The Distortion in Prices due to Passive Investing

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Abstract

We develop a conditional capital asset pricing model (CAPM) that maintains the rationale for market indexing: In equilibrium, it is optimal for nonindex investors to hold the market portfolio. The model demonstrates that passive investment (indexing) is not benign. As more nonindexers become indexers, the statistical fit (measured by R^2) of the CAPM regression decreases; and for any portfolio other than the market portfolio, the Sharpe ratio decreases and the conditional variance of payoff increases.

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It has now been over forty years since the first edition of A Random Walk Down Wall Street. The message of the original edition was a very simple one: Investors would be far better off buying and holding an index fund than attempting to buy and sell individual securities.... Now, over forty years later, I believe even more strongly in that original thesis.

Burton G. Malkiel

1 Introduction

The separation theorem provides the intellectual underpinning of index investment, and the capital asset pricing model (CAPM) is the most important pricing implication of the separation theorem.[1] But the CAPM is silent about the impact of market indexing on pricing. In this paper, we examine the implications of market indexing in an extension of the mean–variance equilibrium analysis in which (i) the separation result holds and (ii) a conditional CAPM holds. Thus, the equilibrium we present in this paper maintains the rationale for market indexing, and the results are framed in the standard CAPM terminology.

To build our model, we depart from the standard CAPM in two ways. First, we adopt a rational expectation framework (Grossman, 1976) in which investors combine their costless[2] private information with the information contained in equilibrium prices. In a multiasset extension of the framework, Grossman (1978) and DeMarzo and Skiadas (1998) show that a conditional CAPM emerges. But this conditional CAPM is silent about the impact of indexing in exactly the same way the standard CAPM is. We therefore deviate further

[1] In this paper, the term indexing is used as a short for market portfolio indexing. In August 1976, when Vanguard started offering its index fund, Samuelson (1976) articulated the separation theorem in the popular press: "What each prudent investor must do is to decide what fraction of savings he can afford, in this age of inflation, to keep in equities and in other things. An unmanaged, low-turnover, low-fee index fund is merely an efficient way of holding that part deemed appropriate for equities." Lo (2016) writes that it was academic research, specifically the CAPM and the efficient market hypothesis, that "provided the seeds from which the index fund business grew."

[2] Evidence that the trade of layman investors conveys, presumably costless, information is provided by Kaniel, Liu, Saar, and Titman (2012), Kelley and Tetlock (2013), and Boehmer, Jones, and Zhang (2017).

from the standard model by explicitly dividing the investors into two groups: indexers and nonindexers. Index investors are confined to investment positions on the capital market line (i.e., combinations of the risk-free asset and the market portfolio); nonindex investors are not confined. The presence of index investors in our model is the second and last departure from the standard CAPM world.

We assume that some investors are market indexers, first and foremost, to facilitate a comparative statics analysis. We recognize that there are valid reasons why some actual investors index and others do not.[3] Instead of performing a comparative statics analysis with respect to any of the valid reasons, we do so with respect to the level of index investment. In particular, we do not pit the different valid reasons for indexing against the different valid reasons for trading individual securities. Having abstracted from those valid reasons for and against indexing, investors are ex ante indifferent between indexing and nonindexing, and we show that when the economy is large they are even interim indifferent.

We prove the existence of a partially revealing rational expectation equilibrium in which Tobin's separation result holds: Nonindexers' investment positions are located, in the volatility–return plane, on the capital market line.[4] Similar to the rational expectation equilibrium described by Grossman (1978) and DeMarzo and Skiadas (1998), a conditional CAPM relation holds. However, asset prices and betas depend on the specific partition of investors into indexers and nonindexers.

By means of comparative statics, we find that as more nonindex investors become index

[3]For example, trading the index is a cost-efficient way to diversify and a suitable strategy for investors who think their investment ability is below average and for investors who are worried about their own behavioral biases. In addition, in some investment accounts (e.g., retirement or college savings accounts), investors cannot trade individual securities. By contrast, an investor who trades individual securities can realize capital losses without leaving the market, whereas the wash-sale rule prevents an index investor from using tax-efficient strategies.

[4]A fully revealing equilibrium is an equilibrium in which, given the aggregate information in the economy, prices are jointly sufficient statistics for the payoff ("future prices") of the assets. A partially revealing equilibrium is an equilibrium in which prices convey information about the payoff of assets, but the equilibrium is not fully revealing.

investors, the proportion of idiosyncratic risk to total risk increases.[5] This increase manifests in different ways. The statistical fit (measured by R^2) of the CAPM regression decreases. Provided that an asset price is positively correlated with the portfolio of the remaining assets, correlation in asset prices increases.[6] In fact, when the proportion of index investors is 100%, forward prices become perfectly correlated.[7] Provided that the return on an asset is positively correlated with the return on the portfolio of remaining assets, correlation in returns decreases. For any portfolio other than the market portfolio, the portfolio's Sharpe ratio decreases, and the variance of the portfolio's payoff increases.[8] By contrast, both the market portfolio's Sharpe ratio and the variance of the market portfolio's payoff are unaffected. Using numerical computations, we find that betas do not gravitate toward one. Finally, considering the complete set of signals (of both indexers and nonindexers) as the "data" and the payoff of the market portfolio as the "parameter," we show that the forward price of the market portfolio is a minimal sufficient statistic for the payoff of the market portfolio.

Interestingly, Campbell, Lettau, Malkiel, and Xu (2001) find that from 1962 to 1997, market variance was stable while firms' variances more than doubled. They find that comovement in returns decreased, and the coefficient of determination also decreased. These authors provide several possible explanations for their findings, such as the breaking up of conglomerates. This paper provides a new explanation, namely the rise of index investment.

Our model is related to those of Levy (1978), Malkiel and Xu (2006), and Merton (1987). These authors also model mean–variance economies in which some investors—much like the

[5]Idiosyncratic risk is the "unexplained variance" of the stock's return. The proportion of idiosyncratic risk to total risk is the fraction of unexplained variance, and it equals $1 - R^2$, where R^2 is the coefficient of determination of the CAPM regression.

[6]As in other conditional CAPM models, prices and betas are realizations of random variables. It is therefore meaningful to study their statistical properties.

[7]We do not have a derivative securities market in our model, but nevertheless we can compute synthetic forward prices. Forward prices are prices divided by the price of the risk-free bond. In other words, these are the prices at which the bond acts as the numeraire. These prices are also known in the asset pricing literature as *discounted prices*.

[8]In this paper, a portfolio with a return r has a Sharpe ratio $(Er - r_f)/\,\mathrm{sd}(r)$.

index investors in our model—do not solve a complete portfolio optimization problem. These models do not obtain the CAPM because idiosyncratic risk is relevant when investors are exposed to it. By contrast, in our model, idiosyncratic risk is irrelevant because no investor (indexer or nonindexer) is exposed to it.

Bond and Garcia (2019) and Liu and Wang (2018) also model mean–variance competitive economies in which a group of investors is confined to an index. These models focus on the impact of index investment on information production and welfare, whereas our model focuses on asset pricing. In addition, in the Bond and Garcia (2019) model, investors also face participation cost in markets: It is costly to participate but cheaper to index, allowing this model to capture the notion that indexing democratizes the investment world. For Liu and Wang (2018), the cost of acquiring information about assets is an increasing, convex, multidimensional function of signal precisions. This cost structure allows their model to demonstrate how a rise in index investment can have different impacts on information production in the index asset and the nonindex asset.

Our model adds to the literature that examines comovements and exchange-traded funds. According to Barberis and Shleifer (2003), rational traders take advantage of the extrapolative expectations of switchers who move their holding from one set of assets to another. Barberis, Shleifer, and Wurgler (2005) review additional theories of comovement that stem from market frictions or noise traders' sentiment. Comovement also shows up in market structure–type models. According to Bhattacharya and O'Hara (2018), the source of comovement is the inability to precisely tease out information relevant to individual assets from the exchange-traded funds. Also, Cong and Xu (2016) and Glosten, Nallareddy, and Zou (2017) show that the presence of a composite security, created to cater to factor investors, enhances comovement. In our paper, comovement in asset prices increases because indexers homogenize the market.[9] At the limit of our model, when all investors are indexers,

[9]See Footnote 6 in Page 3.

forward prices are perfectly correlated.

In the literature on active asset management, the term indexing is sometimes used as short for benchmark indexing. Whenever some investors are exposed to a benchmark index that is not the market portfolio, benchmarking distorts assets pricing. This point was demonstrated in a static, mean-variance setting with proportional fees in Brennan (1993) and in a dynamic setting with symmetric fees in Cuoco and Kaniel (2011). In our model, the index is the market portfolio, and we nevertheless find distortions due to indexing.[10]

Our model also adds to the literature on partially revealing equilibria. To avoid the fully revealing outcome, this literature relies on noise trading (Kyle 1985), supply uncertainty (Hellwig 1980 and Admati 1985), extrinsic noise (DeMarzo and Skiadas 1998), or preference uncertainty (see Ausubel 1990 and the dynamic model by Detemple 2002). Our model relies on none of these. Instead, the equilibrium we compute is partially revealing because index investors only participate in the price discovery process for the market portfolio.

The remainder of this paper is organized as follows. In Section 2, we describe the model. In Sections 3 and 4, we expand Grossman's (1978) notion of artificial economies to a world with index investors. In Section 5, we compute a partially revealing equilibrium. In Section 6, we present comparative statics. In Section 7, we present, as a limiting case of our model, an equilibrium in which all investors are indexers. In Section 8, we study index investment in a large economy. In Section 9, we conclude.

[10] Basak and Pavlova (2013) offer an alternative view to what constitutes a distortion due to the presence of indexers. However, we think the presence of indexers (whom they call institutional investors) in their model distorts prices for a reason more fundamental than benchmarking: Those traders have a different utility function and preferences toward risk matter to asset pricing. Indeed Basak and Pavlova (2013) report that institutional investors distorts prices even in a single stock economy.

2 The Model

We consider a two-period, single-good exchange economy with one financial (i.e., zero-net-supply) risk-free asset (a bond), n risky real assets (firms), and m investors. Investors are labeled $k = 1, \dots m$, and risky assets are labeled $i = 1, \dots n$.

For each risky asset, we normalize the number of outstanding shares to m. A portfolio (of risky assets) is a vector $\mathbf{x} = \begin{bmatrix} x_1 & \dots & x_n \end{bmatrix}'$ in R^n with the interpretation that x_i is the number of shares of the ith risky asset.[11] Let $\mathbf{1} \in R^n$ denote the vector of all-ones, so $m\mathbf{1}$ is the *market portfolio*. Whenever an investor holds a portfolio that is a strictly positive scalar multiplication of $\mathbf{1}$, we say that the investor holds the market.

The prices of the assets are denominated in units of the time-zero consumption good, and the assets' payoffs are denominated in units of the time-one consumption good. The consumption good is perishable, so the only way to transfer consumption between periods is through the capital market.

The payoff of the bond is one. The price of the bond is denoted by p_f. We define the risk-free interest rate as follows: $r_f = 1/p_f - 1$.

The random payoff, per share, of the risky assets is denoted by $\mathbf{v} = \begin{bmatrix} v_1 & \dots & v_n \end{bmatrix}'$.[12] We assume $\mathbf{v} \sim \mathcal{N}(\boldsymbol{\mu}_{\mathbf{v}}, \boldsymbol{\Sigma}_{\mathbf{vv}})$, where $\boldsymbol{\Sigma}_{\mathbf{vv}}$ is a symmetric, positive definite matrix.[13] The random

[11] In this paper, the word "portfolio" is short for "portfolio of risky assets."

[12] Notation: All vectors are column vectors. The transpose operation is denoted by a single quotation mark. Bold lowercase (Greek or upright Roman) letters are used for vectors. Bold uppercase (Greek or upright Roman) letters are used for matrices. If the dimensions of a matrix are 1×1, we treat the matrix as a scalar. We have no special notation to distinguish random variables from their realizations. The context should make our intention clear.

[13] Given two random vectors, $\mathbf{z} = \begin{bmatrix} z_1 & \dots & z_n \end{bmatrix}'$ and $\mathbf{y} = \begin{bmatrix} y_1 & \dots & y_m \end{bmatrix}'$, we interchangeably use the notations $\operatorname{cov}(\mathbf{z}, \mathbf{y})$ and $\Sigma_{\mathbf{zy}}$ to denote the $n \times m$ covariance matrix $\begin{bmatrix} \operatorname{cov}(z_i, y_j) \end{bmatrix}_{n \times m}$. Consequently, using submatrix notation, we have

$$\operatorname{cov}\left(\mathbf{z}, \begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \end{bmatrix}\right) = \begin{bmatrix} \operatorname{cov}(\mathbf{z}, \mathbf{y}_1) & \operatorname{cov}(\mathbf{z}, \mathbf{y}_2) \end{bmatrix}$$

We routinely use the property that if $\mathbf{A}$ and $\mathbf{B}$ are nonrandom matrices, then $\operatorname{cov}(\mathbf{A}\mathbf{x}, \mathbf{B}\mathbf{y}) = \mathbf{A} \operatorname{cov}(\mathbf{x}, \mathbf{y}) \mathbf{B}'$.

payoff of a portfolio $\mathbf{x}$ is $\mathbf{x}'\mathbf{v}$; the mean of the payoff is $\mathbf{x}'\boldsymbol{\mu}_{\mathbf{v}}$; and the variance of the payoff is $\mathbf{x}'\boldsymbol{\Sigma}_{\mathbf{vv}}\mathbf{x}$. The vector of share prices is denoted by $\mathbf{p} = \begin{bmatrix} p_1 & \ldots & p_n \end{bmatrix}'$, so the cost of the portfolio $\mathbf{x}$ is $\mathbf{x}'\mathbf{p}$.

Every portfolio with a nonzero cost has a return $\mathbf{x}'\mathbf{v}/(\mathbf{x}'\mathbf{p})-1$. Two portfolios have the same return if one is a strictly positive scalar multiplication of the other. This is an equivalence relation that is invariant under change of prices.[14] In the portfolio analysis literature, an equivalent class is identified with a vector of market-value weights, termed portfolio weights. (Often, the word "weights" is omitted.) But, under a different set of prices, the same weights represent a different equivalence class. (For example, the weights that represent the market portfolio change as we change prices.) We therefore avoid market-value weights altogether.

Investors effortlessly observe the realizations of private signals centered around $\mathbf{v}$. The signals are[15]

$$\forall k = 1 \ldots m, \quad \mathbf{s}_k = \begin{bmatrix} s_{1k} \\ \vdots \\ s_{nk} \end{bmatrix} = \mathbf{v} + m^{1/2}\boldsymbol{\epsilon}_k$$

where

$$\boldsymbol{\epsilon}_k \sim N\left(\begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}_{n\times 1}, \boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}} \right)$$

$\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}}$ is a symmetric and positive definite matrix, and the random vectors $\{\mathbf{v}, \boldsymbol{\epsilon}_1, \ldots, \boldsymbol{\epsilon}_m\}$ are jointly normally distributed and mutually independent.

Subject to the budget constraint, the kth investor chooses the number of time-zero consumption units, c; the number of bonds, b; and a portfolio of risky assets, $\mathbf{x}$, to maximize the expected value of the utility function:

$$U_k(c, b, \mathbf{x}'\mathbf{v}) \equiv -e^{-\rho_k c} - e^{-\rho_k (b + \mathbf{x}'\mathbf{v})}$$

[14]In other words, if two portfolios have the same return under one set of prices, and we then change prices, then either both portfolios will not have a return or both portfolios will have the same return.

[15]The assumption that we can factor out m from the covariance matrix of errors is without loss of generality: $m > 0$, so this is merely a scale.

Let

$$\bar{\rho} = \left(\frac{1}{m} \sum_{k=1}^{m} \rho_k^{-1} \right)^{-1} \tag{1}$$

denote the harmonic mean of the coefficients of risk aversion. The exponential utility assumption implies that investors' initial endowments are not relevant for their investment decision. So, for simplicity of exposition, we turn off heterogeneity in endowments. That is, we assume each investor is endowed with $\bar{c}$ units of a time-zero consumption good, zero bonds, and the portfolio $\mathbf{1}$.

At some early stage (before signals and prices are observed), some investors decide to confine their investment to bonds and the market portfolio. We call these investors index investors. The remaining investors solve a complete portfolio selection problem. We denote the set of indices of index investors by $\mathcal{I}$ and the set of indices of the nonindex investors by $\mathcal{NI}$. We then have $|\mathcal{I}| + |\mathcal{NI}| = m$.

