e}'_t$ and we have used the fact that $\mathbf{e}'_t\boldsymbol{\Sigma}^{-1}\mathbf{e}_t$ is a scalar (thus equal to its trace), and the properties of the trace operator.

We can now write the conditional distribution $\boldsymbol{\Sigma}|\tilde{\boldsymbol{\beta}}, \tilde{\mathbf{r}}$ as follows:

$$\begin{aligned} f(\boldsymbol{\Sigma}|\tilde{\boldsymbol{\beta}}, \tilde{\mathbf{r}}) &\propto f(\boldsymbol{\Sigma})L(\boldsymbol{\Sigma}|\tilde{\boldsymbol{\beta}}, \tilde{\mathbf{r}}) \\ &\propto |\boldsymbol{\Sigma}|^{-\frac{\nu_0+N+1}{2}} \exp\left(-\frac{1}{2}\,\mathrm{Tr}\left(\boldsymbol{\Phi}_0\boldsymbol{\Sigma}^{-1}\right)\right) \times |\boldsymbol{\Sigma}|^{-\frac{T}{2}} \exp\left(-\frac{1}{2}\,\mathrm{Tr}\,(\boldsymbol{\Sigma}^{-1}\mathbf{S})\right) \\ &\propto |\boldsymbol{\Sigma}|^{-\frac{\nu_0+N+T+1}{2}} \exp\left(-\frac{1}{2}\,\mathrm{Tr}\left(\boldsymbol{\Sigma}^{-1}(\boldsymbol{\Phi}_0 + \mathbf{S}\right)\right), \end{aligned}$$

which establishes $\boldsymbol{\Sigma}|\tilde{\boldsymbol{\beta}}, \tilde{\mathbf{r}} \sim IW(\nu_0 + T, \boldsymbol{\Phi}_0 + \mathbf{S})$. □

Proof of Lemma 2. Recall that $\tilde{\mathbf{X}}$ has dimension $NT \times NK$ and $\boldsymbol{\Omega}$ has dimension $NT \times NT$. Therefore, for large panels (when N is large), the expressions above will require multiplication and inversion of large matrices. An alternative and quicker approach for large panels consists of sampling each $\boldsymbol{\beta}_i$ conditionally on the remaining $\boldsymbol{\beta}_j$, $j \neq i$ and $\boldsymbol{\Sigma}$. Let $\tilde{\boldsymbol{\beta}}_{-i}$ denote the full vector $\tilde{\boldsymbol{\beta}}$ with the entries corresponding to i removed. Assume that

$$\boldsymbol{\beta}_i|\tilde{\boldsymbol{\beta}}_{-i}, \boldsymbol{\Sigma} \sim N(\mathbf{b}_{0,i}, \mathbf{B}_{0,i}), \qquad i = 1, \ldots, N.$$

For simplicity, let's assume that $i = 1$, that is, we are interested in generating $\boldsymbol{\beta}_1|\tilde{\boldsymbol{\beta}}_{-1}, \boldsymbol{\Sigma}$. Partition the SUR system as follows:

$$\tilde{\mathbf{r}} = \begin{bmatrix} \mathbf{r}_1 \\ \mathbf{r}_{-1} \end{bmatrix}, \tilde{\boldsymbol{\beta}} = \begin{bmatrix} \tilde{\boldsymbol{\beta}}_1 \\ \tilde{\boldsymbol{\beta}}_{-1} \end{bmatrix}, \tilde{\mathbf{X}} = \begin{bmatrix} \mathbf{X} & \mathbf{0} \\ \mathbf{0} & \tilde{\mathbf{X}}_{-1} \end{bmatrix},$$

where $\tilde{\mathbf{X}}_{-1}$ collects the structure of $\tilde{\mathbf{X}}$ for the remaining $N-1$ equations. Then we can write

$$\begin{aligned}\tilde{\mathbf{r}} - \mathbf{X}\tilde{\boldsymbol{\beta}} &= \begin{bmatrix}\mathbf{r}_1 \\ \mathbf{r}_{-1}\end{bmatrix} - \begin{bmatrix}\mathbf{X} & \mathbf{0} \\ \mathbf{0} & \tilde{\mathbf{X}}_{-1}\end{bmatrix}\begin{bmatrix}\tilde{\boldsymbol{\beta}}_1 \\ \tilde{\boldsymbol{\beta}}_{-1}\end{bmatrix} \\ &= \begin{bmatrix}\tilde{\mathbf{r}}_1 - \mathbf{X}\tilde{\boldsymbol{\beta}}_1 \\ \tilde{\mathbf{r}}_{-1} - \tilde{\mathbf{X}}_{-1}\tilde{\boldsymbol{\beta}}_{-1}\end{bmatrix} \end{aligned} \tag{A.9}$$

Recall that $\boldsymbol{\Omega}^{-1} = \boldsymbol{\Sigma}^{-1} \otimes \mathbf{I}_T$ and let $\{\boldsymbol{\Sigma}^{-1}\}_{ij} = \sigma^{ij}$ denote element (i, j) of $\boldsymbol{\Sigma}^{-1}$. The corresponding partition of $\boldsymbol{\Omega}^{-1}$ is

$$\boldsymbol{\Omega}^{-1} = \left[\begin{array}{c|ccc}\sigma^{11}\mathbf{I} & \sigma^{12}\mathbf{I} & \cdots & \sigma^{1N}\mathbf{I} \\ \hline \sigma^{21}\mathbf{I} & \sigma^{22}\mathbf{I} & \cdots & \sigma^{2N}\mathbf{I} \\ \vdots & \vdots & \vdots & \vdots \\ \sigma^{N1}\mathbf{I} & \sigma^{N2} & \cdots & \sigma^{NN}\mathbf{I}\end{array}\right] = \begin{bmatrix}\sigma^{11}\mathbf{I} & \mathbf{A}_{-1} \\ \mathbf{A}'_{-1} & \boldsymbol{\Omega}^{-1}_{-1}\end{bmatrix}. \tag{A.10}$$

In the partition of $\boldsymbol{\Omega}^{-1}$ above, we note that $\sigma^{11}\mathbf{I}$ has dimension $T \times T$, $\mathbf{A}_{-1}$ has dimension $T \times (N-1)T$, and $\boldsymbol{\Omega}^{-1}_{-1}$ has dimension $(N-1)T \times (N-1)T$. Using (A.9) and (A.10) we can now write the weighted sum of residuals as follows.

$$(\tilde{\mathbf{r}} - \tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}})'\boldsymbol{\Omega}^{-1}(\tilde{\mathbf{r}} - \tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}}) =$$

$$\begin{bmatrix}(\mathbf{r}_1 - \mathbf{X}\boldsymbol{\beta}_1)' & (\tilde{\mathbf{r}}_{-1} - \tilde{\mathbf{X}}_{-1}\tilde{\boldsymbol{\beta}}_{-1})'\end{bmatrix}\begin{bmatrix}\sigma^{11}\mathbf{I} & \mathbf{A}_{-1} \\ \mathbf{A}'_{-1} & \boldsymbol{\Omega}^{-1}_{-1}\end{bmatrix}\begin{bmatrix}\mathbf{r}_1 - \mathbf{X}\boldsymbol{\beta}_1 \\ \tilde{\mathbf{r}}_{-1} - \tilde{\mathbf{X}}_{-1}\tilde{\boldsymbol{\beta}}_{-1}\end{bmatrix}$$