We can write the investors' problems as follows:

$$\begin{aligned}
\forall k \in \mathcal{NI}, \quad & \max_{c,b,\mathbf{x}} E\left[U_k(c, b, \mathbf{x}'\mathbf{v}) \,|\mathbf{s}_k, \mathbf{p}, p_f\right] \\
& \quad \text{s.t. } \bar{c} - c + (0 - b)p_f + (\mathbf{1} - \mathbf{x})'\mathbf{p} = 0 \\
\forall k \in \mathcal{I}, \quad & \max_{c,b,q} E\left[U_k(c, b, q\mathbf{1}'\mathbf{v}) \,|\mathbf{s}_k, \mathbf{1}'\mathbf{p}, p_f\right] \\
& \quad \text{s.t. } \bar{c} - c + (0 - b)p_f + (1 - q)\mathbf{1}'\mathbf{p} = 0
\end{aligned}$$

Let c_k, b_k, and $\mathbf{x}_k$ denote the optimal solution of the above maximization problems, where $\mathbf{x}_k \equiv q_k\mathbf{1}$, whenever $k \in \mathcal{I}$. The solutions of the maximization problems of the investors are quantities that depend on the realization of the prices and signals.

Denote by $\mathbf{s}$ the concatenation of all signals. Given a partition $\{\mathcal{I}, \mathcal{NI}\}$, a *rational expectation equilibrium* is a random pair $(\mathbf{p}, p_f)$ such that for each joint realization of $\mathbf{s}$ and $(\mathbf{p}, p_f)$, the market for the consumption good, the market for debt, and the market for risky assets clear:

$$\sum_{k=1}^{m} c_k = m\bar{c}, \qquad \sum_{k=1}^{m} b_k = 0, \qquad \sum_{k \in \mathcal{NI}} \mathbf{x}_k + \sum_{k \in \mathcal{I}} q_k \mathbf{1} = m\mathbf{1}$$

Our goal is to characterize the equilibrium for any partition of investors. In Appendix E, we follow Grossman and Stiglitz (1980) and use those equilibrium prices to show that any partition is an overall equilibrium: Before signals and prices are realized, investors are indifferent about which group they want to belong to, indexers or nonindexers. We call this ex ante indifference.

In Section 8, we take the limit as m goes to infinity, so the economy is large and investors are informationally small. We show that even after signals and prices are realized, indexers peeking at the entire set of asset prices do not regret their decision to index. We call this interim indifference.

We therefore proceed with the assumption that the partition of investors into indexers and nonindexers is given. We initially assume that both types of investors are present. In other words, $0 < |\mathcal{I}| < m$. We remove this assumption in Section 7.

3 Artificial Economies

Grossman (1978) devises a heuristic for finding a rational expectation equilibrium.[16] He considers an artificial economy in which each investor has access to all private information in the economy. He proves that if the equilibrium price vector in this artificial economy is a sufficient statistic for the mean of the investors' signals (which is the payoff vector, $\mathbf{v}$), then this price vector is also a rational expectation equilibrium in the actual economy.

This heuristic can be successfully applied to our model because in Grossman's *fully revealing equilibrium* everyone holds the market portfolio; therefore, in the fully revealing equilibrium, the additional constraint on index investors is nonbinding. This means that the fully revealing equilibrium is silent about the implications of index investment in exactly the same

[16] Dutta and Morris (1997) and DeMarzo and Skiadas (1998) consider a certain class of economies for which they can find a rational expectation equilibrium without reference to artificial economies.

way that the standard CAPM is. We are searching for a different rational expectation equilibrium.

For the purpose of finding a new rational expectation equilibrium, we note that statistical sufficiency of prices is a requirement stronger than needed. Indeed, when the price vector is a sufficient statistic, *any decision maker* is indifferent between knowing all the information and knowing only the prices. But we should heed only what the decision makers in our model prefer (in particular, those index investors who solve a constraint problem), not what every hypothetical decision maker prefers.

That said, as in Grossman's fully revealing equilibrium, we are searching for a rational expectation equilibrium in which the equilibrium prices reveal "information to each trader which is of 'higher quality' than his own information" (Grossman 1976):

$$\forall k \in \mathcal{NI}, \forall \mathbf{x} \in R^n \;\; E\left[U_k(c, b, \mathbf{x}'\mathbf{v}) \,|\mathbf{s}_k, \mathbf{p}, p_f\right] = E\left[U_k(c, b, \mathbf{x}'\mathbf{v}) \,|\mathbf{p}, p_f\right]$$

$$\forall k \in \mathcal{I}, \forall q \in R \;\; E\left[U_k(c, b, q\mathbf{1}'\mathbf{v}) \,|\mathbf{s}_k, \mathbf{1}'\mathbf{p}, p_f\right] = E\left[U_k(c, b, q\mathbf{1}'\mathbf{v}) \,|\mathbf{1}'\mathbf{p}, p_f\right]$$

4 The Artificial Economy $\mathcal{E}_\mathbf{y}$

We fix an arbitrary, nondegenerate, multivariate normal random vector $\mathbf{y}$, such that $\mathbf{y}$ and $\mathbf{v}$ are jointly normal. We do not specify the dimension of the vector $\mathbf{y}$.[17]

Let $\boldsymbol{\mu}_\mathbf{y}$ be the expected value of $\mathbf{y}$. Because $\mathbf{v}$ and $\mathbf{y}$ are jointly normally distributed, a standard result in probability theory is that $\mathbf{v}$ conditional on the realization of $\mathbf{y}$ is multivariate normal with a conditional mean and a conditional (deterministic) covariance matrix:

$$\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} = \boldsymbol{\mu}_\mathbf{v} + \boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}(\mathbf{y} - \boldsymbol{\mu}_\mathbf{y}) \tag{2}$$

$$\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}} = \boldsymbol{\Sigma}_{\mathbf{vv}} - \boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\boldsymbol{\Sigma}_{\mathbf{yv}} \tag{3}$$

[17] A multivariate normal random vector is nondegenerate if its covariance matrix is positive definite (and hence invertible).

We define the artificial economy $\mathcal{E}_{\mathbf{y}}$ as follows. Investors have the same initial endowment as in the actual economy. All investors are nonindexers, and investors do not observe realizations of private signals. Instead, they observe the realization of the random vector $\mathbf{y}$. An equilibrium in $\mathcal{E}_{\mathbf{y}}$ is a pair $(p_f, \mathbf{p})$ such that for each realization of $\mathbf{y}$, and for each $k = 1, \ldots, m$, $(c_k, b_k, \mathbf{x}_k)$ solves

$$\begin{aligned} &\max_{c,b,\mathbf{x}} E\left[U_k(c, b, \mathbf{x}'\mathbf{v}) \,|\mathbf{y}\,\right] \\ &\text{s.t. } \bar{c} - c + (0 - b)p_f + (\mathbf{1} - \mathbf{x})'\mathbf{p} = 0 \end{aligned}$$

and the three markets clear:

$$\sum_{k=1}^{m} c_k = m\bar{c}, \qquad \sum_{k=1}^{m} b_k = 0, \qquad \sum_{k=1}^{m} \mathbf{x}_k = m\mathbf{1}$$

The following two results are standard.

Theorem 4.1. *The artificial economy $\mathcal{E}_{\mathbf{y}}$ has a unique equilibrium. The equilibrium asset prices are defined implicitly as follows. Let*

$$\mathbf{f} := \boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} - \bar{\rho}\, \boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1} \tag{4}$$

The equilibrium price of the bond, p_f, is given by

$$\log(p_f) = -\bar{\rho}\left(\mathbf{1}'\mathbf{f} + \frac{\bar{\rho}}{2}\mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1}\right) + \bar{\rho}\bar{c} \tag{5}$$

and the equilibrium price of the risky assets is

$$\mathbf{p} = p_f\mathbf{f} \tag{6}$$

In equilibrium, the portfolio holding of risky assets is

$$\mathbf{x}_k = \frac{\bar{\rho}}{\rho_k}\mathbf{1} \tag{7}$$

The proof of Theorem 4.1 is in Appendix A.

Note that in the artificial economy, the separation result holds: Each investor holds the market. Equation 6 demonstrates that $\mathbf{f}$ is the vector of synthetic *forward prices*. In other words, the price of the risky assets denominated in units of the bond is $\mathbf{f}$. Next, we show that the CAPM risk–return relation holds in the equilibrium in the artificial economy.

Let $r_{\text{mkt}} = \mathbf{1}'\mathbf{v}/(\mathbf{1}'\mathbf{p}) - 1$, $r_i = v_i/p_i - 1$, and

$$\beta_i = \frac{\operatorname{cov}(r_{\text{mkt}}, r_i|\mathbf{y})}{\operatorname{var}(r_{\text{mkt}}|\mathbf{y})} \tag{8}$$

Theorem 4.2. *In the artificial economy $\mathcal{E}_{\mathbf{y}}$, the CAPM holds:*

$$E[r_i|\mathbf{y}] = r_f + \beta_i(E[r_{\text{mkt}}|\mathbf{y}] - r_f) \tag{9}$$

The proof of Theorem 4.2 is in Appendix A. So far, our choice of $\mathbf{y}$ has been arbitrary. We now introduce a strong assumption.

(GR) The random vector $\mathbf{y}$ is such that

$$\begin{cases} \forall k \in \mathcal{NI} & E[\mathbf{v}|\mathbf{s}_k, \mathbf{y}] = \boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} \qquad \operatorname{var}(\mathbf{v}|\mathbf{s}_k, \mathbf{y}) = \boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}} \\ \forall k \in \mathcal{I} & E[\mathbf{1}'\mathbf{v}|\mathbf{s}_k, \mathbf{y}] = \mathbf{1}'\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} \quad \operatorname{var}(\mathbf{1}'\mathbf{v}|\mathbf{s}_k, \mathbf{y}) = \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1} \end{cases}$$

A random vector that trivially satisfies (GR) is $\mathbf{s}$, the concatenation of all signals. Therefore, (GR) is not vacuous.

Our next goal is to show that when $\mathbf{y}$ satisfies (GR), the equilibrium prices in the artificial economy $\mathcal{E}_{\mathbf{y}}$ are the equilibrium prices in the actual economy. To that end, we first need to establish that the prices in the artificial economy carry the same information as $\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}}$, so that the conditioning in (GR) on $\mathbf{y}$ can be replaced with conditioning on prices.

Because equilibrium prices are not normally distributed, we find it easier to replace the conditioning on random vectors by conditioning on the sigma algebras generated by the random vectors. We have the following.

Lemma 4.3. *Assume* $\mathbf{y}$ *satisfies* (*GR*), *and let* p_f *and* $\mathbf{p}$ *be the equilibrium prices in the artificial economy* $\mathcal{E}_{\mathbf{y}}$. *Then,* $\sigma(\mathbf{p}, p_f) = \sigma(\mathbf{f}) = \sigma(\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}}) \subseteq \sigma(\mathbf{y})$.

The proof of Lemma 4.3 is in Appendix A. We also need the following simple result.

Lemma 4.4. *Let* $\mathcal{G}$ *and* $\mathcal{F}$ *be two sigma algebras such that* $\mathcal{G} \subseteq \mathcal{F}$ *(*$\mathcal{F}$ *contains more information than* $\mathcal{G}$*).*

1. *If* $E[\mathbf{v}|\mathcal{F}] \in \mathcal{G}$, *then* $E[\mathbf{v}|\mathcal{G}] = E[\mathbf{v}|\mathcal{F}]$.
2. *If* $E[\mathbf{v}|\mathcal{F}] \in \mathcal{G}$ *and* $\operatorname{var}(\mathbf{v}|\mathcal{F}) \in \mathcal{G}$, *then* $\operatorname{var}(\mathbf{v}|\mathcal{G}) = \operatorname{var}(\mathbf{v}|\mathcal{F})$.

The proof of Lemma 4.4 is in Appendix A.

Corollary 4.5. *Assume* $\mathbf{y}$ *satisfies* (*GR*). *Let* p_f *and* $\mathbf{p}$ *be the equilibrium prices in the artificial economy* $\mathcal{E}_{\mathbf{y}}$. *We have the following.*

1. *The distribution of* $\mathbf{v}$ *conditional on the realization of* p_f *and* $\mathbf{p}$ *is multivariate normal with the same mean and variance as the distribution of* $\mathbf{v}$ *conditional on* $\mathbf{y}$*:*

$$E\big[\mathbf{v}\big|\mathbf{p}, p_f\big] = \boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} \quad \operatorname{var}\big(\mathbf{v}\big|\mathbf{p}, p_f\big) = \boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}$$

2. *For all* $k \in \mathcal{NI}$, *the distribution of* $\mathbf{v}$ *conditional on the realization of* p_f, $\mathbf{p}$, *and* $\mathbf{s}_k$ *is multivariate normal with the same mean and variance as the distribution of* $\mathbf{v}$ *conditional on* $\mathbf{y}$*:*

$$E\big[\mathbf{v}\big|\mathbf{s}_k, \mathbf{p}, p_f\big] = \boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} \quad \operatorname{var}\big(\mathbf{v}\big|\mathbf{s}_k, \mathbf{p}, p_f\big) = \boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}} \tag{10}$$

3. For all $k \in \mathcal{I}$, the distribution of $\mathbf{1}'\mathbf{v}$ conditional on the realization of p_f, $\mathbf{1}'\mathbf{p}$, and $\mathbf{s}_k$ is normal with the same mean and variance as the distribution of $\mathbf{1}'\mathbf{v}$ conditional on $\mathbf{y}$. In other words,

$$E\left[\mathbf{1}'\mathbf{v}\middle|\mathbf{s}_k, \mathbf{1}'\mathbf{p}, p_f\right] = \mathbf{1}'\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} \quad \text{var}\left(\mathbf{1}'\mathbf{v}\middle|\mathbf{s}_k, \mathbf{1}'\mathbf{p}, p_f\right) = \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1} \tag{11}$$

The proof of Corollary 4.5 is in Appendix A.

Corollary 4.6. *Assume that $\mathbf{y}$ satisfies (GR). The equilibrium prices in the artificial economy $\mathcal{E}_{\mathbf{y}}$ form a rational expectation equilibrium in the actual economy. The allocations are identical in both equilibria.*

Proof of Corollary 4.6. Assume that investors in the actual economy face prices that are the equilibrium prices in the artificial economy.

Let $k \in \mathcal{NI}$. The investor's objective is to maximize $E[U_k(c, b, \mathbf{x}'\mathbf{v})|\mathbf{s}_k, \mathbf{p}, p_f]$. We have

$$E[U_k(c, b, \mathbf{x}'\mathbf{v})|\mathbf{s}_k, \mathbf{p}, p_f] \underset{(10)}{=} -e^{-\rho_k c} - e^{-\rho_k \left(b + \mathbf{x}'\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} - \frac{\rho_k}{2}\mathbf{x}'\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{x}\right)} = E[U_k(c, b, \mathbf{x}'\mathbf{v})|\mathbf{y}]$$

Because the budget constraints are the same in both the actual economy and the artificial economy, we conclude that the equilibrium allocation of a nonindex investor in the artificial economy is also optimal in the actual economy.

Let $k \in \mathcal{I}$. The investor's objective is to maximize $E[U_k(c, b, q\mathbf{1}'\mathbf{v})|\mathbf{s}_k, \mathbf{1}'\mathbf{p}, p_f]$. We have

$$
\begin{aligned}
& \max_{c,b,q} \quad E\left[U_k(c, b, q\mathbf{1}'\mathbf{v})\,|\mathbf{s}_k, \mathbf{1}'\mathbf{p}, p_f\right] \\
& \text{s.t.} \quad \bar{c} - c + (0-b)p_f + (1-q)\mathbf{1}'\mathbf{p} = 0 \\
\underset{(11)}{=} \; & \max_{c,b,q} \quad -e^{-\rho_k c} - e^{-\rho_k\left(b + q\mathbf{1}'\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} - \frac{\rho_k}{2}q^2\mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1}\right)} \\
& \text{s.t.} \quad \bar{c} - c + (0-b)p_f + (1-q)\mathbf{1}'\mathbf{p} = 0 \\
= \; & \max_{c,b,q} \quad E\left[U_k(c, b, q\mathbf{1}'\mathbf{v})\,|\mathbf{y}\right] \\
& \text{s.t.} \quad \bar{c} - c + (0-b)p_f + (1-q)\mathbf{1}'\mathbf{p} = 0 \\
= \; & \max_{c,b,\mathbf{x}} \quad E\left[U_k(c, b, \mathbf{x}'\mathbf{v})\,|\mathbf{y}\right] \\
& \text{s.t.} \quad \bar{c} - c + (0-b)p_f + (\mathbf{1}-\mathbf{x})'\mathbf{p} = 0
\end{aligned}
$$

where the last equality arises because in the equilibrium in the artificial economy it is optimal for investors to hold the market (see Theorem 4.1).

We have shown that the equilibrium allocations in the artificial economy are optimal in the actual economy. We are left to show that the three markets clear. Those allocations clear the three markets in the artificial economy; therefore, they also clear the markets in the actual economy.

■

5 A Partially Revealing Equilibrium

Guided by hindsight, we define the vector $\mathbf{g} \in R^n$ as follows:

$$\mathbf{g} := (\boldsymbol{\Sigma}_{\mathbf{vv}} + \boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}})^{-1}\,\boldsymbol{\Sigma}_{\mathbf{vv}}\mathbf{1} \tag{12}$$

and for the remainder of this paper, we set $\mathbf{y} \in R^{n+1}$ to

$$\mathbf{y} := \begin{bmatrix} \dfrac{1}{|\mathcal{NI}|} \displaystyle\sum_{k \in \mathcal{NI}} \mathbf{s}_k \\ \\ \dfrac{1}{m} \mathbf{g}' \displaystyle\sum_{k=1}^{m} \mathbf{s}_k \end{bmatrix}_{(n+1)\times 1} \tag{13}$$

Theorem 5.1. *The vector* $\mathbf{y}$ *satisfies (GR).*

Appendix B contains the proof of Theorem 5.1 together with some preliminary results needed for the proof.

According to Corollary 4.6 and Theorem 5.1, there is a rational expectation equilibrium with prices and allocations identical to those in the artificial economy $\mathcal{E}_{\mathbf{y}}$. In particular, every investor, whether indexer or nonindexer, holds the market portfolio, and a conditional CAPM holds. Importantly, because the first n coordinates of $\mathbf{y}$ depend on the set $\mathcal{NI}$, the equilibrium prices depend on the specific partition of investors into indexers and nonindexers. The next corollary points out that the equilibrium prices are informationally equivalent to $\mathbf{y}$.

Corollary 5.2. *We have* $\sigma(\mathbf{p}, p_f) = \sigma(\mathbf{f}) = \sigma(\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}}) = \sigma(\mathbf{y})$.

The proof of Corollary 5.2 is in Appendix C. For notational consistency and brevity, we continue to condition on $\mathbf{y}$. Corollary 5.2 implies that doing so is equivalent to conditioning on equilibrium prices.

We have constructed a rational expectation equilibrium. But what is the information content of $\mathbf{y}$ (or, equivalently, the equilibrium prices $(\mathbf{p}, p_f)$)? The first n coordinates of $\mathbf{y}$ are the average of the nonindexers' signals. It is a well-known result in statistics that, in the case of normal distribution with a known variance, the sample mean is a sufficient statistic for the mean. Here, the mean is the asset payoff vector, $\mathbf{v}$, and the variance is known. Thus, the first n coordinates of $\mathbf{y}$ contain all the information about $\mathbf{v}$ that there is in the entire pool of nonindexers' private information.

The next theorem articulates the informational content of the $(n+1)$th coordinate of $\mathbf{y}$, $y_{n+1} = \frac{1}{m}\mathbf{g}' \sum_{k=1}^{m} \mathbf{s}_k$. Recall that we use $\mathbf{s}$ (without a subscript) to denote the concatenation of all signals.

Theorem 5.3. *We have*

1. $E[\mathbf{1}'\mathbf{v}|\mathbf{s}] = E[\mathbf{1}'\mathbf{v}|y_{n+1}]$, *and* $\mathrm{var}(\mathbf{1}'\mathbf{v}|\mathbf{s}) = \mathrm{var}(\mathbf{1}'\mathbf{v}|y_{n+1})$.

2. *Given* $\mathbf{s}$, y_{n+1} *is a minimal sufficient statistic for* $\mathbf{1}'\mathbf{v}$.

In part 2 of the Theorem, $\mathbf{s}$ plays the role of the data, y_{n+1} the role of the statistic, and $\mathbf{1}'\mathbf{v}$ the role of the parameter.

The proof of Theorem 5.3 is in Appendix C.

The next theorem shows that the forward price of the market portfolio, $\mathbf{1}'\mathbf{f}$, contains *all* the information in the economy about the future payoff of the market portfolio. The proof is based on the observation that $\mathbf{1}'\mathbf{f}$ is informationally equivalent to y_{n+1}.

Theorem 5.4 (Sufficient Statistic). *We have*

1. $E[\mathbf{1}'\mathbf{v}|\mathbf{s}] = E[\mathbf{1}'\mathbf{v}|\mathbf{1}'\mathbf{f}]$, *and* $\mathrm{var}(\mathbf{1}'\mathbf{v}|\mathbf{s}) = \mathrm{var}(\mathbf{1}'\mathbf{v}|\mathbf{1}'\mathbf{f})$.

2. *Given* $\mathbf{s}$, $\mathbf{1}'\mathbf{f}$ *is a minimal sufficient statistic for* $\mathbf{1}'\mathbf{v}$.

The proof of Theorem 5.4 is in Appendix C.

In this section, we have constructed a partially revealing equilibrium in which prices only convey indexers' information about the market portfolio. Therefore, some information about individual assets is lost. In the next section, we re-express this equilibrium property in different ways, emphasizing the point that many statistics relevant in empirical work can be linked to indexing.

6 Comparative Statics

So far, the sets $\mathcal{NI}$ and $\mathcal{I}$ have been fixed. In this section, we study how the equilibrium outcomes depend on the level of index investment.

The next result is based on the observation that the $(n+1)$th element of $\mathbf{y}$, $y_{n+1} = \frac{1}{m}\mathbf{g}' \sum_{k=1}^{m} \mathbf{s}_k$, is independent of the partition of the group of investors into indexers and nonindexers.

Theorem 6.1. *Fix a joint realization of* $\mathbf{v}$ *and* $\mathbf{s}$*. Then,* p_f*,* r_f*, the price of the market portfolio, the return on the market portfolio, and the capital market line do not depend on the specific partition of investors into indexers and nonindexers.*

The proof of Theorem 6.1 is in Appendix C.

Figure 1 shows an example in which the realization of the signals is fixed. The figure depicts, in the volatility–return plane, the capital market line and the efficient frontiers for two different partitions of the set of investors. As stated in Theorem 6.1, the capital market line is the same in both examples. The figure shows the most common situation we found in the many simulations we tried: The efficient frontier that corresponds to a partition of the investors with a large set of indexers is nested in the efficient frontier that corresponds to a partition with a smaller set of indexers.

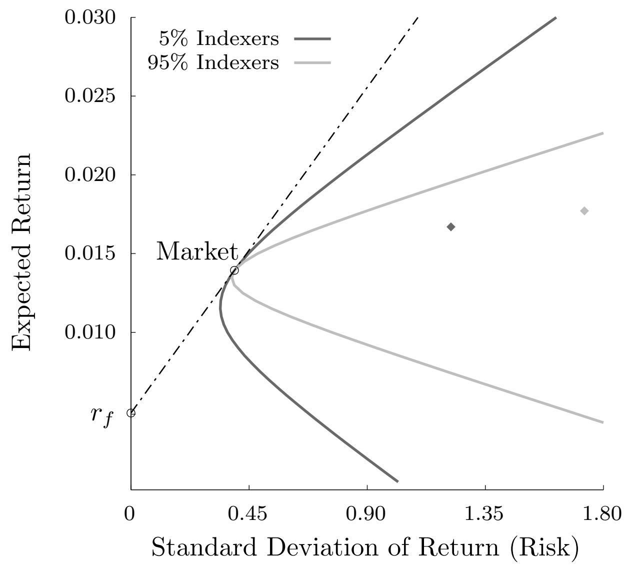

Figure 1: The efficient frontiers and the capital market line in the volatility–return plane. These are the realized efficient frontiers in an example with six risky assets and 10,000 investors. The capital market line and the position of the market portfolio (*tangency point*) are the same in both cases. The two points in the center of the frontiers stand for the same risky asset. The conditional Sharpe ratios are the slopes of the straight lines joining these points and the risk-free asset. These lines are not depicted, but it is apparent that the Sharpe ratio is lower (the slope of the invisible line is gradual) when 95% of the investors are indexers.

In Theorem 6.1, the realizations of the signals and payoffs were fixed. In contrast, in the remainder of this section, we study outcomes that depend solely on conditional covariance matrices, which are matrices of scalars. Even the conditional Sharpe ratio (Theorem 6.3), after algebraic simplifications, can be expressed in terms of scalars taken from covariance matrices. Thus, in the rest of this section, we need not assume that the realization of $\mathbf{v}$ or the realization of $\mathbf{s}$ is fixed. In particular, when we compare two partitions of the set of investors, one with $\mathcal{I}_1$ and the other with $\mathcal{I}_2$ such that $|\mathcal{I}_1| < |\mathcal{I}_2|$, we do not assume that $\mathcal{I}_1 \subset \mathcal{I}_2$ (the two sets may even be disjoint).

Theorem 6.2 (Conditional Variance of the Portfolio's Payoff). *Let* $\mathbf{x} \in R^n$ *be a portfolio, and consider changes as we increase* $|\mathcal{I}|$*. If* $\mathbf{x}$ *is a scalar multiplication of the market portfolio, then the conditional variance,* $\mathrm{var}(\mathbf{x}'\mathbf{v}|\mathbf{y})$*, does not change. For all other portfolios,* $\mathrm{var}(\mathbf{x}'\mathbf{v}|\mathbf{y})$ *strictly increases.*

The proof of Theorem 6.2 is in Appendix C.

For any portfolio with a return (i.e., a portfolio with a nonzero cost), we define the conditional Sharpe ratio as

$$\frac{E\left[\dfrac{\mathbf{x}'\mathbf{v}}{\mathbf{x}'\mathbf{p}} - 1 \,\middle|\, \mathbf{y}\right] - r_f}{\sqrt{\mathrm{var}\left(\dfrac{\mathbf{x}'\mathbf{v}}{\mathbf{x}'\mathbf{p}} - 1 \,\middle|\, \mathbf{y}\right)}}$$

Theorem 6.3 (Conditional Sharpe Ratio). *Let* $\mathbf{x} \in R^n$ *be a portfolio with a positive Sharpe ratio, and consider changes as we increase* $|\mathcal{I}|$*. If* $\mathbf{x}$ *is a scalar multiplication of the market portfolio, then the Sharpe ratio does not change. For all other portfolios, the Sharpe ratio strictly decreases.*

The proof of Theorem 6.3 is in Appendix C.

We can always write

$$r_i = r_f + \beta_i(r_{\text{mkt}} - r_f) + \epsilon \tag{14}$$

where

$$\epsilon \equiv r_i - r_f - \beta_i(r_{\text{mkt}} - r_f)$$

Because the conditional CAPM holds, we know that $E[\epsilon|\mathbf{y}] = 0$. From the definition of β_i (see Equation 8), it is immediately apparent that $E\left[(r_{\text{mkt}} - r_f)\epsilon \,|\, \mathbf{y}\right] = 0$. Thus, it is meaningful to use R^2 as a measure of the strength of the CAPM regression (Equation 14). In practice, one computes the sample R^2. We compute the population R^2. We now ask how R^2 depends on $|\mathcal{I}|$.

Theorem 6.4 (Conditional $\boldsymbol{R}^2$). *For every asset i, R^2 of the CAPM relation decreases with $|\mathcal{I}|$.*

The proof of Theorem 6.4 is in Appendix C.

Fix i. Let $\mathbf{1} - \mathbf{e}_i$ be the portfolio that includes all assets except for asset i. Denote the payoff and return by v_{-i} and r_{-i}, respectively.

Theorem 6.5 (Conditional Correlation in Returns). *Assume* $\text{corr}(r_i, r_{-i}|\mathbf{y}) > 0$. *Then, this correlation decreases with $|\mathcal{I}|$.*

The proof of Theorem 6.5 is in Appendix C.

Theorem 6.6 (Unconditional Variance of Portfolio's Price). *Let $\mathbf{x} \in R^n$ be a portfolio, and consider changes as we increase $|\mathcal{I}|$. If $\mathbf{x}$ is a scalar multiplication of the market portfolio, then* $\text{var}(\mathbf{x}'\mathbf{p})$ *does not change. For all other portfolios,* $\text{var}(\mathbf{x}'\mathbf{p})$ *strictly decreases.*

The proof of Theorem 6.6 is in Appendix C.

Theorem 6.7 (Unconditional Correlation in Asset Prices). *For every i, assume* $\operatorname{corr}(\mathbf{e}_i'\mathbf{p}, (\mathbf{1}-\mathbf{e}_i)'\mathbf{p}) > 0$*. Then, this correlation strictly increases with* $|\mathcal{I}|$*.*

Proof of Theorem 6.7. We have

$$\operatorname{corr}(\mathbf{e}_i'\mathbf{p}, (\mathbf{1}-\mathbf{e}_i)'\mathbf{p}) = \frac{\operatorname{cov}(\mathbf{e}_i'\mathbf{p}, (\mathbf{1}-\mathbf{e}_i)'\mathbf{p})}{\sqrt{\operatorname{var}(\mathbf{e}_i'\mathbf{p})}\sqrt{\operatorname{var}((\mathbf{1}-\mathbf{e}_i)'\mathbf{p})}}$$

To see that the denominator decreases and the numerator increases, we write

$$\operatorname{var}(\mathbf{1}'\mathbf{p}) = \operatorname{var}(\mathbf{e}_i'\mathbf{p}) + \operatorname{var}((\mathbf{1}-\mathbf{e}_i)'\mathbf{p}) + 2\operatorname{cov}(\mathbf{e}_i'\mathbf{p}, (\mathbf{1}-\mathbf{e}_i)'\mathbf{p}))$$

According to Theorem 6.6, $\operatorname{var}(\mathbf{1}'\mathbf{p})$ does not change, whereas both $\operatorname{var}(\mathbf{e}_i'\mathbf{p})$ and $\operatorname{var}((\mathbf{1}-\mathbf{e}_i)'\mathbf{p})$ decrease. Therefore, $\operatorname{cov}(\mathbf{e}_i'\mathbf{p}, (\mathbf{1}-\mathbf{e}_i)'\mathbf{p})$ increases.

■

7 The Limiting Case

We have already pointed out that, regardless of what the set of index investors is, the concatenation of all signals, $\mathbf{s}$, satisfies (GR). Therefore, regardless of what the partition of investors into indexers and nonindexers is, there is always a fully revealing equilibrium. We think that in the presence of indexers, the fully revealing equilibrium is unappealing.

That said, the fully revealing equilibrium is the equilibrium that corresponds to the limiting case of the partially revealing equilibrium, in which all investors are nonindexers; that is, $|\mathcal{NI}| = m$. When all investors are nonindexers, the $(n+1)$th coordinate of $\mathbf{y}$ is a linear function of the first n coordinates. Therefore, $\mathbf{y}$ is degenerate, and its covariance matrix is noninvertible. We can still use the artificial economy apparatus. We simply remove the redundant $(n+1)$th coordinate, and we are left with the nondegenerate n-dimensional vector, $\frac{1}{m}\sum_{k=1}^{m}\mathbf{s}_k$. This vector satisfies (GR) because a sample mean of a multivariate normal random

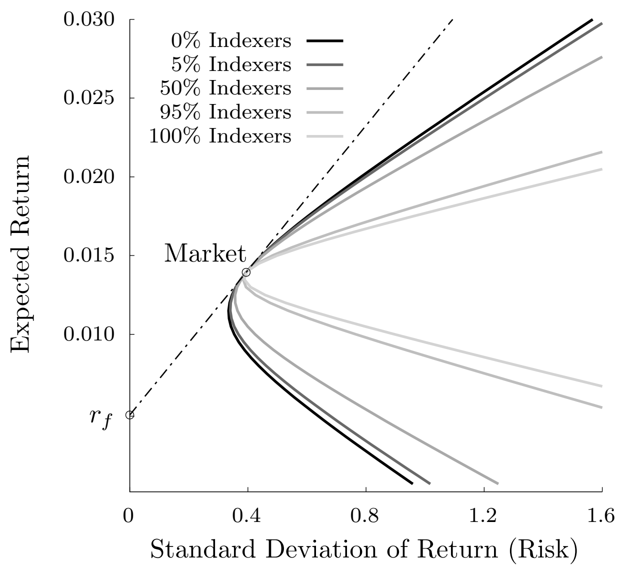

Figure 2: The efficient frontiers and the capital market line. This is a continuation of the example shown in Figure 1. These are the realized efficient frontiers in an example with six risky assets and 10,000 investors. The capital market line and the position of the market portfolio (*tangency point*) are the same in all cases.

vector with a known covariance matrix is a sufficient statistic for its mean. Moreover, this is a fully revealing equilibrium.[18] Therefore, the limiting case in which all investors are nonindexers is a fully revealing equilibrium.