Expanding the right-hand side and collecting terms, we obtain

$$\begin{aligned}&(\tilde{\mathbf{r}} - \tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}})'\boldsymbol{\Omega}^{-1}(\tilde{\mathbf{r}} - \tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}}) = \\ &\sigma^{11}(\mathbf{r}_1 - \mathbf{X}\tilde{\boldsymbol{\beta}}_1)'(\mathbf{r}_1 - \mathbf{X}\tilde{\boldsymbol{\beta}}_1) + 2(\mathbf{r}_1 - \mathbf{X}\boldsymbol{\beta}_1)'\mathbf{A}_{-1}(\tilde{\mathbf{r}}_{-1} - \tilde{\mathbf{X}}_{-1}\tilde{\boldsymbol{\beta}}_{-1}) \\ &+ (\tilde{\mathbf{r}}_{-1} - \tilde{\mathbf{X}}_{-1}\tilde{\boldsymbol{\beta}}_{-1})'\boldsymbol{\Omega}^{-1}_{-1}(\mathbf{r}_1 - \mathbf{X}\boldsymbol{\beta}_1)\end{aligned} \tag{A.11}$$

Now the posterior of $\boldsymbol{\beta}_1|\tilde{\boldsymbol{\beta}}_{-1}, \boldsymbol{\Sigma}, \tilde{\mathbf{r}}$ can be calculated as

$$
\begin{aligned}
f(\boldsymbol{\beta}_1|\tilde{\boldsymbol{\beta}}_{-1},\boldsymbol{\Sigma},\tilde{\mathbf{r}}) &\propto \exp\left(-\frac{1}{2}(\boldsymbol{\beta}_1-\mathbf{b}_{0,1})'\mathbf{B}_{0,1}^{-1}(\boldsymbol{\beta}_1-\mathbf{b}_{0,1})\right)\\
&\quad\times\exp\left(-\frac{1}{2}(\tilde{\mathbf{r}}-\tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}})'\boldsymbol{\Omega}^{-1}(\tilde{\mathbf{r}}-\tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}})\right)\\
&\propto \exp\Big(-\frac{1}{2}\Big[(\boldsymbol{\beta}_1-\mathbf{b}_{0,1})'\mathbf{B}_{0,1}^{-1}(\boldsymbol{\beta}_1-\mathbf{b}_{0,1})\\
&\quad+\sigma^{11}(\mathbf{r}_1-\mathbf{X}\tilde{\boldsymbol{\beta}}_1)'(\mathbf{r}_1-\mathbf{X}\tilde{\boldsymbol{\beta}}_1)+2(\mathbf{r}_1-\mathbf{X}\boldsymbol{\beta}_1)'\mathbf{A}_{-1}(\tilde{\mathbf{r}}_{-1}-\tilde{\mathbf{X}}_{-1}\tilde{\boldsymbol{\beta}}_{-1})\\
&\quad+(\tilde{\mathbf{r}}_{-1}-\tilde{\mathbf{X}}_{-1}\tilde{\boldsymbol{\beta}}_{-1})'\boldsymbol{\Omega}_{-1}^{-1}(\mathbf{r}_1-\mathbf{X}\boldsymbol{\beta}_1)\Big]\Big),
\end{aligned}
$$

where we have substituted (A.11). Expanding the expression above and removing terms that are constant or do not depend on $\boldsymbol{\beta}_1$ yields:

$$
\begin{aligned}
f(\boldsymbol{\beta}_1|\tilde{\boldsymbol{\beta}}_{-1},\boldsymbol{\Sigma},\tilde{\mathbf{r}}) &\propto \exp\Big(-\frac{1}{2}\Big[\boldsymbol{\beta}_1'\mathbf{B}_{0,1}^{-1}\boldsymbol{\beta}_1-2\boldsymbol{\beta}_1'\mathbf{B}_{0,1}^{-1}\mathbf{b}_{0,1}+\sigma^{11}(\boldsymbol{\beta}_1'\mathbf{X}'\mathbf{X}\boldsymbol{\beta}_1\\
&- 2\mathbf{r}_1'\mathbf{X}\boldsymbol{\beta}_1)-2\boldsymbol{\beta}_1\mathbf{X}'\mathbf{A}_{-1}(\tilde{\mathbf{r}}_{-1}-\tilde{\mathbf{X}}_{-1}\tilde{\boldsymbol{\beta}}_{-1})\Big]\Big)\\
&\propto \exp\Big(-\frac{1}{2}\Big[\boldsymbol{\beta}_1'(\mathbf{B}_{0,1}^{-1}+\sigma^{11}\mathbf{X}'\mathbf{X})\boldsymbol{\beta}_1\\
&- 2\boldsymbol{\beta}_1'(\mathbf{B}_{0,1}^{-1}\mathbf{b}_{0,1}+\sigma^{11}\mathbf{X}'(\mathbf{r}_1-(\sigma^{11})^{-1}\mathbf{A}_{-1}(\tilde{\mathbf{r}}_{-1}-\tilde{\mathbf{X}}_{-1}\tilde{\boldsymbol{\beta}}_{-1})))\Big]\Big)
\end{aligned}
$$

Now letting:

$$
\begin{aligned}
\mathbf{r}_1^* &= \mathbf{r}_1-(\sigma^{11})^{-1}\mathbf{A}_{-1}(\tilde{\mathbf{r}}_{-1}-\tilde{\mathbf{X}}_{-1}\tilde{\boldsymbol{\beta}}_{-1})\\
\mathbf{B}_{1,1} &= (\mathbf{B}_{0,1}^{-1}+\sigma^{11}\mathbf{X}'\mathbf{X})^{-1}\\
\mathbf{b}_{1,1} &= (\mathbf{B}_{0,1}^{-1}+\sigma^{11}\mathbf{X}'\mathbf{X})^{-1}(\mathbf{B}_{0,1}^{-1}\mathbf{b}_{0,1}+\sigma^{11}\mathbf{X}'\mathbf{r}_1^*)
\end{aligned}
$$

and completing the squares, we obtain

$$
f(\boldsymbol{\beta}_1|\tilde{\boldsymbol{\beta}}_{-1},\boldsymbol{\Sigma},\tilde{\mathbf{r}}) \propto \exp\left(-\frac{1}{2}\,(\boldsymbol{\beta}_1'-\mathbf{b}_{1,1})'\,\mathbf{B}_{1,1}^{-1}\,(\boldsymbol{\beta}_1'-\mathbf{b}_{1,1})\right),
$$

therefore establishing $\boldsymbol{\beta}_1|\tilde{\boldsymbol{\beta}}_{-1},\boldsymbol{\Sigma},\tilde{\mathbf{r}} \sim N(\mathbf{b}_{1,1},\mathbf{B}_{1,1})$. More generally, we could have placed any of the equations in the first position in our partition, so it follows that $\boldsymbol{\beta}_i|\tilde{\boldsymbol{\beta}}_{-i},\boldsymbol{\Sigma},\tilde{\mathbf{r}} \sim N(\mathbf{b}_{1,i},\mathbf{B}_{1,i})$, with

$$
\begin{aligned}
\mathbf{r}_i^* &= \mathbf{r}_i-(\sigma^{ii})^{-1}\mathbf{A}_{-i}(\tilde{\mathbf{r}}_{-i}-\tilde{\mathbf{X}}_{-i}\tilde{\boldsymbol{\beta}}_{-i})\\
\mathbf{B}_{1,i} &= (\mathbf{B}_{0,i}^{-1}+\sigma^{ii}\mathbf{X}'\mathbf{X})^{-1}\\
\mathbf{b}_{1,i} &= (\mathbf{B}_{0,i}^{-1}+\sigma^{ii}\mathbf{X}'\mathbf{X})^{-1}(\mathbf{B}_{0,i}^{-1}\mathbf{b}_{0,i}+\sigma^{ii}\mathbf{X}'\mathbf{r}_i^*),
\end{aligned}
$$

where $\mathbf{A}_{-i}$ now is defined appropriately to contain the terms for $j \neq i$.