When all investors are indexers, it is not clear how individual assets are priced. It is conceivable that there are infinitely many equilibria, all of which agree on the price of the market portfolio but disagree on the prices of individual assets. Our model can be used to pick one of these equilibria, the equilibrium that corresponds to the limiting case of our model in which all investors are indexers.

When all investors are indexers, the random vector $\mathbf{y}$ is not defined (because of the division by zero of the first n coordinates). It is natural to remove the first n coordinates altogether, and use only the $(n+1)$th coordinate. Indeed, $y_{n+1} = \frac{1}{m}\mathbf{g}' \sum_{k=1}^{m}$ satisfies (GR) because, according

[18]The artificial economy in which everyone observes the sufficient statistic has the same outcomes as the artificial economy in which everyone observes $\mathbf{s}$ (Grossman, 1978).

to Theorem 5.3, this random variable is a sufficient statistic for $\mathbf{1}'\mathbf{v}$. Thus, the conditions in (GR) with regard to the set of indexers are satisfied. Moreover, the conditions in (GR) with regard to the set of nonindexers are trivially satisfied because the set of nonindexers is empty. Thus, the equilibrium in the artificial economy in which everyone observes only y_{n+1} is also a rational expectation equilibrium when all investors are indexers.

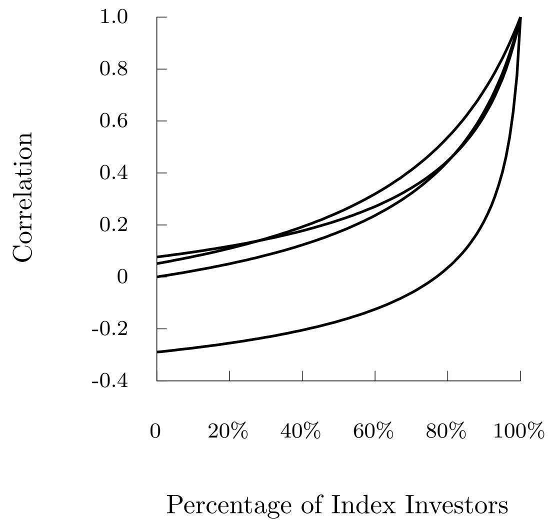

Figure 3: Correlation in forward prices becomes perfect when the percentage of index investors is 100%. In this example, there are four risky assets, and for each risky asset we compute the correlation between the asset and the portfolio of the remaining assets. The payoff of one of the assets is negatively correlated with the payoff of the remaining assets. The parameters in this example are $n = 4$, $m = 10,000$, $\boldsymbol{\Sigma}_{\mathbf{vv}} = \begin{pmatrix} 5 & 1 & 1 & -1 \\ 1 & 20 & 2 & -2 \\ 1 & 2 & 10 & -3 \\ -1 & -2 & -3 & 10 \end{pmatrix}$, and $\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}} = \boldsymbol{\Sigma}_{\mathbf{vv}}$. The values of $\bar{\rho}$, $\boldsymbol{\mu}_{\mathbf{v}}$, and $\bar{c}$ are irrelevant for the purpose of computing these correlations.

Figure 2 repeats the same example shown in Figure 1, but with the addition of the middle case (50% indexers) and the two extreme cases. It is apparent that even when 100% of the investors are indexers, the efficient frontier is not degenerate. By contrast, when all investors are indexers, forward prices are perfectly correlated. In other words, if $f_i = p_i/p_f$ is the forward price of the ith asset, then $\text{corr}(f_i, f_j)$ is either 1 or -1.[19] Figure 3 demonstrates how the correlation between forward prices changes as the level of index investment increases,

[19]When all investors are indexers, then Equations 2 and 4 imply that for each i, $f_i = a_i + b_i y_{n+1}$ for some scalars a_i and b_i. Thus, f_i and f_j are perfectly correlated.

and becomes perfect when all investors are indexers. Interestingly, in this example, the payoff of one asset is negatively correlated with the payoff of each of the remaining assets. Accordingly, when the number of indexers is low, the forward price of this asset tends to move in the opposite direction from the forward prices of the remaining assets. However, when the level of index investors is sufficiently high, in this example, the correlation become positive. When the percentage of index investors is 100%, the comovement in forward prices is perfectly positive.

As in other conditional CAPM models, betas are realizations of random variables. In our model, the distributions of betas are ratios of Gaussian random variables, and therefore their moments do not exist. However, we can examine densities. We have computed many examples, and find that as $\mathcal{I}$ increases, the dispersion of a beta decreases. However, even when the percentage of index investors is 100%, the betas are still random.

8 Large Economy

In this section, we follow Hellwig (1980) and McLean and Postlewaite (2002) and study a large economy with asymmetric information by means of taking the limit of a sequence of growing economies. Here, not only does the size of the economy grow to infinity but also the accuracies of the private signals shrink to zero. When the economy is large, the price taking assumption is appealing. When the signals are pure noise, the assumption that signals are costless is appealing. We show that, as we pass to the limit, (i) the indexers' constraint to remain on the capital market line is not binding even after signals are realized and indexers can peek at the entire set of asset prices, and (ii) the qualitative comparative statics results, reported in Section 6, continue to hold.

The mode of convergence we use is almost sure convergence. We therefore assume the existence of a single probability space in which the payoff per share $\mathbf{v}$ and the multivariate random vectors $\{\boldsymbol{\epsilon}_k\}_{k=1}^{\infty}$ are defined. Next, we turn our attention to the set of investors. The set of investors corresponds to the set of natural numbers, although in the mth economy only the first m of them exist. We let $\mathcal{I}$ and $\mathcal{NI}$ denote a partition of the natural numbers such that when we set

$$\pi^m = \frac{|\mathcal{I} \cap \{1, \ldots, m\}|}{m} \tag{15}$$

then $\lim_{m\to\infty} \pi^m$ exists. For simplicity, we require the limit to be strictly between zero and one. Finally, we take a sequence of strictly positive coefficients of risk aversion, $\{\rho_k\}_{k=1}^{\infty}$, such that if $\bar{\rho}^m$ is the harmonic mean of the first m elements, then $\lim_{m\to\infty} \bar{\rho}^m$ exists and is strictly positive.

In every economy $m \geq k$, the coefficient of risk aversion of the kth investor is ρ_k, the investor is an indexer if $k \in \mathcal{I}$, and the signal the kth investor observes is $s_k = \mathbf{v} + m^{1/2}\boldsymbol{\epsilon}_k$. Each of the economies is exactly as described in Section 2. Importantly, in the mth economy, there are m investors, and each risky asset has m shares outstanding; so the sequence of economies is increasing in size. In the mth economy, the covariance matrix of the signal noise is $m\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}}$; so as the size of the economy increases, the investor becomes informationally small.

We now fix a joint realization $\mathbf{v}$ and $\{\boldsymbol{\epsilon}_k\}_{k=1}^{\infty}$. Thus, for each m, we know the signals and the equilibrium prices in the mth economy. We ask ourselves, What if an indexer picks at the entire set of asset prices? Will the investor regret the early-stage decision to be an indexer? The next theorem shows that in a large economy the investor does not regret this decision.

Theorem 8.1 (Interim Optimality of Index Investment in the Large Economy). *Fix $k \in \mathcal{I}$. For any $m \geq k$, let $\mathbf{p}^m, p_f^m$ be the equilibrium prices and let $\mathbf{s}_k^m$ be the investor's signal in the mth economy. Let $\mathbf{x}_k^m$ denote the optimal portfolio when the index investor takes those prices as given, but solves*

$$\begin{aligned}
&\max_{c,b,\mathbf{x}} E\left[U_k(c, b, \mathbf{x}'\mathbf{v}) \,\middle|\, \mathbf{s}_k^m, \mathbf{p}^m, p_f^m\right] \\
&\text{s.t. } \bar{c} - c + (0 - b)p_f^m + (\mathbf{1} - \mathbf{x})'\mathbf{p}^m = 0
\end{aligned}$$

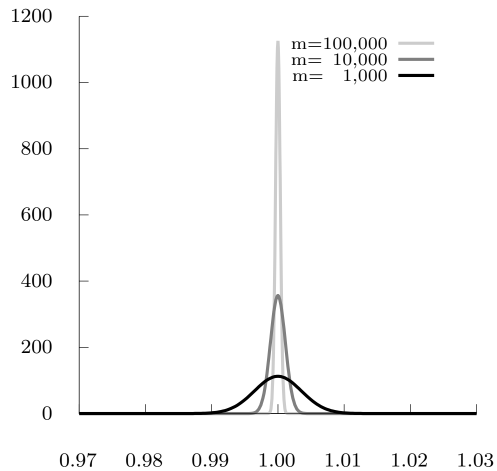

Figure 4: Interim optimality of index investment in the large economy. $\mathbf{x}^m = [x_1^m \ \dots \ x_n^m]'$ is the optimal unconstrained portfolio of an indexer. The figure shows the densities of x_2^m/x_1^m, demonstrating that $\lim_m x_2^m/x_1^m = 1$. The parameters in this example are $n = 2$, $\boldsymbol{\Sigma}_{\mathbf{vv}} = \left(\begin{smallmatrix} 10 & 1 \\ 1 & 20 \end{smallmatrix}\right)$, and $\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}} = \boldsymbol{\Sigma}_{\mathbf{vv}}$, and for every m, $\pi^m = 1/2$ and $\bar{\rho}^m = 2$. The values of $\boldsymbol{\mu}_{\mathbf{v}}$ and $\bar{c}$ are irrelevant for the purpose of computing these densities.

Then,

$$\mathbf{x}_k^m = \frac{\bar{\rho}^m}{\rho_k}\mathbf{1} + \frac{1}{\rho_k}\boldsymbol{\xi}_k^m$$

where $\frac{1}{\rho_k}\boldsymbol{\xi}_k^m$ *is a zero-mean random portfolio (i.e.,* $\boldsymbol{\xi}_k^m$ *depends on prices and the signal).*

However, with probability one,

$$\lim_{m\to\infty} \boldsymbol{\xi}_k^m = \mathbf{0}_{n\times 1}$$

The proof of Theorem 8.1 is in Appendix C. Figure 4 demonstrates the convergence of the unconstrained portfolio by showing the density of the ratio of holdings: When the unconstrained portfolio converges to a scalar multiplication of the market portfolio, $\mathbf{1}$, then the ratio of share holding in asset i to share holding in asset j is 1.

The result we report in Theorem 8.1 is intuitive: An informationally small investor leaves little on the table when adhering to Tobin's investment rule. In a large economy (i.e., the limit), an index investor is interim indifferent between investing in individual securities and investing in the market portfolio. Therefore, any partition of investors into indexers and nonindexers is interim rational. Our final task is to illustrate that the impact of index investment on asset prices passes to the limit.

The qualitative comparative statics analysis presented in Section 6 is mostly the study of the sign of certain derivatives. It is possible that a sequence of those derivatives can be strictly positive, but its limit is nevertheless zero. Our goal is to prove that the limit of those derivatives is bounded away from zero, and hence the qualitative results pass to the limit.

Consider the conditional Sharpe ratio for the return on a portfolio $\mathbf{x}$. In Theorem 6.3, we proved that, provided that the portfolio is not a scalar multiplication of the market portfolio, the Sharpe ratio strictly decreases as we increase the numbers of index investors. In fact, in the proof of Theorem 6.3, we expressed the Sharpe ratio as a function of the proportion of index investors. Once expressed as a function of the proportion, neither m, nor the set of indexers, nor the set of nonindexers shows up in the expression for the Sharpe ratio. In particular, if $m_1 \neq m_2$, but $\bar{\rho}^{m_1} = \bar{\rho}^{m_2}$ and $\pi^{m_1} = \pi^{m_2}$, then Sharpe ratio is the same in both economies. We therefore have the following.

Lemma 8.2. *Consider the sequence of economies parameterized by m. Let $\mathbf{x}$ be a specific portfolio. There exists a function f such that in the mth economy, the conditional Sharpe ratio equals*

$$\bar{\rho}^m f(\mathbf{x}, \mathbf{\Sigma_{vv}}, \mathbf{\Sigma_{\epsilon\epsilon}}, \pi^m)$$

In addition, if $\mathbf{x}$ is not a positive scalar multiplication of the market portfolio, then $\dfrac{\partial f}{\partial \pi}(\mathbf{x}, \mathbf{\Sigma_{vv}}, \mathbf{\Sigma_{\epsilon\epsilon}}, \pi^m) < 0$.

For proof, see the proofs of Theorems 6.2 and 6.3. The function f in the lemma is strictly decreasing with respect to π because Theorem 6.3 is applied to each of the economies in the sequence.

We now consider two sequences of finite economies that are identical in every aspect, except for the decomposition of investors into indexers and nonindexers. We assume that $\lim_m \pi_1^m < \lim_m \pi_2^m$. We fix a portfolio $\mathbf{x}$. We want to show that the Sharpe ratio is smaller in the large economy with larger fractions of indexers:

$$\lim_m f(\mathbf{x}, \mathbf{\Sigma_{vv}}, \mathbf{\Sigma}_{\boldsymbol{\epsilon\epsilon}}, \pi_1^m) \overset{?}{>} \lim_m f(\mathbf{x}, \mathbf{\Sigma_{vv}}, \mathbf{\Sigma}_{\boldsymbol{\epsilon\epsilon}}, \pi_2^m)$$

According to Lemma 8.2, f is differentiable with respect to π. Thus, it is also continuous, and the inequality above can be written as

$$f(\mathbf{x}, \mathbf{\Sigma_{vv}}, \mathbf{\Sigma}_{\boldsymbol{\epsilon\epsilon}}, \lim_m \pi_1^m) \overset{?}{>} f(\mathbf{x}, \mathbf{\Sigma_{vv}}, \mathbf{\Sigma}_{\boldsymbol{\epsilon\epsilon}}, \lim_m \pi_2^m)$$

According to Lemma 8.2, f is decreasing in π, which confirms the inequality. Similarly, we can show that the other qualitative results we proved in Section 6 pass to the limit.

9 Concluding Remarks

Markowitz (1952) studies mean–variance portfolio selection and discovers the efficient frontier. Tobin (1958) adds the risk-free asset, discovers the separation theorem (Tobin 1958, page 84), and explains that "Markowitz's main interest is prescription of rules of rational behaviour for investors; the main concern of [my] paper is the implications for economic theory, mainly comparative statics, that can be derived from assuming that investors do in fact follow [Markowitz's] rules" (Tobin 1958, p. 85). We add costless private signals, and our main concern is the implications, mainly comparative statics, that can be derived from assuming that some investors follow Tobin's rule. Just as Markowitz's rules are compatible with Tobin's extension, Tobin's rule is compatible with our extension: In our model, it is optimal for nonindex investors to index.

For our analysis, we have used the Rational Expectation setup. This setup was famously criticized by Hellwig (1980). His criticism has two components. First, is the

Our model shows that as more nonindex investors become index investors, the proportion of idiosyncratic risk to total risk increases, the R^2 of the CAPM regression decreases, comovement in returns decreases, and comovement in asset prices increases.[20] For any portfolio other than the market portfolio, the portfolio's Sharpe ratio decreases, and the variance of the portfolio's payoff increases. The following examples illustrate some of the implications of our model.

There is a known link between corporate underinvestment in real projects and total risk. Panousi and Papanikolaou (2012) find that the link is stronger when managers hold a large equity stake in the firm, and Deng, Chen, and Kong (2014) go even further and document that the link tends to be insignificant when managerial ownership is very low. Those empirical papers support the notion that when managers are exposed to a firm's total risk, they are reluctant to invest in risky real projects. Our model shows that the larger the set of index investors is, the greater is the uncertainty about future value of individual assets. Thus, our model suggests a possible link between index investment and corporate underinvestment.

Similarly, the cost of financial hedging depends on the volatility of the future payoff of the asset. In particular, our model suggests that the corporate practice of awarding options to management is costlier in the presence of index investment.

Finally, a firm's ability to raise financing (bank loans or bonds) is likely to depend on its stock price. Our model shows that the larger the set of index investors is, the greater is the comovement in pricing. It is therefore conceivable that in the presence of index investors, a large negative shock to one firm may make it difficult for another firm to raise the capital needed to invest in real projects or repay old debt. The former implies corporate underinvestment; the latter implies financial contagion.

[20] See Footnote 6 in Page 3.

Appendices

A Artificial Economies: Proofs

Proof of Theorem 4.1. As stated in the theorem, $\mathbf{f}$ is given in Equation 4; the price of the bond, p_f, is given in Equation 5; and $\mathbf{p}$ is given in Equation 6. Our goal is to show not only that these prices clear the markets but also that they are the only prices that can clear the markets.

In the artificial economy, the problem of the kth investor is

$$\begin{aligned}
&\max_{c,b,\mathbf{x}} E\left[U_k(c,b,\mathbf{x}'\mathbf{v})\,|\mathbf{y}\right], \text{ subject to } \bar{c}-c+(0-b)p_f+(\mathbf{1}-\mathbf{x})'\mathbf{p}=0\\
&=\max_{c\in R,\mathbf{x}\in R^n} E\left[U_k\left(c,(\bar{c}-c)\frac{1}{p_f}+(\mathbf{1}-\mathbf{x})'\frac{1}{p_f}\mathbf{p},\mathbf{x}'\mathbf{v}\right)\middle|\mathbf{y}\right]\\
&=\max_{c\in R,\mathbf{x}\in R^n} -e^{-\rho_k c}-e^{-\rho_k\left((\bar{c}-c)\frac{1}{p_f}+(\mathbf{1}-\mathbf{x})'\frac{1}{p_f}\mathbf{p}+\mathbf{x}'\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}}-\frac{\rho_k}{2}\mathbf{x}'\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{x}\right)}\\
&=\max_{c\in R} -e^{-\rho_k c}+e^{-\rho_k\left((\bar{c}-c)\frac{1}{p_f}+\mathbf{1}'\frac{1}{p_f}\mathbf{p}\right)}\times\max_{\mathbf{x}\in R^n} -e^{-\rho_k\left(\mathbf{x}'\left(\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}}-\frac{1}{p_f}\mathbf{p}\right)-\frac{\rho_k}{2}\mathbf{x}'\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{x}\right)}
\end{aligned}\tag{A.1}$$

We solve the maximization problem "backward." The first-order condition with respect to $\mathbf{x}$ is

$$-\frac{1}{p_f}\mathbf{p}+\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}}-\frac{\rho_k}{2}\left(\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}+\boldsymbol{\Sigma}'_{\mathbf{vv}|\mathbf{y}}\right)\mathbf{x}=0$$

We replace $\mathbf{x}$ with $\mathbf{x}_k$ to emphasize that this is the optimal portfolio of the kth investor. Using the symmetry of the covariance matrix, we rearrange and obtain

$$\mathbf{x}_k=\frac{1}{\rho_k}\boldsymbol{\Sigma}^{-1}_{\mathbf{vv}|\mathbf{y}}\left(\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}}-\frac{1}{p_f}\mathbf{p}\right)\tag{A.2}$$

When summing all portfolios, market clearing implies that in equilibrium they add up to the market portfolio. When summing all reciprocals of coefficient of risk aversions, the definition of the harmonic mean (Equation 1) implies that they add up to $m/\bar{\rho}$. Thus, summing the first-order conditions (Equation A.2), we obtain

$$\begin{array}{ccc} \sum_{k=1}^{m} \mathbf{x}_k & = & \sum_{k=1}^{m} \frac{1}{\rho_k} \mathbf{\Sigma}_{\mathbf{vv|y}}^{-1} \left(\boldsymbol{\mu}_{\mathbf{v|y}} - \frac{1}{p_f}\mathbf{p} \right) \\ \| & & \| \\ m\mathbf{1} & & \frac{m}{\bar{\rho}} \mathbf{\Sigma}_{\mathbf{vv|y}}^{-1} \left(\boldsymbol{\mu}_{\mathbf{v|y}} - \frac{1}{p_f}\mathbf{p} \right) \end{array}$$

We multiply the above parity by $\bar{\rho}\mathbf{\Sigma}_{\mathbf{vv|y}}$, and conclude that whatever $\mathbf{p}$ and p_f are, their ratio in any equilibrium is uniquely defined:

$$\frac{1}{p_f}\mathbf{p} = \boldsymbol{\mu}_{\mathbf{v|y}} - \bar{\rho}\, \mathbf{\Sigma}_{\mathbf{vv|y}}\mathbf{1} \tag{A.3}$$

In other words, we have shown that the market for risky assets clears if and only if the ratio of prices is given by Equation A.3.

Plugging the equilibrium ratio of prices (Equation A.3) back into the first-order condition (Equation A.2), we conclude that

$$\mathbf{x}_k = \frac{\bar{\rho}}{\rho_k}\mathbf{1} \tag{A.4}$$

Inserting Equation A.4 back into the investors' problem (Equation A.1), we can write the problem of the kth investor as

$$\max_{c \in R} \; - e^{-\rho_k c} - e^{-\rho_k \left((\bar{c} - c)\frac{1}{p_f} + \mathbf{1}'\frac{1}{p_f}\mathbf{p} + \frac{\bar{\rho}}{\rho_k}\mathbf{1}' \left(\boldsymbol{\mu}_{\mathbf{v|y}} - \frac{1}{p_f}\mathbf{p} \right) - \frac{\bar{\rho}^2}{2\rho_k}\mathbf{1}'\mathbf{\Sigma}_{\mathbf{vv|y}}\mathbf{1} \right)}$$

The first-order condition with respect to c is

$$\rho_k e^{-\rho_k c} = \frac{\rho_k}{p_f} e^{-\rho_k \left((\bar{c} - c)\frac{1}{p_f} + \mathbf{1}'\frac{1}{p_f}\mathbf{p} + \frac{\bar{\rho}}{\rho_k}\mathbf{1}' \left(\boldsymbol{\mu}_{\mathbf{v|y}} - \frac{1}{p_f}\mathbf{p} \right) - \frac{\bar{\rho}^2}{2\rho_k}\mathbf{1}'\mathbf{\Sigma}_{\mathbf{vv|y}}\mathbf{1} \right)}$$

We take log on both sides, simplify, and replace c with c_k to emphasize that this is the optimal consumption of the kth investor:

$$c_k = \frac{1}{\rho_k}\log(p_f) + (\bar{c} - c_k)\frac{1}{p_f} + \mathbf{1}'\frac{1}{p_f}\mathbf{p} + \frac{\bar{\rho}}{\rho_k}\mathbf{1}'\left(\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} - \frac{1}{p_f}\mathbf{p}\right) - \frac{\bar{\rho}^2}{2\rho_k}\mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1}$$

Adding up the m first-order conditions of all investors yields

$$\sum_{k=1}^{m} c_k = \left(\sum_{k=1}^{m}\frac{1}{\rho_k}\right)\log(p_f) + \left(\sum_{k=1}^{m}(\bar{c} - c_k)\right)\frac{1}{p_f} + m\mathbf{1}'\frac{1}{p_f}\mathbf{p} + \left(\sum_{k=1}^{m}\frac{\bar{\rho}}{\rho_k}\right)\mathbf{1}'\left(\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} - \frac{1}{p_f}\mathbf{p}\right) - \frac{\bar{\rho}}{2}\left(\sum_{k=1}^{m}\frac{\bar{\rho}}{\rho_k}\right)\mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1}$$

The market-clearing condition implies $\sum_{k=1}^{m}(\bar{c} - c_k) = 0$. In addition, the definition of the harmonic mean (Equation 1) implies

$$\sum_{k=1}^{m}\frac{\bar{\rho}}{\rho_k} = m$$

Thus, the sum of the m first-order conditions and the market-clearing condition implies that in every equilibrium we must have

$$m\bar{c} = \frac{m}{\bar{\rho}}\log(p_f) + m\mathbf{1}'\frac{1}{p_f}\mathbf{p} + m\mathbf{1}'\left(\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} - \frac{1}{p_f}\mathbf{p}\right) - m\frac{\bar{\rho}}{2}\mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1}$$

which simplifies to

$$\bar{c} = \frac{1}{\bar{\rho}}\log(p_f) + \mathbf{1}'\left(\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} - \frac{\bar{\rho}}{2}\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1}\right) \underset{(4)}{=} \frac{1}{\bar{\rho}}\log(p_f) + \mathbf{1}'\left(\mathbf{f} + \frac{\bar{\rho}}{2}\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1}\right) \tag{A.5}$$

We conclude that in every equilibrium, the logarithm of the bond price is

$$\log(p_f) = -\bar{\rho}\left(\mathbf{1}'\mathbf{f} + \frac{\bar{\rho}}{2}\mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1}\right) + \bar{\rho}\bar{c} \tag{A.6}$$

We already proved that in every equilibrium, the ratio of prices must satisfy Equation A.3, and since we have demonstrated that in all equilibria the bond price is given by Equation A.6, we conclude that the vector of asset prices is also uniquely defined and given by

$$\mathbf{p} = p_f\left(\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} - \bar{\rho}\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1}\right) \tag{A.7}$$

To conclude the proof, we note that the equilibrium prices stated in the theorem and the equilibrium portfolio of risky assets are the same at the equilibrium identities we computed in the proof. That is, Equations 4, 5, 6, and 7 are the same as Equations A.3, A.6, A.7, and A.4, respectively.

■

Proof of Theorem 4.2. Fix an investor k.

Let c_k^*, b_k^*, and x_k^* be the investor's decisions in equilibrium. From Theorem 4.1, we know that the investor holds the market. In other words, there is a scalar q_k^* such that $x_k^* = q_k^* \mathbf{1}$.[21]

Define $w_k^* = b_k^* p_f + q_k^* \mathbf{1}'\mathbf{p}$, where p_f and $\mathbf{p}$ are the equilibrium prices in the artificial economy. We invoke a calculus of a variation-type argument. Instead of looking at the full problem, we restrict our attention to a subclass of feasible allocations that includes the optimal one. Specifically, let us say that the investor contemplates consuming the optimal c_k^* and investing a fraction φ of w_k^* in the market portfolio, a fraction κ of w_k^* in asset i, and the remaining $(1-\varphi-\kappa)w_k^*$ in bonds. In other words, the allocation the investor contemplates is to buy $w_k^*(1-\varphi-\kappa)/p_f$ bonds, a fraction $w_k^*\varphi/(\mathbf{1}'\mathbf{p})$ of the portfolio $\mathbf{1}$, and an additional $w_k^*\kappa/p_i$ shares of asset i. The optimal fraction invested in asset i must satisfy $\kappa = 0$.

We can write the investor's problem as follows:

$$
\begin{aligned}
&\max_{c,b,\mathbf{x}} E\left[U_k(c,b,\mathbf{x}'\mathbf{v})\,|\mathbf{y}\right], \text{ subject to } \bar{c} - c + (0-b)p_f + (\mathbf{1}-\mathbf{x})'\mathbf{p} = 0 \\
&= \max_{b,\mathbf{x}\in R^n} E\left[U_k\left(c_k^*, b, \mathbf{x}'\mathbf{v}\right)|\,\mathbf{y}\right], \text{ subject to } bp_f + \mathbf{x}'\mathbf{p} = w_k^* \\
&= -\,e^{-\rho_k c^*} + \max_{b,\mathbf{x}\in R^n} -E\left[e^{-\rho_k\,(b+\mathbf{x}'\mathbf{v})}\middle|\,\mathbf{y}\right], \text{ subject to } bp_f + \mathbf{x}'\mathbf{p} = w_k^* \\
&= -\,e^{-\rho_k c^*} + \max_{\varphi,\kappa} -E\left[\exp\left(-\rho_k w_k^*\left(\frac{1-\varphi-\kappa}{p_f} + \frac{\varphi}{\mathbf{1}'\mathbf{p}}\mathbf{1}'\mathbf{v} + \frac{\kappa}{p_i}v_i\right)\right)\middle|\,\mathbf{y}\right]
\end{aligned}
$$

[21] In Theorem 4.1, we have shown that the scalar is $\bar{\rho}/\rho_k$. But for the proof, we only need to know that the investor holds the market.

Thus, the maximization problem is equivalent to

$$\max_{\varphi,\kappa}(1-\varphi-\kappa)(1+r_f)+\varphi(1+E[r_{\text{mkt}}|\mathbf{y}])+\kappa(1+E[r_i|\mathbf{y}]) \\ -\frac{\rho_k w_k^*}{2}\left(\varphi^2 \operatorname{var}\left(r_{\text{mkt}}|\,\mathbf{y}\right)+2\varphi\kappa \operatorname{cov}\left(r_{\text{mkt}},r_i|\,\mathbf{y}\right)+\kappa^2 \operatorname{var}\left(r_i|\,\mathbf{y}\right)\right)$$

Taking the first-order condition with respect to φ, and evaluating at $\kappa=0$, yields

$$E[r_{\text{mkt}}|\mathbf{y}]-r_f-\varphi\rho_k w_k^* \operatorname{var}\left(r_{\text{mkt}}|\,\mathbf{y}\right)=0 \quad\longrightarrow\quad \varphi\rho_k w_k^*=\frac{E[r_{\text{mkt}}|\mathbf{y}]-r_f}{\operatorname{var}\left(r_{\text{mkt}}|\,\mathbf{y}\right)}$$

Taking the first-order condition with respect to κ, and evaluating at $\kappa=0$, yields

$$E[r_i|\mathbf{y}]-r_f-\varphi\rho_k w_k^* \operatorname{cov}\left(r_{\text{mkt}},r_i|\,\mathbf{y}\right)=0$$

Combining both conditions, we obtain

$$E[r_i|\mathbf{y}]-r_f-\beta_i(E[r_{\text{mkt}}|\mathbf{y}]-r_f)=0$$

■

Proof of Lemma 4.3. In this proof, we repeatedly use the Doob–Dynkin lemma. The pair $(\mathbf{p},p_f)$ is defined as a measurable mapping of $\mathbf{f}$. Indeed, p_f, given in Equation 5, is a measurable function of $\mathbf{f}$. So $\mathbf{p}$, given in Equation 6, is also a function of $\mathbf{f}$. Therefore, $\sigma(\mathbf{p},p_f)\subseteq\sigma(\mathbf{f})$. The reverse is also true: Given the pair $(\mathbf{p},p_f)$, we have $\mathbf{f}=\frac{1}{p_f}\mathbf{p}$. Therefore, $\sigma(\mathbf{p},p_f)\supseteq\sigma(\mathbf{f})$, and we conclude that $\sigma(\mathbf{p},p_f)=\sigma(\mathbf{f})$. Next, Equation 4 implies $\sigma(\mathbf{f})=\sigma(\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}})$. Finally, from the definition of conditional expectation, we know that $\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}}$ is a measurable function of $\mathbf{y}$, and hence $\sigma(\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}})\subseteq\sigma(\mathbf{y})$.

■

Proof of Lemma 4.4. For part 1, we have

$$E[\mathbf{v}|\mathcal{G}]\underset{\mathcal{G}\subseteq\mathcal{F}}{=}E[E[\mathbf{v}|\mathcal{F}]|\mathcal{G}]\underset{E[\mathbf{v}|\mathcal{F}]\in\mathcal{G}}{=}E[\mathbf{v}|\mathcal{F}]$$

For part 2, we use the result from part 1:

$$
\begin{aligned}
\operatorname{var}(\mathbf{v}|\mathcal{G}) &\underset{\text{def.}}{=} E\Big[\,(\mathbf{v}-E[\mathbf{v}|\mathcal{G}])\,(\mathbf{v}-E[\mathbf{v}|\mathcal{G}])'\,\Big|\mathcal{G}\Big] \\
&\underset{\text{part 1}}{=} E\Big[\,(\mathbf{v}-E[\mathbf{v}|\mathcal{F}])\,(\mathbf{v}-E[\mathbf{v}|\mathcal{F}])'\,\Big|\mathcal{G}\Big] \\
&\underset{\mathcal{G}\subseteq\mathcal{F}}{=} E\Big[E\Big[\,(\mathbf{v}-E[\mathbf{v}|\mathcal{F}])\,(\mathbf{v}-E[\mathbf{v}|\mathcal{F}])'\,\Big|\mathcal{F}\Big]\Big|\mathcal{G}\Big] \\
&\underset{\text{def.}}{=} E\Big[\operatorname{var}(\mathbf{v}|\mathcal{F})\Big|\mathcal{G}\Big] \underset{\operatorname{var}(\mathbf{v}|\mathcal{F})\in\mathcal{G}}{=} \operatorname{var}(\mathbf{v}|\mathcal{F})
\end{aligned}
$$

■

Proof of Corollary 4.5. We study conditional distributions, where the conditioning is on prices (and, in parts 2 and 3, also on signals). Lemma 4.3 implies that whenever we condition on prices, we can condition instead on $\mathbf{f}$, which is Gaussian. Thus, all the conditional distributions stated in the corollary are indeed Gaussian. We now verify that the means and the covariance matrices are as stated in each part of the corollary.