□

Note that $\mathbf{r}_i^*$ is the vector of responses for equation i, subtracted from a weighted average of the residuals from the remaining $N-1$ equations, where the weights depend on the elements of $\boldsymbol{\Sigma}^{-1}$. Thus, the posterior variance of $\boldsymbol{\beta}_1|\tilde{\boldsymbol{\beta}}_{-1}, \boldsymbol{\Sigma}, \tilde{\mathbf{r}}$ depends on the covariance of the residuals of the equations. If these are zero, that is, if the system is compose of actually unrelated regressions, then $\mathbf{r}_1^* = \mathbf{r}_1$ and the posterior covariance matrix reduces to the one that would be obtained for the single regression equation i, as one would expect.

Appendix B. Bayesian Variable Selection in SUR

This section derives the conditional distributions required for our variable selection methodology using the Gibbs sampler. Let $\mathbf{X}_\gamma$ represent the matrix $\mathbf{X}$ where each column has been multiplied by the corresponding γ_j. Then we can write the model with variable selection as $\mathbf{r}_i = \mathbf{X}_\gamma \boldsymbol{\beta}_i + \mathbf{e}_i, i = 1, \ldots, N$. Stacking the N equations, we can also represent the model as:

$$\begin{bmatrix} \mathbf{r}_1 \\ \mathbf{r}_2 \\ \vdots \\ \mathbf{r}_N \end{bmatrix} = \begin{bmatrix} \mathbf{X}_\gamma & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{X}_\gamma & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{X}_\gamma \end{bmatrix} \begin{bmatrix} \boldsymbol{\beta}_1 \\ \boldsymbol{\beta}_2 \\ \vdots \\ \boldsymbol{\beta}_N \end{bmatrix} + \begin{bmatrix} \mathbf{e}_1 \\ \mathbf{e}_2 \\ \vdots \\ \mathbf{e}_N \end{bmatrix}$$

or

$$\tilde{\mathbf{r}} = \tilde{\mathbf{X}}_\gamma \tilde{\boldsymbol{\beta}} + \tilde{\mathbf{e}}. \tag{B.1}$$

Proof of Proposition 1. Note that, conditional on $\boldsymbol{\gamma}$, the model reduces to a SUR with the corresponding predictors for which $\gamma_j = 1$. Therefore, we can apply the results of Lemma 1 for $\tilde{\boldsymbol{\beta}}|\boldsymbol{\Sigma}, \boldsymbol{\gamma}, \tilde{\mathbf{r}}$ and $\boldsymbol{\Sigma}|\tilde{\boldsymbol{\beta}}, \boldsymbol{\gamma}, \tilde{\mathbf{r}}$, substituting $\tilde{\mathbf{X}}$ by $\tilde{\mathbf{X}}_\gamma$.

Distribution of $\tilde{\boldsymbol{\beta}}|\boldsymbol{\Sigma}, \boldsymbol{\gamma}, \tilde{\mathbf{r}}$

Using the results from the previous section, treating $\boldsymbol{\Sigma}$ and $\boldsymbol{\gamma}$ as known, the posterior distribution of $\tilde{\boldsymbol{\beta}}|\boldsymbol{\Sigma}, \boldsymbol{\gamma}, \tilde{\mathbf{r}}$ is $N(\mathbf{b}_1, \mathbf{B}_1)$, where

$$\begin{aligned} \mathbf{b}_1 &= (\mathbf{B}_0^{-1} + \tilde{\mathbf{X}}_\gamma' \boldsymbol{\Omega}^{-1} \tilde{\mathbf{X}}_\gamma)^{-1} (\mathbf{B}_0 \mathbf{b}_0 + \tilde{\mathbf{X}}_\gamma' \boldsymbol{\Omega}^{-1} \tilde{\mathbf{r}}), \\ \mathbf{B}_1 &= (\mathbf{B}_0^{-1} + \tilde{\mathbf{X}}_\gamma' \boldsymbol{\Omega}^{-1} \tilde{\mathbf{X}}_\gamma)^{-1}. \end{aligned}$$

Distribution of $\boldsymbol{\Sigma}|\tilde{\boldsymbol{\beta}}, \boldsymbol{\gamma}, \tilde{\mathbf{r}}$

Using the results from the previous section, treating $\tilde{\boldsymbol{\beta}}$ and $\boldsymbol{\gamma}$ as known, we have $\boldsymbol{\Sigma}|\tilde{\boldsymbol{\beta}}, \boldsymbol{\gamma}, \tilde{\mathbf{r}} \sim IW(\nu_0 + T, \boldsymbol{\Phi}_0 + \mathbf{S}_\gamma)$, where $\mathbf{S}_\gamma$ is calculated using the residuals from equation (B.1).

Distribution of $\boldsymbol{\gamma}|\boldsymbol{\Sigma}, \tilde{\boldsymbol{\beta}}, \tilde{\mathbf{r}}$

The simplest approach to generate $\boldsymbol{\gamma}|\boldsymbol{\Sigma}, \tilde{\boldsymbol{\beta}}, \tilde{\mathbf{r}}$ is to use the Gibbs sampler to generate each value of $\boldsymbol{\gamma}$ component-wise, that is, we can generate each γ_j, conditionally on the remaining $\gamma_i, i \neq j$, which we denote as $\boldsymbol{\gamma}_{-j}$, $\boldsymbol{\Sigma}$, and $\tilde{\boldsymbol{\beta}}$. For a given j, denote by $L_{j,1} = L(\gamma_j = 1|\boldsymbol{\gamma}_{-j}, \boldsymbol{\Sigma}, \tilde{\boldsymbol{\beta}}, \tilde{\mathbf{r}})$ the likelihood function evaluated at $\gamma_j = 1$, considering $\boldsymbol{\gamma}_{-j}, \boldsymbol{\Sigma}$ and $\tilde{\boldsymbol{\beta}}$ known, and likewise by $L_{j,0} = L(\gamma_j = 0|\boldsymbol{\gamma}_{-j}, \boldsymbol{\Sigma}, \tilde{\boldsymbol{\beta}}, \tilde{\mathbf{r}})$ the likelihood evaluated at $\gamma_j = 0$. Then, using the fact that the prior distribution of the γ_j is $B(1, \pi_j)$, $j = 1, \ldots, N$, we have

$$P(\gamma_j = 1|\gamma_{-j}, \boldsymbol{\Sigma}, \tilde{\boldsymbol{\beta}}, \tilde{\mathbf{r}}) = \frac{\pi_j L_{j,1}}{\pi_j L_{j,1} + (1 - \pi_j) L_{j,0}}. \tag{B.2}$$