For part 1, we have $\sigma(p_f, \mathbf{p}) \subseteq \sigma(\mathbf{y})$ and $E[\mathbf{v}|\mathbf{y}] = \boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} \in \sigma(p_f, \mathbf{p})$. Thus, we can apply part 1 of Lemma 4.4 to conclude that $E[\mathbf{v}|p_f, \mathbf{p}] = \boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}}$. Next, we have $\operatorname{var}(\mathbf{v}|\mathbf{y}) = \boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}$, which is nonrandom. Thus, we can apply part 2 of Lemma 4.4 to conclude that $\operatorname{var}(\mathbf{v}|p_f, \mathbf{p}) = \boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}$. This concludes the proof of part 1.

For part 2, let $k \in \mathcal{NI}$. We have $\sigma(\mathbf{s}_k, p_f, \mathbf{p}) \subseteq \sigma(\mathbf{s}_k, \mathbf{y})$. According to (GR), $E[\mathbf{v}|\mathbf{s}_k, \mathbf{y}] = \boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}}$, which is measurable with respect to $\sigma(\mathbf{s}_k, p_f, \mathbf{p})$. Thus, we can apply part 1 of Lemma 4.4 to conclude that $E[\mathbf{v}|\mathbf{s}_k, p_f, \mathbf{p}] = \boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}}$.

Next, according to (GR), $\operatorname{var}(\mathbf{v}|\mathbf{s}_k, \mathbf{y}) = \boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}$, which is nonrandom. Thus, we can apply part 2 of Lemma 4.4 to conclude that $\operatorname{var}(\mathbf{v}|\mathbf{s}_k, p_f, \mathbf{p}) = \boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}$. This concludes the proof of Equation 10.

For part 3, we first note that $\sigma(\mathbf{1}'\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}}) = \sigma(\mathbf{1}'\mathbf{f}) = \sigma(p_f)$: To obtain the first equality, we multiply each side of Equation 4 from the left by $\mathbf{1}'$. The second equality is implied by

Equation 5. Thus, for every $k \in \mathcal{I}$, we have $\sigma(\mathbf{1}'\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}}) \subseteq \sigma(\mathbf{s}_k, p_f, \mathbf{1}'\mathbf{p}) \subseteq \sigma(\mathbf{s}_k, p_f, \mathbf{p}) \subseteq \sigma(\mathbf{s}_k, \mathbf{y})$. According to (GR), $E[\mathbf{1}'\mathbf{v}|\mathbf{s}_k, \mathbf{y}] = \mathbf{1}'\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}}$, which is measurable with respect to $\sigma(\mathbf{s}_k, p_f, \mathbf{1}'\mathbf{p})$. Thus, we can apply part 1 of Lemma 4.4 to conclude that $E[\mathbf{1}'\mathbf{v}|\mathbf{s}_k, p_f, \mathbf{p}] = \mathbf{1}'\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}}$.

Finally, according to (GR), $\mathrm{var}(\mathbf{1}'\mathbf{v}|\mathbf{s}_k, \mathbf{y}) = \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1}$, which is nonrandom. Thus, we can apply part 2 of Lemma 4.4 to conclude that $\mathrm{var}(\mathbf{1}'\mathbf{v}|\mathbf{s}_k, p_f, \mathbf{p}) = \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1}$. This concludes the proof of Equation 11.

■

B Proof of Theorem 5.1

Before we prove the theorem, we need some preliminary results.

First, we define the auxiliary matrix as follows:

$$\mathbf{M} := \begin{bmatrix} \mathbf{I}_{n\times n} & \dfrac{|\mathcal{NI}|}{m}\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}}^{-1}\boldsymbol{\Sigma}_{\mathbf{vv}}(\mathbf{1}-\mathbf{g}) \\ \\ \mathbf{0}_{n\times n} & -\dfrac{|\mathcal{NI}|}{m}\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}}^{-1}\boldsymbol{\Sigma}_{\mathbf{vv}}(\mathbf{1}-\mathbf{g}) + \mathbf{g} \end{bmatrix}_{2n\times(n+1)} \tag{B.1}$$

We can now write

$$\boldsymbol{\Sigma}_{\mathbf{vy}} = \begin{bmatrix} \boldsymbol{\Sigma}_{\mathbf{vv}} & \boldsymbol{\Sigma}_{\mathbf{vv}}\mathbf{g} \end{bmatrix} \tag{B.2}$$

$$= \begin{bmatrix} \boldsymbol{\Sigma}_{\mathbf{vv}} & \boldsymbol{\Sigma}_{\mathbf{vv}} \end{bmatrix} \mathbf{M} \tag{B.3}$$

Also,

$$\forall k \in \mathcal{NI}, \quad \mathrm{cov}\left(\mathbf{y}, \mathbf{s}_k\right) = \begin{bmatrix} \boldsymbol{\Sigma}_{\mathbf{vv}} + \dfrac{m}{|\mathcal{NI}|}\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}} \\ \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}} \end{bmatrix}_{(n+1)\times n} \tag{B.4}$$

$$\forall k \in \mathcal{I} \quad \mathrm{cov}\left(\mathbf{y}, \mathbf{s}_k\right) = \begin{bmatrix} \boldsymbol{\Sigma}_{\mathbf{vv}} \\ \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}} \end{bmatrix}_{(n+1)\times n} \tag{B.5}$$

So, for any nind $\in \mathcal{NI}$ and ind $\in \mathcal{I}$, we have

$$\mathbf{1}' \begin{bmatrix} \boldsymbol{\Sigma}_{\mathbf{vv}} & \boldsymbol{\Sigma}_{\mathbf{vv}} \end{bmatrix} = \begin{bmatrix} \mathbf{0}_{1\times n} & 1_{1\times 1} \end{bmatrix} \begin{bmatrix} \operatorname{cov}(\mathbf{y}, \mathbf{s}_{\text{nind}}) & \operatorname{cov}(\mathbf{y}, \mathbf{s}_{\text{ind}}) \end{bmatrix} \tag{B.6}$$

and

$$\begin{bmatrix} \operatorname{cov}(\mathbf{y}, \mathbf{s}_{\text{nind}}) & \operatorname{cov}(\mathbf{y}, \mathbf{s}_{\text{ind}}) \end{bmatrix} = \begin{bmatrix} \boldsymbol{\Sigma}_{\mathbf{vv}} + \frac{m}{|\mathcal{NI}|}\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}} & \boldsymbol{\Sigma}_{\mathbf{vv}} \\ \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}} & \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}} \end{bmatrix}_{(n+1)\times 2n}$$

The latter implies that

$$\boldsymbol{\Sigma}_{\mathbf{yy}} = \begin{bmatrix} \boldsymbol{\Sigma}_{\mathbf{vv}} + \frac{m}{|\mathcal{NI}|}\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}} & \boldsymbol{\Sigma}_{\mathbf{vv}}\mathbf{1} \\ \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}} & \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}}\mathbf{g} \end{bmatrix} = \begin{bmatrix} \operatorname{cov}(\mathbf{y}, \mathbf{s}_{\text{nind}}) & \operatorname{cov}(\mathbf{y}, \mathbf{s}_{\text{ind}}) \end{bmatrix} \mathbf{M} \tag{B.7}$$

Lemma B.1. *Let $\mathbf{x} \in R^n$ be an arbitrary portfolio. By means of matching terms, define $\mathbf{q} \in R^n$ and the scalar q to be*

$$\begin{bmatrix} \mathbf{q}' & q \end{bmatrix}_{1\times(n+1)} := \mathbf{x}'\boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1} \tag{B.8}$$

Then, $\mathbf{q} = \mathbf{0}_{n\times 1}$ if and only if $\mathbf{x}$ is a scalar multiplier of $\mathbf{1}$ with $\mathbf{x} = q\mathbf{1}$.

Proof of Lemma B.1. Let $\mathbf{x}$ be arbitrary, and multiply both sides of Equation B.8 by $\boldsymbol{\Sigma}_{\mathbf{yy}}$ on the right:

$$\begin{bmatrix} \mathbf{q}' & q \end{bmatrix} \boldsymbol{\Sigma}_{\mathbf{yy}} = \mathbf{x}'\boldsymbol{\Sigma}_{\mathbf{vy}}$$

We use Equations B.2 and B.7 to obtain

$$\begin{bmatrix} \mathbf{q}'\left(\boldsymbol{\Sigma}_{\mathbf{vv}} + \frac{m}{|\mathcal{NI}|}\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}}\right) + q\mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}} & \mathbf{q}'\boldsymbol{\Sigma}_{\mathbf{vv}}\mathbf{1} + q\mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}}\mathbf{g} \end{bmatrix}_{1\times(n+1)} = \begin{bmatrix} \mathbf{x}'\boldsymbol{\Sigma}_{\mathbf{vv}} & \mathbf{x}'\boldsymbol{\Sigma}_{\mathbf{vv}}\mathbf{g} \end{bmatrix}_{1\times(n+1)}$$

Matching terms makes it clear that $\mathbf{q} = \mathbf{0}$ implies $\mathbf{x} = q\mathbf{1}$, and hence $\mathbf{x}$ is a scalar multiplier of $\mathbf{1}$. We need to show that the opposite is also true. Let us say that $\mathbf{x} = q\mathbf{1}$, and assume by means of contradiction that $\mathbf{q} \neq \mathbf{0}$. Matching terms must yield

$$\mathbf{q}'\left(\boldsymbol{\Sigma}_{\mathbf{vv}} + \frac{m}{|\mathcal{NI}|}\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}}\right) = \mathbf{0}_{1\times n}$$

Multiplying on the right by $\mathbf{q}$ and noticing that $\left(\boldsymbol{\Sigma}_{\mathbf{vv}} + \frac{m}{|\mathcal{NI}|}\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}}\right)$ is a positive definite matrix, we obtain a contradiction:

$$0 < \mathbf{q}'\left(\boldsymbol{\Sigma}_{\mathbf{vv}} + \frac{m}{|\mathcal{NI}|}\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}}\right)\mathbf{q} = \mathbf{0}_{1\times n}\mathbf{q} = 0$$

■

Applying Lemma B.1 to $\mathbf{x} = \mathbf{1}$, we obtain

$$\begin{bmatrix}\mathbf{0}_{1\times n} & 1\end{bmatrix} = \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1} \tag{B.9}$$

We define the n-dimensional random vector as follows:

$$\mathbf{z} := \mathbf{v} - \boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\mathbf{y} \tag{B.10}$$

Lemma B.2. *We have*

$$E\mathbf{z} = \boldsymbol{\mu}_{\mathbf{v}} - \boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\boldsymbol{\mu}_{\mathbf{y}} \tag{B.11}$$

$$\operatorname{var}(\mathbf{z}) = \boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}} \tag{B.12}$$

Proof of Lemma B.2. Equation B.11 follows from the definition of $\mathbf{z}$. As for Equation B.12, we have

$$\begin{aligned}\operatorname{var}(\mathbf{z}) &= \operatorname{var}(\mathbf{v} - \boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\mathbf{y}) \\ &= \boldsymbol{\Sigma}_{\mathbf{vv}} + \boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\boldsymbol{\Sigma}_{\mathbf{yy}}\Sigma_{\mathbf{yy}}^{-1}\boldsymbol{\Sigma}_{\mathbf{yv}} - \boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\boldsymbol{\Sigma}_{\mathbf{yv}} - \boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\boldsymbol{\Sigma}_{\mathbf{yv}} \\ &= \boldsymbol{\Sigma}_{\mathbf{vv}} - \boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\boldsymbol{\Sigma}_{\mathbf{yv}} \\ &\underset{(3)}{=} \boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\end{aligned}$$

■

Lemma B.3. *We have*

1. $\operatorname{cov}(\mathbf{z}, \mathbf{y}) = \mathbf{0}_{n\times(n+1)}$.

2. $\forall k \in \mathcal{NI}$, $\mathrm{cov}(\mathbf{z}, \mathbf{s}_k) = \mathbf{0}_{n\times n}$.

3. $\forall k \in \mathcal{I}$, $\mathrm{cov}(\mathbf{1}'\mathbf{z}, \mathbf{s}_k) = \mathbf{0}_{1\times n}$.

Proof of Lemma B.3. For part 1 of the lemma,

$$\mathrm{cov}(\mathbf{z}, \mathbf{y}) = \mathrm{cov}(\mathbf{v} - \boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\mathbf{y}, \mathbf{y}) = \boldsymbol{\Sigma}_{\mathbf{vy}} - \boldsymbol{\Sigma}_{\mathbf{vy}} = \mathbf{0}_{n\times(n+1)}$$

For part 2 of the lemma, it is convenient to compute an $n \times 2n$ covariance matrix. For any nind $\in \mathcal{NI}$ and any ind $\in \mathcal{I}$, we have

$$\begin{aligned}
&\begin{bmatrix}\mathrm{cov}\left(\mathbf{z}, \mathbf{s}_{\mathrm{nind}}\right) & \mathrm{cov}\left(\mathbf{z}, \mathbf{s}_{\mathrm{ind}}\right)\end{bmatrix} = \begin{bmatrix}\mathrm{cov}\left(\mathbf{v}, \mathbf{s}_{\mathrm{nind}}\right) & \mathrm{cov}\left(\mathbf{v}, \mathbf{s}_{\mathrm{ind}}\right)\end{bmatrix} - \boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\begin{bmatrix}\mathrm{cov}\left(\mathbf{y}, \mathbf{s}_{\mathrm{nind}}\right) & \mathrm{cov}\left(\mathbf{y}, \mathbf{s}_{\mathrm{ind}}\right)\end{bmatrix} \\
&= \begin{bmatrix}\boldsymbol{\Sigma}_{\mathbf{vv}} & \boldsymbol{\Sigma}_{\mathbf{vv}}\end{bmatrix} - \boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\begin{bmatrix}\mathrm{cov}\left(\mathbf{y}, \mathbf{s}_{\mathrm{nind}}\right) & \mathrm{cov}\left(\mathbf{y}, \mathbf{s}_{\mathrm{ind}}\right)\end{bmatrix}
\end{aligned}$$

We now multiply both sides of the equations on the right by $\mathbf{M}$:

$$\begin{aligned}
\begin{bmatrix}\mathrm{cov}\left(\mathbf{z}, \mathbf{s}_{\mathrm{nind}}\right) & \mathrm{cov}\left(\mathbf{z}, \mathbf{s}_{\mathrm{ind}}\right)\end{bmatrix}\mathbf{M} &= \underbrace{\begin{bmatrix}\boldsymbol{\Sigma}_{\mathbf{vv}} & \boldsymbol{\Sigma}_{\mathbf{vv}}\end{bmatrix}\mathbf{M}}_{\overset{=}{(B.3)}\boldsymbol{\Sigma}_{\mathbf{vy}}} - \boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\underbrace{\begin{bmatrix}\mathrm{cov}\left(\mathbf{y}, \mathbf{s}_{\mathrm{nind}}\right) & \mathrm{cov}\left(\mathbf{y}, \mathbf{s}_{\mathrm{ind}}\right)\end{bmatrix})\mathbf{M}}_{\overset{=}{(B.7)}\boldsymbol{\Sigma}_{\mathbf{yy}}} \\
&= \boldsymbol{\Sigma}_{\mathbf{vy}} - \boldsymbol{\Sigma}_{\mathbf{vy}} \\
&= \mathbf{0}_{n\times(n+1)}
\end{aligned}$$

In submatrix notation, we can write the above, using the definition of $\mathbf{M}$ from Equation B.1, as

$$\begin{bmatrix}\mathrm{cov}(\mathbf{z}, \mathbf{s}_{\mathrm{nind}}) & \mathbf{t}\end{bmatrix} = \begin{bmatrix}\mathbf{0}_{n\times n} & \mathbf{0}_{n\times 1}\end{bmatrix}$$

where $\mathbf{t}$ is some vector.[22] This proves that $\mathrm{cov}(\mathbf{z}, \mathbf{s}_{\mathrm{nind}}) = \mathbf{0}_{n\times n}$.[23]

[22]Specifically,

$$\mathbf{t} = \left(\mathrm{cov}(\mathbf{z}, \mathbf{s}_{\mathrm{nind}}) - \mathrm{cov}(\mathbf{z}, \mathbf{s}_{\mathrm{ind}})\right)\frac{|\mathcal{NI}|}{m}\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}}^{-1}\boldsymbol{\Sigma}_{\mathbf{vv}}(\mathbf{1} - \mathbf{g}) + \mathrm{cov}(\mathbf{z}, \mathbf{s}_{\mathrm{ind}})\mathbf{g}$$

[23]Although it does not prove, and it is not true, that $\mathrm{cov}(\mathbf{z}, \mathbf{s}_{\mathrm{ind}}) = \mathbf{0}$.