Let $\boldsymbol{\gamma}_j^1$ and $\boldsymbol{\gamma}_j^0$ represent the vector $\boldsymbol{\gamma}$ with the $j - th$ position fixed at 1 or 0, respectively. That is,

$$\begin{aligned} \boldsymbol{\gamma}_j^1 &= [\gamma_1, \cdots, \gamma_{j-1}, 1, \gamma_{j+1} \cdots \gamma_K]', \\ \boldsymbol{\gamma}_j^0 &= [\gamma_1, \cdots, \gamma_{j-1}, 0, \gamma_{j+1} \cdots \gamma_K]'. \end{aligned}$$

Further, let $\mathbf{e}_t^1$ and $\mathbf{e}_t^0$ represent the residuals, at observation t, if $\gamma_j = 1$ and if $\gamma_j = 0$, respectively. Let $\mathbf{S}_\gamma^1$ and $\mathbf{S}_\gamma^0$ represent the corresponding residual matrices. Then we can write, using (A.8):

$$\begin{aligned} L_{j,1} &= (2\pi)^{-\frac{NT}{2}} |\boldsymbol{\Sigma}|^{-\frac{T}{2}} \exp\left(-\frac{1}{2} \operatorname{Tr}(\boldsymbol{\Sigma}^{-1}\mathbf{S}_\gamma^1)\right) \\ L_{j,0} &= (2\pi)^{-\frac{NT}{2}} |\boldsymbol{\Sigma}|^{-\frac{T}{2}} \exp\left(-\frac{1}{2} \operatorname{Tr}(\boldsymbol{\Sigma}^{-1}\mathbf{S}_\gamma^0)\right) \end{aligned}$$

Substituting the above into (B.2), we get

$$\begin{aligned} P(\gamma_j = 1|\gamma_{-j}, \boldsymbol{\Sigma}, \tilde{\boldsymbol{\beta}}, \tilde{\mathbf{r}}) &= \frac{\pi_j \exp\left(-\frac{1}{2} \operatorname{Tr}(\boldsymbol{\Sigma}^{-1}\mathbf{S}_\gamma^1)\right)}{\pi_j \exp\left(-\frac{1}{2} \operatorname{Tr}(\boldsymbol{\Sigma}^{-1}\mathbf{S}_\gamma^1)\right) + (1 - \pi_j) \exp\left(-\frac{1}{2} \operatorname{Tr}(\boldsymbol{\Sigma}^{-1}\mathbf{S}_\gamma^0)\right)} \\ &= \left(1 + \frac{1 - \pi_j}{\pi_j} \exp\left[-\frac{1}{2} \operatorname{Tr}\left(\boldsymbol{\Sigma}^{-1}(\mathbf{S}_\gamma^1 - \mathbf{S}_\gamma^0)\right)\right]\right)^{-1}, \end{aligned} \tag{B.3}$$

where we have taken the inverse of the expression on the right-hand side twice. □

Proof of Proposition 2. We can also use the sequential generation of $\boldsymbol{\beta}_i, i = 1, \ldots, N$ as in Lemma 2. In this case, we rewrite the partition in equation (A.9) in terms of $\tilde{\mathbf{X}}_\gamma$ and define $\tilde{\mathbf{X}}_{\gamma,-i}$ as the matrix that collects the structure of $\tilde{\mathbf{X}}_\gamma$ for the remaining $N-1$ equations. Then, assuming $\boldsymbol{\gamma}$ known, we have $\boldsymbol{\beta}_i|\tilde{\boldsymbol{\beta}}_{-i}, \boldsymbol{\gamma}, \boldsymbol{\Sigma}, \tilde{\mathbf{r}} \sim N(\mathbf{b}_{1,i}, \mathbf{B}_{1,i})$, with

$$\begin{aligned}
\mathbf{r}_i^* &= \mathbf{r}_i - (\sigma^{ii})^{-1}\mathbf{A}_{-i}(\tilde{\mathbf{r}}_{-i} - \tilde{\mathbf{X}}_{\gamma,-i}\tilde{\boldsymbol{\beta}}_{-i}) \\
\mathbf{B}_{1,i} &= (\mathbf{B}_{0,i}^{-1} + \sigma^{ii}\mathbf{X}_\gamma'\mathbf{X}_\gamma)^{-1} \\
\mathbf{b}_{1,i} &= (\mathbf{B}_{0,i}^{-1} + \sigma^{ii}\mathbf{X}_\gamma'\mathbf{X}_\gamma)^{-1}(\mathbf{B}_{0,i}^{-1}\mathbf{b}_{0,i} + \sigma^{ii}\mathbf{X}'\mathbf{r}_i^*).
\end{aligned}$$

□

Appendix C. Robustness Results

[Table C.1 about here.]

[Table C.2 about here.]

[Table C.3 about here.]

[Table C.4 about here.]

[Table C.5 about here.]

[Table C.6 about here.]

Table C.1: Posterior model probabilities for non-microcap stocks, 3 sub-sample periods, empirical Bayes prior with $c = 5$

We apply the Bayesian variable selection method to all non-microcap stocks in each sub-sample period and report the models with the highest posterior probability. The set of candidate factors includes all available factors in each sub-sample period. The prior for the factor sensitivities is an empirical Bayes prior centered on OLS factor sensitivities, *i.e.* we set $\boldsymbol{\beta}_i \sim N((\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{r}_i, c\sigma_i^2(\mathbf{X}'\mathbf{X})^{-1})$, with $c = 5$.

Panel A. January 1980 - December 1991, # stocks = 807, # factors =75

Model	**# Factors**	**Posterior probability**
mkt, chmom	2	0.28
mkt	1	0.24
mkt, chmom, mom1m	3	0.24
mkt, ms	2	0.12
mkt, chmom, mom1m, ms	4	0.08
mkt, chmom, ep, mom1m	4	0.04

Factors with marginal posterior probability > 0: mkt, chmom, ep, mom1m, ms
Factors with marginal posterior probability > 0.5: mkt, chmom

Panel B. January 1992 - December 2003, # stocks = 893, # factors = 81

Model	**# Factors**	**Posterior probability**
mkt	1	0.72
mkt, aeavol	2	0.28

Factors with marginal posterior probability > 0: mkt, aeavol, pctacc
Factors with marginal posterior probability > 0.5: mkt

Panel C. January 2004 - December 2016, # stocks = 967, # factors = 83

Model	**# Factors**	**Posterior probability**
mkt, herf, mom1m	3	0.16
intercept, mkt, chnanalyst, herf, mom1m	5	0.16
mkt, ear, herf, mom1m	4	0.08
intercept, mkt, herf, mom1m, ms	5	0.08
mkt, mom1m, ms	3	0.04
mkt, herf, mom1m, ms, saleinv	5	0.04
mkt, ear, herf	3	0.04
mkt, chnanalyst, mom1m	3	0.04
mkt, chnanalyst, herf, mom1m	4	0.04
mkt, chnanalyst, herf, mom1m, saleinv	5	0.04
mkt, chnanalyst, ear, herf, mom1m	5	0.04
intercept, mkt, herf, mom1m	4	0.04
intercept, mkt, herf, mom1m, saleinv	5	0.04
intercept, mkt, herf, mom1m, ms, saleinv	6	0.04
intercept, mkt, chnanalyst, herf	4	0.04
intercept, mkt, chnanalyst, herf, saleinv	5	0.04
intercept, mkt, chnanalyst, herf, ms	5	0.04

Factors with marginal posterior probability > 0: intercept, mkt, chnanalyst, ear, herf, mom1m, ms, saleinv
Factors with marginal posterior probability > 0.5: mkt, herf, mom1m

Table C.2: Posterior model probabilities for non-microcap stocks, 3 sub-sample periods, prior centered on zeros with $c = 1$

We apply the Bayesian variable selection method to all non-microcap stocks in each sub-sample period and report the models with the highest posterior probability. The set of candidate factors includes all available factors in each sub-sample period. The prior for the factor sensitivities is centered on a vector of zeros, *i.e.* $\tilde{\boldsymbol{\beta}} \sim N(\mathbf{0}, c\mathbf{I})$ with $c = 1$.

Panel A. January 1980 - December 1991, # stocks = 807, # factors =75

Model	**# Factors**	**Posterior probability**
mkt, chmom	2	0.24
mkt	1	0.2
mkt, chmom, mom1m	3	0.2
mkt, ms	2	0.16
mkt, mom1m	2	0.12
mkt, mom1m, ms	3	0.04
mkt, chmom, ms	3	0.04

Factors with marginal posterior probability > 0: mkt, chmom, mom1m, ms
Factors with marginal posterior probability > 0.5: mkt

Panel B. January 1992 - December 2003, # stocks = 893, # factors = 81

Model	**# Factors**	**Posterior probability**
mkt	1	0.6
mkt, aeavol	2	0.32
mkt, pctacc	2	0.04
mkt, aeavol, pctacc	3	0.04

Factors with marginal posterior probability > 0: mkt, aeavol, pctacc
Factors with marginal posterior probability > 0.5: mkt

Panel C. January 2004 - December 2016, # stocks = 967, # factors = 83

Model	**# Factors**	**Posterior probability**
mkt, herf, mom1m	3	0.16
mkt, chnanalyst, herf, mom1m	4	0.12
intercept, mkt, herf, mom1m	4	0.12
mkt, chnanalyst, ear, herf, mom1m	5	0.08
intercept, mkt, chnanalyst, herf, mom1m	5	0.08
intercept, mkt, chnanalyst, herf, mom1m, saleinv	6	0.08
intercept, mkt, chnanalyst, herf, mom1m, ms, saleinv	7	0.08
mkt, herf, mom1m, saleinv	4	0.04
mkt, herf, mom1m, ms	4	0.04
mkt, ear, herf, mom1m	4	0.04
mkt, chnanalyst	2	0.04
mkt, chnanalyst, herf, ms	4	0.04
mkt, chnanalyst, ear, herf, mom1m, saleinv	6	0.04
intercept, mkt, herf, mom1m, saleinv	5	0.04

Factors with marginal posterior probability > 0: intercept, mkt, chnanalyst, ear, herf, mom1m, ms, saleinv
Factors with marginal posterior probability > 0.5: mkt, chnanalyst, herf, mom1m

Table C.3: Posterior model probabilities for non-microcap stocks, 3 sub-sample periods, prior centered on zeros with $c = 5$

We apply the Bayesian variable selection method to all non-microcap stocks in each sub-sample period and report the models with the highest posterior probability. The set of candidate factors includes all available factors in each sub-sample period. The prior for the factor sensitivities is centered on a vector of zeros, *i.e.* $\tilde{\boldsymbol{\beta}} \sim N(\mathbf{0}, c\mathbf{I})$ with $c = 5$.

Panel A. January 1980 - December 1991, # stocks = 807, # factors =75

Model	# Factors	Posterior probability
mkt, chmom, mom1m	3	0.32
mkt	1	0.2
mkt, chmom	2	0.2
mkt, ms	2	0.08
mkt, mom1m	2	0.04
mkt, mom1m, ms	3	0.04
mkt, ep, mom1m	3	0.04
mkt, chmom, ms	3	0.04
mkt, chmom, ms, tb	4	0.04

Factors with marginal posterior probability > 0: mkt, chmom, ep, mom1m, ms, tb
Factors with marginal posterior probability > 0.5: mkt, chmom

Panel B. January 1992 - December 2003, # stocks = 893, # factors = 81

Model	# Factors	Posterior probability
mkt	1	0.64
mkt, aeavol	2	0.32
mkt, aeavol, pctacc	3	0.04

Factors with marginal posterior probability > 0: mkt, aeavol, pctacc
Factors with marginal posterior probability > 0.5: mkt

Panel C. January 2004 - December 2016, # stocks = 967, # factors = 83

Model	# Factors	Posterior probability
intercept, mkt, chnanalyst, herf, mom1m	5	0.2
mkt, herf, mom1m	3	0.16
mkt, chnanalyst, herf, mom1m	4	0.16
mkt, chnanalyst, mom1m	3	0.08
intercept, mkt, herf, mom1m, saleinv	5	0.08
mkt, herf, mom1m, ms	4	0.04
mkt, chnanalyst, herf, mom1m, ms	5	0.04
mkt, chnanalyst, ear, herf, mom1m	5	0.04
intercept, mkt, ear, herf, mom1m	5	0.04
intercept, mkt, chnanalyst, herf	4	0.04
intercept, mkt, chnanalyst, herf, mom1m, saleinv	6	0.04
intercept, mkt, chnanalyst, herf, mom1m, ms	6	0.04
intercept, mkt, chnanalyst, ear, herf, mom1m	6	0.04

Factors with marginal posterior probability > 0: intercept, mkt, chnanalyst, ear, herf, mom1m, ms, saleinv
Factors with marginal posterior probability > 0.5: mkt, chnanalyst, herf, mom1m

Table C.4: Highest posterior probability models for sets of portfolios, 1980-2016, empirical Bayes prior with $c = 5$

We apply the Bayesian variable selection methodology to sets of portfolios formed according to various criteria, for the period 1980 to 2016. The table reports the best model, *i.e.* the model with highest posterior probability, the number of factors in the model, and the posterior probability. The prior for the factor sensitivities is an empirical Bayes prior centered on OLS factor sensitivities, *i.e.* we set $\boldsymbol{\beta}_i \sim N((\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{r}_i, c\sigma_i^2(\mathbf{X}'\mathbf{X})^{-1})$, with $c = 5$.