Next, for part 3 of the lemma, we need to prove that $\text{cov}(\mathbf{1}'\mathbf{z}, \mathbf{s}_{\text{ind}}) = \mathbf{0}_{1\times n}$. Again, to facilitate linear algebra manipulations, it is convenient to compute a vector of dimension $2n$:

$$\begin{aligned}
&\begin{bmatrix}\text{cov}\left(\mathbf{1}'\mathbf{z}, \mathbf{s}_{\text{nind}}\right) & \text{cov}\left(\mathbf{1}'\mathbf{z}, \mathbf{s}_{\text{ind}}\right)\end{bmatrix} = \mathbf{1}'\begin{bmatrix}\text{cov}\left(\mathbf{z}, \mathbf{s}_{\text{nind}}\right) & \text{cov}\left(\mathbf{z}, \mathbf{s}_{\text{ind}}\right)\end{bmatrix} \\
&= \mathbf{1}'\begin{bmatrix}\text{cov}\left(\mathbf{v}, \mathbf{s}_{\text{nind}}\right) & \text{cov}\left(\mathbf{v}, \mathbf{s}_{\text{ind}}\right)\end{bmatrix} - \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\begin{bmatrix}\text{cov}\left(\mathbf{y}, \mathbf{s}_{\text{nind}}\right) & \text{cov}\left(\mathbf{y}, \mathbf{s}_{\text{ind}}\right)\end{bmatrix} \\
&= \mathbf{1}'\begin{bmatrix}\boldsymbol{\Sigma}_{\mathbf{vv}} & \boldsymbol{\Sigma}_{\mathbf{vv}}\end{bmatrix} - \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\begin{bmatrix}\text{cov}\left(\mathbf{y}, \mathbf{s}_{\text{nind}}\right) & \text{cov}\left(\mathbf{y}, \mathbf{s}_{\text{ind}}\right)\end{bmatrix} \\
&\underset{(\text{B.9})}{=} \mathbf{1}'\begin{bmatrix}\boldsymbol{\Sigma}_{\mathbf{vv}} & \boldsymbol{\Sigma}_{\mathbf{vv}}\end{bmatrix} - \begin{bmatrix}\mathbf{0}_{1\times n} & 1_{1\times 1}\end{bmatrix}\begin{bmatrix}\text{cov}\left(\mathbf{y}, \mathbf{s}_{\text{nind}}\right) & \text{cov}\left(\mathbf{y}, \mathbf{s}_{\text{ind}}\right)\end{bmatrix} \\
&\underset{(\text{B.6})}{=} \mathbf{0}_{1\times 2n}
\end{aligned}$$

■

Lemma B.4. *For all $k \in \mathcal{NI}$, we have*

$$E\left[\mathbf{v}\,|\mathbf{y}, \mathbf{s}_k\right] = E[\mathbf{v}|\mathbf{y}]$$
$$\text{var}\left(\mathbf{v}\middle|\mathbf{y}, \mathbf{s}_k\right) = \boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}$$

Proof of Lemma B.4. Let $k \in \mathcal{NI}$. Part 1 of Lemma B.3 states that $\text{cov}(\mathbf{z}, \mathbf{y}) = \mathbf{0}$, and part 2 states that $\text{cov}(\mathbf{z}, \mathbf{s}_k) = \mathbf{0}$. Therefore, $\text{cov}\left(\mathbf{z}, \begin{bmatrix}\mathbf{y}\\ \mathbf{s}_k\end{bmatrix}\right) = \mathbf{0}_{n\times(2n+1)}$.

Thus,

$$E\left[\mathbf{z}\,|\mathbf{y}, \mathbf{s}_k\right] = E\mathbf{z} \tag{B.13}$$
$$\text{var}\left(\mathbf{z}\middle|\mathbf{y}, \mathbf{s}_k\right) = \text{var}(\mathbf{z}) \tag{B.14}$$

We have

$$E\left[\mathbf{v}\,|\mathbf{y}, \mathbf{s}_k\right] \underset{(\text{B.10})}{=} E\left[\mathbf{z} + \boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\mathbf{y}\,|\mathbf{y}, \mathbf{s}_k\right] \underset{(\text{B.13})}{=} E\mathbf{z}+\boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\mathbf{y} \underset{(\text{B.11})}{=} \boldsymbol{\mu}_{\mathbf{v}}+\boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}(\mathbf{y}-\boldsymbol{\mu}_{\mathbf{y}}) \underset{(2)}{=} E[\mathbf{v}|\mathbf{y}] \tag{B.15}$$

Next,

$$\text{var}\left(\mathbf{v}\,|\mathbf{y}, \mathbf{s}_k\right) \underset{(\text{B.10})}{=} \text{var}\left(\mathbf{z} + \boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\mathbf{y}\,|\mathbf{y}, \mathbf{s}_k\right) = \text{var}\left(\mathbf{z}\,|\mathbf{y}, \mathbf{s}_k\right) \underset{(\text{B.14})}{=} \text{var}(\mathbf{z}) \underset{(\text{B.12})}{=} \boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}$$

$\blacksquare$

Lemma B.5. *For all $k \in \mathcal{I}$, we have*

$$E\left[\mathbf{1}'\mathbf{v}\,|\mathbf{y},\mathbf{s}_k\right] = \mathbf{1}'E[\mathbf{v}|\mathbf{y}]$$
$$\operatorname{var}\left(\mathbf{1}'\mathbf{v}\middle|\mathbf{y},\mathbf{s}_k\right) = \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1}$$

Proof of Lemma B.5. Let $k \in \mathcal{I}$. Part 1 of Lemma B.3 implies that $\operatorname{cov}(\mathbf{1}'\mathbf{z},\mathbf{y}) = \mathbf{0}$, and part 3 states that $\operatorname{cov}(\mathbf{1}'\mathbf{z},\mathbf{s}_k) = \mathbf{0}$. Therefore, $\operatorname{cov}\left(\mathbf{1}'\mathbf{z},\begin{bmatrix}\mathbf{y}\\ \mathbf{s}_k\end{bmatrix}\right) = \mathbf{0}_{1\times(2n+1)}$.

Thus,

$$E\left[\mathbf{1}'\mathbf{z}\,|\mathbf{y},\mathbf{s}_k\right] = E\mathbf{1}'\mathbf{z} \tag{B.16}$$
$$\operatorname{var}\left(\mathbf{1}'\mathbf{z}\middle|\mathbf{y},\mathbf{s}_k\right) = \operatorname{var}(\mathbf{1}'\mathbf{z}) \tag{B.17}$$

Now,

$$\begin{aligned}E\left[\mathbf{1}'\mathbf{v}\,|\mathbf{y},\mathbf{s}_k\right] &\underset{(B.10)}{=} E\left[\mathbf{1}'\mathbf{z}\,|\mathbf{y},\mathbf{s}_k\right] + \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\mathbf{y} \underset{(B.16)}{=} E\mathbf{1}'\mathbf{z} + \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\mathbf{y}\\ &= \mathbf{1}'\left(\boldsymbol{\mu}_{\mathbf{v}} + \boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}(\mathbf{y}-\boldsymbol{\mu}_{\mathbf{y}})\right) \underset{(2)}{=} \mathbf{1}'E[\mathbf{v}|\mathbf{y}]\end{aligned} \tag{B.18}$$

Next,

$$\operatorname{var}\left(\mathbf{1}'\mathbf{v}\middle|\mathbf{y},\mathbf{s}_k\right) \underset{(B.10)}{=} \operatorname{var}\left(\mathbf{1}'\mathbf{z}+\mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\mathbf{y}\middle|\mathbf{y},\mathbf{s}_k\right) = \operatorname{var}\left(\mathbf{1}'\mathbf{z}\middle|\mathbf{y},\mathbf{s}_k\right) \underset{(B.17)}{=} \operatorname{var}(\mathbf{1}'\mathbf{z}) \underset{(B.12)}{=} \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1}$$

$\blacksquare$

Proof of Theorem 5.1. The proof follows from the fact that Lemmas B.5 and B.4 show that the four conditions in (GR) are satisfied.

$\blacksquare$

C Additional Lemmas and Proofs

Lemma C.1. *We have*

$$\mathbf{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1} = \mathbf{\Sigma}_{\mathbf{vv}}(\mathbf{1} - \mathbf{g}) \tag{C.1}$$

$$\mathbf{1}'\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} = \mathbf{1}'\boldsymbol{\mu}_{\mathbf{v}} + \frac{1}{m}\mathbf{g}'\sum_{k=1}^{m}(\mathbf{s}_k - \boldsymbol{\mu}_{\mathbf{v}}) \tag{C.2}$$

$$\mathbf{1}'\mathbf{f} = \mathbf{1}'\boldsymbol{\mu}_{\mathbf{v}} + \frac{1}{m}\mathbf{g}'\sum_{k=1}^{m}(\mathbf{s}_k - \boldsymbol{\mu}_{\mathbf{v}}) - \bar{\rho}\mathbf{1}'\mathbf{\Sigma}_{\mathbf{vv}}(\mathbf{1} - \mathbf{g}) \tag{C.3}$$

Proof of Lemma C.1. To prove Equation C.1, we have

$$\begin{aligned}
\mathbf{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1} &\underset{(3)}{=} \mathbf{\Sigma}_{\mathbf{vv}}\mathbf{1} - \mathbf{\Sigma}_{\mathbf{vy}}\mathbf{\Sigma}_{\mathbf{yy}}^{-1}\mathbf{\Sigma}_{\mathbf{yv}}\mathbf{1} \\
&\underset{(B.9)}{=} \mathbf{\Sigma}_{\mathbf{vv}}\mathbf{1} - \mathbf{\Sigma}_{\mathbf{vy}}\begin{bmatrix}\mathbf{0}_{n\times 1} \\ 1_{1\times 1}\end{bmatrix} \\
&\underset{(B.2)}{=} \mathbf{\Sigma}_{\mathbf{vv}}\mathbf{1} - \mathbf{\Sigma}_{\mathbf{vv}}\mathbf{g} \\
&= \mathbf{\Sigma}_{\mathbf{vv}}(\mathbf{1} - \mathbf{g})
\end{aligned}$$

This proves Equation C.1. To prove Equation C.2, we have

$$\begin{aligned}
\mathbf{1}'\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} &\underset{(2)}{=} \mathbf{1}'\boldsymbol{\mu}_{\mathbf{v}} + \mathbf{1}'\mathbf{\Sigma}_{\mathbf{vy}}\mathbf{\Sigma}_{\mathbf{yy}}^{-1}(\mathbf{y} - \boldsymbol{\mu}_{\mathbf{y}}) \\
&\underset{(B.9)}{=} \mathbf{1}'\boldsymbol{\mu}_{\mathbf{v}} + \begin{bmatrix}\mathbf{0}_{1\times n} & 1_{1\times 1}\end{bmatrix}(\mathbf{y} - \boldsymbol{\mu}_{\mathbf{y}}) \\
&\underset{(13)}{=} \mathbf{1}'\boldsymbol{\mu}_{\mathbf{v}} + \frac{1}{m}\mathbf{g}'\sum_{k=1}^{m}(\mathbf{s}_k - \boldsymbol{\mu}_{\mathbf{v}})
\end{aligned}$$

This proves Equation C.2.

Now, we use Equation C.1 to re-express Equation 4, which yields the following equation:

$$\mathbf{f} = \boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} - \bar{\rho}\mathbf{\Sigma}_{\mathbf{vv}}(\mathbf{1} - \mathbf{g})$$

We multiply the above by $\mathbf{1}'$ from the left, and we use Equation C.2 to obtain Equation C.3.

■

Proof of Corollary 5.2. This corollary adds only one more property to Lemma 4.3: The last set inequality in Lemma 4.3 is an equality. Therefore, to prove the corollary, it is sufficient to show that $\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}}$ reveals $\mathbf{y}$.

Equation C.2 implies that $\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}}$ reveals the $(n+1)$th coordinate of $\mathbf{y}$. Indeed, by rearranging Equation C.2, we obtain $y_{n+1} = \mathbf{1}'(\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} - \boldsymbol{\mu}_{\mathbf{v}}) + \mathbf{g}'\boldsymbol{\mu}_{\mathbf{v}}$.

Taking advantage of the fact that $\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}}$ reveals the $(n+1)$th coordinate of $\mathbf{y}$, we rewrite Equation 2:

$$\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} = \boldsymbol{\mu}_{\mathbf{v}} + \boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\begin{bmatrix} y_1 - Ey_1 \\ \vdots \\ y_n - Ey_n \\ y_{n+1} - Ey_{n+1} \end{bmatrix} = \boldsymbol{\mu}_{\mathbf{v}} + \boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\begin{bmatrix} y_1 - Ev_1 \\ \vdots \\ y_n - Ev_n \\ \mathbf{1}'(\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} - \boldsymbol{\mu}_{\mathbf{v}}) \end{bmatrix}$$

To obtain the first n coordinates of $\mathbf{y}$, we solve the above system of n linear equations; the unknowns are the first n coordinates of $\mathbf{y}$. Thus, $\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}}$ reveals all $n+1$ coordinates of $\mathbf{y}$.

■

Proof of Theorem 5.3. Because $\mathbf{s}$ and $\mathbf{1}'\mathbf{v}$ are jointly normally distributed, the conditional distribution of $\mathbf{1}'\mathbf{v}$, given $\mathbf{s}$, is normal with mean $E[\mathbf{1}'\mathbf{v}|\mathbf{s}]$ and variance $\text{var}(\mathbf{1}'\mathbf{v}|\mathbf{s})$.