Portfolio formation	**# Portfolios**	**Best model**	**# Factors**	**Probability**
Univariate Sorts				
Size	10	mkt,ill,mve,mve_ia	4	0.30
Book-to-market	10	mkt,lev	2	0.80
Operating profitability	10	mkt,roic	2	0.60
Investment	10	mkt,agr,roavol	3	0.22
Earnings-to-price	10	mkt,chcsho,ep	3	0.20
Cashflow-to-price	10	mkt,bm,roavol	3	0.32
Dividend Yield	10	mkt,absacc,cashpr	3	0.22
Momentum	10	mkt,absacc,mom12m	3	0.26
Short-term reversal	10	mkt,mom1m	2	0.34
Long-term reversal	10	mkt,chcsho,mom36m	3	0.22
Beta	10	mkt,beta	2	0.75
Variance	10	mkt,idiovol	2	0.70
Residual variance	10	mkt,beta,idiovol,retvol	4	0.20
Bivariate Sorts				
Size and book-to-market	25	mkt,ill,lev,mve_ia	4	0.40
Size and operating profitability	25	mkt,beta,ill,roic,std_dolvol	5	0.20
Size and investing	25	mkt,beta,ill,mve_ia,std_dolvol	5	0.60
Book-to-market and operating profitability	25	mkt,bm,idiovol,lev,roavol,std_turn	6	0.40
Book-to-market and investment	25	mkt,bm,lev	3	0.80
Operating profitability and investment	25	mkt,beta,roic,tang	4	0.40
Other Portfolios				
Industries	49	mkt,beta,ill,lev,orgcap	5	0.40
Decile Portfolios + Industries	751	mkt, beta, chinv, ill, ms, orgcap, tang	7	0.30

Table C.5: Highest posterior probability models for sets of portfolios, 1980-2016, prior centered on zeros with $c = 1$

We apply the Bayesian variable selection methodology to sets of portfolios formed according to various criteria, for the period 1980 to 2016. The table reports the best model, *i.e.* the model with highest posterior probability, the number of factors in the model, and the posterior probability. The prior for the factor sensitivities is centered on a vector of zeros, *i.e.* $\tilde{\boldsymbol{\beta}} \sim N(\mathbf{0}, c\mathbf{I})$ with $c = 1$.

Portfolio formation	**# Portfolios**	**Best model**	**# Factors**	**Probability**
Univariate Sorts				
Size	10	mkt, mve_ia	2	0.80
Book-to-market	10	mkt	1	0.60
Operating profitability	10	mkt	1	0.80
Investment	10	mkt	1	0.80
Earnings-to-price	10	mkt	1	0.80
Cashflow-to-price	10	mkt	1	0.80
Dividend Yield	10	mkt	1	0.80
Momentum	10	mkt, beta, mom12m	3	0.89
Short-term reversal	10	mkt, mom1m	2	0.60
Long-term reversal	10	mkt	1	0.60
Beta	10	mkt	1	0.60
Variance	10	mkt, retvol	2	0.40
Residual variance	10	mkt, idiovol, retvol	3	0.80
Bivariate Sorts				
Size and book-to-market	25	mkt, bm, ill, lev, mve_ia	5	0.60
Size and operating profitability	25	mkt, beta, ill, mve_ia, roic	5	0.60
Size and investing	25	mkt, ill, mve_ia, roavol	4	0.40
Book-to-market and operating profitability	25	mkt, age, baspread, bm, currat, lev, std_turn	7	0.50
Book-to-market and investment	25	mkt, lev	2	0.80
Operating profitability and investment	25	mkt	1	0.80
Other Portfolios				
Industries	49	mkt, ill, orgcap, sp	4	0.40
Decile Portfolios + Industries	751	mkt, chinv, ill, mom12m, ms, orgcap, turn	7	0.60

Table C.6: Highest posterior probability models for sets of portfolios, 1980-2016, prior centered on zeros with $c = 5$

We apply the Bayesian variable selection methodology to sets of portfolios formed according to various criteria, for the period 1980 to 2016. The table reports the best model, *i.e.* the model with highest posterior probability, the number of factors in the model, and the posterior probability. The prior for the factor sensitivities is centered on a vector of zeros, *i.e.* $\tilde{\boldsymbol{\beta}} \sim N(\mathbf{0}, c\mathbf{I})$ with $c = 5$.

Portfolio formation	**# Portfolios**	**Best model**	**# Factors**	**Probability**
Univariate Sorts				
Size	10	mkt, ill	2	0.60
Book-to-market	10	mkt, bm, lev	3	0.46
Operating profitability	10	mkt, roic	2	0.80
Investment	10	mkt	1	0.60
Earnings-to-price	10	mkt	1	0.80
Cashflow-to-price	10	mkt	1	0.80
Dividend Yield	10	mkt	1	0.80
Momentum	10	mkt, mom12m	2	0.40
Short-term reversal	10	mkt, beta, mom1m	3	0.99
Long-term reversal	10	mkt	1	0.40
Beta	10	mkt	1	0.60
Variance	10	mkt	1	0.40
Residual variance	10	mkt	1	0.40
Bivariate Sorts				
Size and book-to-market	25	mkt, bm, idiovol, ill, lev, mve_ia	6	0.63
Size and operating profitability	25	mkt, ill, mve_ia, std_turn	4	0.40
Size and investing	25	mkt, beta, ill, mve_ia, std_dolvol	5	0.60
Book-to-market and operating profitability	25	mkt, beta, bm, lev	4	0.40
Book-to-market and investment	25	mkt, bm, lev	3	0.40
Operating profitability and investment	25	mkt, agr, currat, roavol, roic	5	0.40
Other Portfolios				
Industries	49	mkt	1	0.60
Decile Portfolios + Industries	751	mkt, chinv, ill, ms, orgcap, turn	6	0.70

Appendix D. A Simulation Study

In Section 2.2 we suggest two possibilities for the prior on $\boldsymbol{\beta}$, namely to assume $\tilde{\boldsymbol{\beta}} \sim N(\mathbf{0}, c\mathbf{I})$, reflecting a complete lack of knowledge about the predictors, or using an empirical Bayes prior, *i.e.* center each $\boldsymbol{\beta}_i$ around their OLS or maximum likelihood estimate: $\boldsymbol{\beta}_i \sim N((\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{r}_i, c\sigma_i^2(\mathbf{X}'\mathbf{X})^{-1})$. We have conducted a simulation to analyze the impact of prior choice on factor selection. Specifically, we have simulated monthly returns on $N = 1000$ assets over $T = 240$ months, assuming a data generating process with $K_{true} = 5$ normally distributed true factors, whose means and volatilities correspond to the monthly average returns and volatilities of the five Fama & French (2015) factors over the 20-year period ending in December 2016. The data-generating process for each asset is as follows:

$$r_{i,t} = \beta_{i,1}x_{t,1} + \beta_{i,2}x_{t,2} + \beta_{i,3}x_{t,3} + \beta_{i4}x_{t,4} + \beta_{i,5}x_{t,5} + \varepsilon_{i,t}.$$

The factor sensitivities of each asset i are assumed to be normally distributed across the assets, as follows:

$$\begin{aligned} \beta_{i,1} &\sim N(1, 0.35) \\ \beta_{i,j} &\sim N(0, 0.75), \quad j = 2, \ldots, 5. \end{aligned}$$

The idiosyncratic or asset-specific returns ε_{it} are assumed to be normally distributed, with idiosyncratic volatilities uniformly distributed between 0.05 and 0.10. In addition to the 5 true factors, we simulated an additional $K_{false} = 45$ factors uncorrelated to the true factors. With these choices, we can simulate a large cross-section of assets with an exact factor structure, but relatively high idiosyncratic variance, such that the average R^2 is around 0.45, similar to what we would obtain with monthly returns on individual stocks. The first factor, x_1, is the "market" factor, whose statistical significance is much stronger than that of the other factors. We then consider the problem of factor selection when once has access to different subsamples of individual assets' returns and a set of $K = 1 + K_{true} + K_{false} = 51$ factors (including the intercept), but no information on which factors are the true ones.

The experiment is designed as follows. We consider subsets consisting of the first 50, 100, 250, 500 and 1000 assets, and sub-sample periods consisting of the first 60, 120 and 240 months. To eliminate a possible impact of different factor mean returns on different sub-samples, we force the factors to have the same means over each 60-month period. Then, for each combination of number of assets and months, we apply our factor selection procedure using the two choices of prior for $\boldsymbol{\beta}$ mentioned above, with $c = 1$ and $c = 5$, *i.e.* a total of 4 different priors in total. We run our Bayesian variable selection 5 times using 5000 draws each time, a total of 25,000 draws for each combination.

Tables D.1 and D.2 report, respectively, the results using the prior centered on zeros and the empirical Bayes prior. For each prior distribution and combination of number of assets (N) and months (T), we report the posterior probability of each of the true factors, the average posterior probability of the false factors, and the posterior probability of the exact model. With the prior centered on zeros, the method in general correctly selects all the true factors, and does not select false factors, identifying the exact model with high probability, with the exception of the case when the sample is short ($T = 60$). A similar result obtains with the empirical Bayes prior, although we find that the method is more prone to selecting false factors, especially with $c = 1$ and when the sample is long and the number of assets is very high.

[Table D.1 about here.]

[Table D.2 about here.]

Table D.1: Results of a simulation study with $\tilde{\boldsymbol{\beta}} \sim N(\mathbf{0}, c\mathbf{I})$, $c = 1, 5$

We simulate monthly returns on $N = 1000$ assets over $T = 240$ months, assuming a data generating process with $K_{true} = 5$ normally distributed true factors, whose means and volatilities correspond to the monthly average returns and volatilities of the five Fama & French (2015) factors over the 20-year period ending in December 2016. The factor sensitivities of each asset i are assumed to be normally distributed across the assets. In addition to the 5 true factors, we simulate an additional $K_{false} = 45$ factors uncorrelated to the true factors, and apply the Bayesian variable selection methodology using a prior $\tilde{\boldsymbol{\beta}} \sim N(\mathbf{0}, c\mathbf{I})$ with $c = 1$ and $c = 5$ to the first 50, 100, 250, 500 and 1000 assets, considering the first 60, 120 or 240 monthly returns.

		$c = 1$			$c = 5$		
	Posterior probabilities	$T = 60$	$T = 120$	$T = 240$	$T = 60$	$T = 120$	$T = 240$
	x_1	1.00	1.00	1.00	1.00	1.00	1.00
	x_2	0.80	1.00	1.00	0.80	1.00	1.00
	x_3	0.84	1.00	1.00	0.84	1.00	1.00
$N = 50$	x_4	0.77	1.00	1.00	0.73	1.00	1.00
	x_5	0.76	1.00	1.00	0.00	1.00	1.00
	Average of false factors	0.00	0.00	0.00	0.00	0.00	0.00
	Exact model	0.37	1.00	1.00	0.37	1.00	1.00
	x_1	1.00	1.00	1.00	1.00	1.00	1.00
	x_2	0.20	1.00	1.00	0.60	1.00	1.00
	x_3	1.00	1.00	1.00	1.00	1.00	1.00
$N = 100$	x_4	0.20	1.00	1.00	0.20	1.00	1.00
	x_5	0.00	1.00	1.00	0.00	1.00	1.00
	Average of false factors	0.00	0.01	0.00	0.00	0.00	0.00
	Exact model	-	0.88	0.98	-	0.96	0.99
	x_1	1.00	1.00	1.00	1.00	1.00	1.00
	x_2	1.00	1.00	1.00	0.80	1.00	1.00
	x_3	1.00	1.00	1.00	1.00	1.00	1.00
$N = 250$	x_4	0.00	1.00	1.00	0.00	1.00	1.00
	x_5	0.00	1.00	1.00	0.00	1.00	1.00
	Average of false factors	0.00	0.04	0.05	0.00	0.04	0.05
	Exact model	-	0.94	0.89	-	0.93	0.92
	x_1	1.00	1.00	1.00	1.00	1.00	1.00
	x_2	0.60	1.00	1.00	0.40	1.00	1.00
	x_3	1.00	1.00	1.00	1.00	1.00	1.00
$N = 500$	x_4	0.00	1.00	1.00	0.20	1.00	1.00
	x_5	0.00	1.00	1.00	0.00	1.00	1.00
	Average of false factors	0.00	0.04	0.05	0.00	0.04	0.05
	Exact model	-	0.94	0.90	-	0.95	0.95
	x_1	1.00	1.00	1.00	1.00	1.00	1.00
	x_2	1.00	1.00	1.00	1.00	1.00	1.00
	x_3	0.20	1.00	1.00	0.00	1.00	1.00
$N = 1000$	x_4	1.00	1.00	1.00	1.00	1.00	1.00
	x_5	1.00	1.00	1.00	1.00	1.00	1.00
	Average of false factors	0.00	0.05	0.06	0.00	0.04	0.05
	Exact model	0.20	0.56	0.50	0.00	0.95	0.95

Table D.2: Results of a simulation study with $\boldsymbol{\beta}_i \sim N((\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{r}_i, c\sigma_i^2(\mathbf{X}'\mathbf{X})^{-1})$, $c = 1, 5$

We simulate monthly returns on $N = 1000$ assets over $T = 240$ months, assuming a data generating process with $K_{true} = 5$ normally distributed true factors, whose means and volatilities correspond to the monthly average returns and volatilities of the five Fama & French (2015) factors over the 20-year period ending in December 2016. The factor sensitivities of each asset i are assumed to be normally distributed across the assets. In addition to the 5 true factors, we simulate an additional $K_{false} = 45$ factors uncorrelated to the true factors, and apply the Bayesian variable selection methodology using a prior $\boldsymbol{\beta}_i \sim N((\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{r}_i, c\sigma_i^2(\mathbf{X}'\mathbf{X})^{-1})$ with $c = 1$ and $c = 5$ to the first 50, 100, 250, 500 and 1000 assets, considering the first 60, 120 or 240 monthly returns.

		$c = 1$			$c = 5$		
	Posterior probabilities	$T = 60$	$T = 120$	$T = 240$	$T = 60$	$T = 120$	$T = 240$
$N = 50$	x_1	1.00	1.00	1.00	0.80	1.00	1.00
	x_2	0.00	1.00	1.00	0.06	1.00	1.00
	x_3	1.00	1.00	1.00	1.00	1.00	1.00
	x_4	1.00	1.00	1.00	0.80	1.00	1.00
	x_5	0.00	1.00	1.00	0.00	1.00	1.00
	Average of false factors	0.00	0.00	0.00	0.00	0.00	0.00
	Exact model	-	0.99	0.98	-	1.00	1.00
$N = 100$	x_1	0.84	1.00	1.00	1.00	1.00	1.00
	x_2	0.00	1.00	1.00	0.00	1.00	1.00
	x_3	1.00	1.00	1.00	1.00	1.00	1.00
	x_4	0.80	1.00	1.00	0.80	1.00	1.00
	x_5	0.00	1.00	1.00	0.00	1.00	1.00
	Average of false factors	0.00	0.09	0.03	0.00	0.01	0.00
	Exact model	-	0.69	0.84	-	0.98	0.99
$N = 250$	x_1	0.80	1.00	1.00	0.80	1.00	1.00
	x_2	0.00	1.00	1.00	0.00	1.00	1.00
	x_3	1.00	1.00	1.00	1.00	1.00	1.00
	x_4	1.00	1.00	1.00	1.00	1.00	1.00
	x_5	0.00	1.00	1.00	0.00	1.00	1.00
	Average of false factors	0.00	0.06	0.09	0.00	0.04	0.05
	Exact model	-	0.26	0.15	-	0.95	0.91
$N = 500$	x_1	1.00	1.00	1.00	1.00	1.00	1.00
	x_2	0.00	1.00	1.00	0.00	1.00	1.00
	x_3	1.00	1.00	1.00	1.00	1.00	1.00
	x_4	1.00	1.00	1.00	1.00	1.00	1.00
	x_5	0.00	1.00	1.00	0.00	1.00	1.00
	Average of false factors	0.00	0.10	0.16	0.00	0.04	0.05
	Exact model	-	-	-	-	0.95	0.88
$N = 1000$	x_1	1.00	1.00	1.00	1.00	1.00	1.00
	x_2	1.00	1.00	1.00	1.00	1.00	1.00
	x_3	0.20	1.00	1.00	0.00	1.00	1.00
	x_4	1.00	1.00	1.00	1.00	1.00	1.00
	x_5	1.00	1.00	1.00	1.00	1.00	1.00
	Average of false factors	0.00	0.20	0.60	0.00	0.04	0.05
	Exact model	0.20	0.69	-	-	0.95	0.83

Appendix E. Factor Construction

Table E.1: The Factor Zoo: candidate factors/firm characteristics

The table lists the 82 firm characteristics used to construct tradable factors.

Acronym	Firm Characteristic/Factor	Reference
mkt	Market return	Sharpe (1994)
absacc	Absolute accruals	Bandyopadhyay *et al.* (2010)
acc	Working capital accruals	Sloan (1996)
aeavol	Abnormal earnings announcement volume	Lerman *et al.* (2008)
age	# years since first Compustat coverage	Jiang *et al.* (2005)
agr	Asset growth	Cooper *et al.* (2008)
baspread	Bid-ask spread	Amihud & Mendelson (1989)
beta	Beta	Fama & MacBeth (1973)
bm	Book-to-market	Rosenberg *et al.* (1985)
bm_ia	Industry-adjusted book to market	Asness *et al.* (2000)
cash	Cash holdings	Palazzo (2012)
cashdebt	Cash flow to debt	Ou & Penman (1989)
cashpr	Cash productivity	Chandrashekar & Rao (2009)
cfp	Cash-flow-to-price ratio	Desai *et al.* (2004)
cfp_ia	Industry-adjusted cash-flow-to-price ratio	Asness *et al.* (2000)
chatoia	Industry-adjusted change in asset turnover	Soliman (2008)
chcsho	Change in shares outstanding	Pontiff & Woodgate (2008)
chempia	Industry-adjusted change in employees	Asness *et al.* (2000)
chfeps	Change in forecasted EPS	Hawkins *et al.* (1984)
chinv	Change in inventory	Thomas & Zhang (2002)
chmom	Change in 6-month momentum	Gettleman & Marks (2006)
chnanalyst	Change in number of analysts	Scherbina (2008)
chpmia	Industry-adjusted change in profit margin	Soliman (2008)
chtx	Change in tax expense	Thomas & Zhang (2002)
cinvest	Corporate investment	Titman *et al.* (2004)
currat	Current ratio	Ou & Penman (1989)
depr	Depreciation / PP&E	Holthausen & Larcker (1992)
disp	Dispersion in forecasted EPS	Diether *et al.* (2002)
ear	Earnings announcement return	Brandt *et al.* (2008)
egr	Growth in common shareholder equity	Richardson *et al.* (2005)
ep	Earnings to price	Basu (1977)
fgr5yr	Forecasted growth in 5-year EPS	Bauman & Dowen (1988)
gma	Gross profitability	Novy-Marx (2013)

Table E.1: (continued)

Acronym	Firm Characteristic/Factor	Reference
grcapx	Growth in capital expenditures	Anderson & Garcia-Feijóo (2006)
grltnoa	Growth in long-term net operating assets	Fairfield *et al.* (2003)
herf	Industry sales concentration	Hou & Robinson (2006)
hire	Employee growth rate	Belo *et al.* (2014)
idiovol	Idiosyncratic return volatility	Ali *et al.* (2003)
ill	Illiquidity	Amihud (2002)
indmom	Industry momentum	Moskowitz & Grinblatt (1999)
invest	Capital expenditures and inventory	Chen & Zhang (2010)
lev	Leverage	Bhandari (1988)
mom12m	12-month momentum	Jegadeesh (1990)
mom1m	1-month momentum	Jegadeesh & Titman (1993)
mom36m	36-month momentum	Jegadeesh & Titman (1993)
ms	Financial statement score	Mohanram (2005b)
mve	Size	Banz (1981)
mve_ia	Industry-adjusted size	Asness *et al.* (2000)
nanalyst	Number of analysts covering stock	Elgers *et al.* (2001)
operprof	Operating profitability	Fama & French (2015)
orgcap	Organizational capital	Eisfeldt & Papanikolaou (2013)
pchcapx_ia	Industry adjusted change in capex	Abarbanell & Bushee (1998)
pchcurrat	change in current ratio	Ou & Penman (1989)
pchdepr	change in depreciation	Holthausen & Larcker (1992)
pchgm_pchsale	change in gross margin - change in sales	Abarbanell & Bushee (1998)
pchsaleinv	change sales-to-inventory	Ou & Penman (1989)
pchsale_pchinvt	change in sales - change in inventory	Abarbanell & Bushee (1998)
pchsale_pchrect	change in sales - change in A/R	Abarbanell & Bushee (1998)
pchsale_pchxsga	change in sales - change in SG&A	Abarbanell & Bushee (1998)
pctacc	Percent accruals	Hafzalla *et al.* (2011)
pricedelay	Price delay	Hou & Moskowitz (2005)
ps	Financial statements score	Piotroski (2000)
realestate	Real estate holdings	Tuzel (2010)
retvol	Return volatility	Ang *et al.* (2006)
roaq	Return on assets	Balakrishnan *et al.* (2010)
roavol	Earnings volatility	Francis *et al.* (2004)

Table E.1: (continued)

Acronym	Firm Characteristic/Factor	Reference
roeq	Return on equity	Hou *et al.* (2015b)
roic	Return on invested capital	Brown & Rowe (2007)
rsup	Revenue surprise	Kama (2009)
salecash	Sales to cash	Ou & Penman (1989)
saleinv	Sales to inventory	Ou & Penman (1989)
salerec	Sales to receivables	Ou & Penman (1989)
sfe	Scaled earnings forecast	Elgers *et al.* (2001)
sgr	Sales growth	Lakonishok *et al.* (1994)
sp	Sales to price	Barbee Jr *et al.* (1996)
stdcf	Cash flow volatility	Huang (2009)
std_dolvol	Volatility of liquidity (dollar trading volume)	Chordia *et al.* (2001)
std_turn	Volatility of liquidity (share turnover)	Chordia *et al.* (2001)
sue	Unexpected quarterly earnings	Rendleman *et al.* (1982)
tang	Debt capacity/firm tangibility	Almeida & Campello (2007)
tb	Tax income to book income	Lev & Nissim (2004)
turn	Share turnover	Datar *et al.* (1998)
zerotrade	Zero trading days	Liu (2006)