We have

$$\boldsymbol{\Sigma}_{\mathbf{ss}} = \begin{bmatrix} \boldsymbol{\Sigma}_{\mathbf{vv}} + m\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}} & \boldsymbol{\Sigma}_{\mathbf{vv}} & \cdots & \boldsymbol{\Sigma}_{\mathbf{vv}} \\ \boldsymbol{\Sigma}_{\mathbf{vv}} & \boldsymbol{\Sigma}_{\mathbf{vv}} + m\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}} & \cdots & \boldsymbol{\Sigma}_{\mathbf{vv}} \\ \vdots & & \ddots & \vdots \\ \boldsymbol{\Sigma}_{\mathbf{vv}} & \boldsymbol{\Sigma}_{\mathbf{vv}} & \cdots & \boldsymbol{\Sigma}_{\mathbf{vv}} + m\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}} \end{bmatrix}_{nm\times nm}$$

Thus,

$$\begin{bmatrix} \mathbf{I}_{n\times n} & \cdots & \mathbf{I}_{n\times n} \end{bmatrix}_{n\times nm} = \begin{bmatrix} (m\boldsymbol{\Sigma}_{\mathbf{vv}} + m\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}})^{-1} & \cdots & (m\boldsymbol{\Sigma}_{\mathbf{vv}} + m\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}})^{-1} \end{bmatrix}_{n\times nm} \boldsymbol{\Sigma}_{\mathbf{ss}} \tag{C.4}$$

We also have

$$\boldsymbol{\Sigma}_{\mathbf{vs}} = \begin{bmatrix} \boldsymbol{\Sigma}_{\mathbf{vv}} & \cdots & \boldsymbol{\Sigma}_{\mathbf{vv}} \end{bmatrix}$$

Therefore, by multiplying each side of Equation C.4 on the right by $\mathbf{\Sigma}_{\mathbf{ss}}^{-1}$ and on the left by $\mathbf{\Sigma}_{\mathbf{vv}}$, we obtain

$$\mathbf{\Sigma}_{\mathbf{vs}}\mathbf{\Sigma}_{\mathbf{ss}}^{-1} = \left[\mathbf{\Sigma}_{\mathbf{vv}}\left(m\mathbf{\Sigma}_{\mathbf{vv}} + m\mathbf{\Sigma}_{\boldsymbol{\epsilon\epsilon}}\right)^{-1} \quad \cdots \quad \mathbf{\Sigma}_{\mathbf{vv}}\left(m\mathbf{\Sigma}_{\mathbf{vv}} + m\mathbf{\Sigma}_{\boldsymbol{\epsilon\epsilon}}\right)^{-1}\right]_{n\times nm}$$

Multiplying both sides of the above equation on the left by $\mathbf{1}'$, and recalling the definition of $\mathbf{g}$ (see Equation 12), we conclude that

$$\mathbf{1}'\mathbf{\Sigma}_{\mathbf{vs}}\mathbf{\Sigma}_{\mathbf{ss}}^{-1} = \frac{1}{m}\left[\mathbf{g}' \quad \cdots \quad \mathbf{g}'\right]_{1\times nm}$$

Thus,

$$\begin{aligned} E[\mathbf{1}'\mathbf{v}|\mathbf{s}] &= \mathbf{1}'\boldsymbol{\mu}_{\mathbf{v}} + \mathbf{1}'\mathbf{\Sigma}_{\mathbf{vs}}\mathbf{\Sigma}_{\mathbf{ss}}^{-1}(\mathbf{s} - E\mathbf{s}) = \mathbf{1}'\boldsymbol{\mu}_{\mathbf{v}} + \frac{1}{m}\mathbf{g}'\sum_{k=1}^{m}(\mathbf{s}_k - \boldsymbol{\mu}_{\mathbf{v}}) \\ &= (\mathbf{1}' - \mathbf{g}')\boldsymbol{\mu}_{\mathbf{v}} + y_{n+1} \end{aligned} \tag{C.5}$$

depends on $\mathbf{s}$ only through y_{n+1}. Therefore, applying part 1 of Lemma 4.4, we conclude that

$$E[\mathbf{1}'\mathbf{v}|\mathbf{s}] = E[\mathbf{1}'\mathbf{v}|y_{n+1}]$$

Next, we note that

$$\operatorname{var}(\mathbf{1}'\mathbf{v}|\mathbf{s})$$

is merely a scalar;[24] therefore, we can apply part 2 of Lemma 4.4 to conclude that

$$\operatorname{var}(\mathbf{1}'\mathbf{v}|\mathbf{s}) = \operatorname{var}(\mathbf{1}'\mathbf{v}|y_{n+1})$$

To prove that y_{n+1} is a sufficient statistic, we note that the density of a normal random variable depends only on the mean and variance. Therefore, from part 1 of the lemma, we conclude that the conditional density satisfies $f(\mathbf{1}'\mathbf{v}|\mathbf{s}) = f(\mathbf{1}'\mathbf{v}|y_{n+1})$. In our model, the "data," $\mathbf{s}$; the "statistic," y_{n+1}; and the "parameter," $\mathbf{1}'\mathbf{v}$, have a known joint distribution. Thus, we use Bayes's rule (see theorem 2.2.1 of Geweke 2005) to conclude that y_{n+1} is a sufficient statistic for $\mathbf{1}'\mathbf{v}$.

[24]Specifically,

$$\operatorname{var}(\mathbf{1}'\mathbf{v}|\mathbf{s}) = \mathbf{1}'\mathbf{\Sigma}_{\mathbf{vv}}\mathbf{1} - \mathbf{1}'\mathbf{\Sigma}_{\mathbf{vs}}\mathbf{\Sigma}_{\mathbf{ss}}^{-1}\mathbf{\Sigma}_{\mathbf{sv}}\mathbf{1} = \mathbf{1}'\mathbf{\Sigma}_{\mathbf{vv}}\mathbf{1} - \mathbf{g}'\mathbf{\Sigma}_{\mathbf{vv}}\mathbf{1}$$

Now, let $t(\mathbf{s})$ be another arbitrary sufficient statistic. To show that y_{n+1} is minimal, we need to show that y_{n+1} is a measurable function of $t(\mathbf{s})$.[25] From Bayes's rule (again, see theorem 2.2.1 of Geweke 2005), it follows that $f(\mathbf{1}'\mathbf{v}|\mathbf{s}) = f(\mathbf{1}'\mathbf{v}|t(\mathbf{s}))$. Thus,

$$E[\mathbf{1}'\mathbf{v}|t(\mathbf{s})] = E[\mathbf{1}'\mathbf{v}|\mathbf{s}] \underset{\text{(C.5)}}{=} (\mathbf{1}' - \mathbf{g}')\boldsymbol{\mu}_{\mathbf{v}} + y_{n+1}$$

In other words,

$$y_{n+1} = E[\mathbf{1}'\mathbf{v}|t(\mathbf{s})] - (\mathbf{1}' - \mathbf{g}')\boldsymbol{\mu}_{\mathbf{v}}$$

which shows that y_{n+1} is a measurable function of $t(\mathbf{s})$, and hence minimal.

■

Proof of Theorem 5.4. From Equation C.3, we have

$$\mathbf{1}'\mathbf{f} = y_{n+1} + (\mathbf{1}' - \mathbf{g}')\boldsymbol{\mu}_{\mathbf{v}} - \bar{\rho}\mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}}(\mathbf{1} - \mathbf{g})$$

Thus, there is a one-to-one mapping between $\mathbf{1}'\mathbf{f}$ and y_{n+1}. As a result, $\sigma(\mathbf{1}'\mathbf{f}) = \sigma(y_{n+1})$. The proof follows from Theorem 5.3.

■

Proof of Theorem 6.1. The price of the bond, $p_f = 1/(1 + r_f)$, is given in Equation 5. Two terms in Equation 5 can cause p_f to depend on how the investors are divided into index and nonindex investors. The first term is $\boldsymbol{\Sigma}_{\mathbf{vv|y}}\mathbf{1}$. Equation C.1 shows that this term depends on $\boldsymbol{\Sigma}_{\mathbf{vv}}$ and $\mathbf{g}$, which do not depend on the specific partition. The second term is $\mathbf{1}'\mathbf{f}$. According to Equation C.3, $\mathbf{1}'\mathbf{f}$ does not depend on the specific partition, so we conclude that p_f and r_f also do not depend on the specific partition.

[25] The intuition that underlies the formal definition of the minimality of a sufficient statistic is as follows. If y_{n+1} is a measurable function of $t(\mathbf{s})$, then $y_{n+1} \in \sigma(t(\mathbf{s}))$. Therefore, $\sigma(y_{n+1}) \subseteq \sigma(t(\mathbf{s}))$, so y_{n+1} contains less (not necessarily in a strict sense) information than $t(\mathbf{s})$.

The price of the market portfolio is $\mathbf{1}'\mathbf{p} \underset{(6)}{=} \dfrac{\mathbf{1}'\mathbf{f}}{1+r_f}$. Therefore, the price of the market portfolio is also independent of the specific partition. Because payoffs are exogenous, and the price is independent, we conclude that the return on the market portfolio is independent of the specific partition. In particular, the conditional expected return on the market portfolio and the conditional variance of return on the market portfolio must be independent of the specific partition, so the capital market line remains unchanged as we change $\mathcal{I}$.

■

Proof of Theorem 6.2. We use the following standard notation. If $\mathbf{A} = \left[a_{ij}\right]$ is an arbitrary matrix with elements that depend on a parameter π, then $\dfrac{\partial \mathbf{A}}{\partial \pi}$ is the matrix $\left[\dfrac{\partial a_{ij}}{\partial \pi}\right]$. If $\mathbf{B}$ is an arbitrary matrix with elements that do not depend on the parameter π, then[26]

$$\frac{\partial \mathbf{B}\mathbf{A}^{-1}\mathbf{B}'}{\partial \pi} = -\mathbf{B}\mathbf{A}^{-1}\frac{\partial \mathbf{A}}{\partial \pi}\mathbf{A}^{-1}\mathbf{B}' \tag{C.6}$$

For a qualitative comparative statics, any monotonic increasing transformation of $|\mathcal{I}|$ is a measure of the level of index investment. We use as a measure of index investment the *proportion of index investors*:

$$\pi = \frac{|\mathcal{I}|}{m}$$

Although π takes values only on a discrete set of numbers, we can nevertheless differentiate $\mathbf{x}'\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{x}$ with respect to π. Note that since $0 < |\mathcal{I}| < m$, we have $\pi \in (0,1)$.

From Equation 3, we have

$$\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}} = \boldsymbol{\Sigma}_{\mathbf{vv}} - \boldsymbol{\Sigma}_{\mathbf{vy}}\boldsymbol{\Sigma}_{\mathbf{yy}}^{-1}\boldsymbol{\Sigma}_{\mathbf{yv}}$$

---

[26]We obtain Equation C.6 as follows. First, we have $\dfrac{\partial \mathbf{B}\mathbf{A}^{-1}\mathbf{B}'}{\partial \pi} = \mathbf{B}\dfrac{\partial \mathbf{A}^{-1}}{\partial \pi}\mathbf{B}'$ (see Horn and Johnson, 1991, equation 6.5.3). Second we have $\dfrac{\partial \mathbf{A}^{-1}}{\partial \pi} = \mathbf{A}^{-1}\dfrac{\partial \mathbf{A}}{\partial \pi}\mathbf{A}^{-1}$ (see Horn and Johnson, 1991, equation 6.5.7). Combining both, we obtain Equation C.6.

where $\mathbf{\Sigma_{vv}}$ and $\mathbf{\Sigma_{vy}} = \begin{bmatrix}\mathbf{\Sigma_{vv}} & \mathbf{\Sigma_{vv}g}\end{bmatrix}$ (see Equation B.2) are independent of π. We use Equation C.6 with $A = \mathbf{\Sigma_{yy}}$ and $B = \mathbf{\Sigma_{vy}}$.

Equation B.7 shows that

$$\frac{\partial \mathbf{\Sigma_{yy}}}{\partial \pi} = \frac{1}{(1-\pi)^2}\begin{bmatrix}\mathbf{\Sigma}_{\boldsymbol{\epsilon\epsilon}} & \mathbf{0}_{n\times 1}\\ \mathbf{0}_{1\times n} & 0_{1\times 1}\end{bmatrix} \tag{C.7}$$

By matching terms, we define the vector $\mathbf{q}$ and the scalar q such that $\begin{bmatrix}\mathbf{q}', q\end{bmatrix} = \mathbf{x}'\mathbf{\Sigma_{vy}}\mathbf{\Sigma_{yy}^{-1}}$.

We have

$$\frac{\partial\,\mathrm{var}(\mathbf{x}'\mathbf{v}|\mathbf{y})}{\partial \pi} = \frac{\partial \mathbf{x}'\mathbf{\Sigma_{vv|y}x}}{\partial \pi} = \mathbf{x}'\mathbf{\Sigma_{vy}}\mathbf{\Sigma_{yy}^{-1}}\frac{\partial \mathbf{\Sigma_{yy}}}{\partial \pi}\mathbf{\Sigma_{yy}^{-1}}\mathbf{\Sigma_{yv}x} = \frac{1}{(1-\pi)^2}\mathbf{q}'\mathbf{\Sigma}_{\boldsymbol{\epsilon\epsilon}}\mathbf{q} \geq 0$$

where the inequality arises because $\mathbf{\Sigma}_{\boldsymbol{\epsilon\epsilon}}$ is positive definite. The inequality is strict whenever $\mathbf{q} \neq \mathbf{0}$. According to Lemma B.1, $\mathbf{q} = \mathbf{0}$ if and only if $\mathbf{x}$ is a scalar multiplication of $\mathbf{1}$.

■

Proof of Theorem 6.3. The numerator of the Sharpe ratio is

$$E\left[\frac{\mathbf{x}'\mathbf{v}}{\mathbf{x}'\mathbf{p}} - 1\middle|\mathbf{y}\right] - r_f = \frac{1}{\mathbf{x}'\mathbf{p}}\left(\mathbf{x}'\boldsymbol{\mu}_{\mathbf{v|y}} - \mathbf{x}'\mathbf{p}(1+r_f)\right) \underset{(6)}{=} \frac{1}{\mathbf{x}'\mathbf{p}}\bar{\rho}\mathbf{x}'\mathbf{\Sigma_{vv|y}1} \underset{(C.1)}{=} \frac{1}{\mathbf{x}'\mathbf{p}}\bar{\rho}\mathbf{x}'\mathbf{\Sigma_{vv}}(\mathbf{1}-\mathbf{g})$$

The denominator of the Sharpe ratio is

$$\sqrt{\mathrm{var}\left(\frac{\mathbf{x}'\mathbf{v}}{\mathbf{x}'\mathbf{p}} - 1\middle|\mathbf{y}\right)} = \frac{1}{\mathbf{x}'\mathbf{p}}\sqrt{\mathrm{var}(\mathbf{x}'\mathbf{v}|\mathbf{y})}$$

Therefore, the Sharpe ratio equals

$$\frac{\bar{\rho}\mathbf{x}'\mathbf{\Sigma_{vv}}(\mathbf{1}-\mathbf{g})}{\sqrt{\mathrm{var}(\mathbf{x}'\mathbf{v}|\mathbf{y})}}$$

and its numerator is a scalar that is independent of the sets $\mathcal{NI}$ and $\mathcal{I}$. The numerator must be positive because in the statement of the theorem we assume the Sharpe ratio is positive. Theorem 6.2 states that as long as $\mathbf{x}$ is not a scalar multiplication of the market portfolio, the denominator increases as the proportion of index investors increases.

$\blacksquare$

Proof of Theorem 6.4. We have

$$
\begin{aligned}
R^2 &= \operatorname{corr}^2(r_i, r_f + \beta_i(r_{\text{mkt}} - r_f)|\mathbf{y}) = \frac{\operatorname{cov}^2(r_i, \beta_i r_{\text{mkt}}|\mathbf{y})}{\operatorname{var}(r_i|\mathbf{y}) \times \operatorname{var}(\beta_i r_{\text{mkt}}|\mathbf{y})} \\
&= \frac{\operatorname{cov}^2(v_i, \mathbf{1}'\mathbf{v}|\mathbf{y})}{\operatorname{var}(v_i|\mathbf{y}) \times \operatorname{var}(\mathbf{1}'\mathbf{v}|\mathbf{y})} = \frac{\left(\mathbf{e}_i'\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1}\right)^2}{\operatorname{var}(\mathbf{e}_i'\mathbf{v}|\mathbf{y}) \times \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1}} \\
&\underset{(C.1)}{=} \frac{(\mathbf{e}_i'\boldsymbol{\Sigma}_{\mathbf{vv}}(\mathbf{1} - \mathbf{g}))^2}{\operatorname{var}(\mathbf{e}_i'\mathbf{v}|\mathbf{y}) \times \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}}(\mathbf{1} - \mathbf{g})}
\end{aligned}
$$

where $\mathbf{e}_i$ is the vector with one in the ith coordinate and zero elsewhere.

Because R^2 is positive and the only term that depends on the level of index investment is $\operatorname{var}(\mathbf{e}_i'\mathbf{v}|\mathbf{y})$, whether or not R^2 decreases depends on whether or not $\operatorname{var}(\mathbf{e}_i'\mathbf{v}|\mathbf{y})$ increases. We apply Theorem 6.2 with $\mathbf{x} = \mathbf{e}_i$ to conclude that this conditional variance increases with $|\mathcal{I}|$. Therefore, R^2 of the CAPM regression decreases with $|\mathcal{I}|$.

$\blacksquare$

Proof of Theorem 6.5. We have

$$
\operatorname{corr}(r_i, r_{-i}|\mathbf{y}) = \frac{\operatorname{cov}(r_i, r_{-i}|\mathbf{y})}{\sqrt{\operatorname{var}(r_i|\mathbf{y})}\sqrt{\operatorname{var}(r_{-i}|\mathbf{y})}} = \frac{\operatorname{cov}(v_i, v_{-i}|\mathbf{y})}{\sqrt{\operatorname{var}(v_i|\mathbf{y})}\sqrt{\operatorname{var}(v_{-i}|\mathbf{y})}}
$$

$$
= \frac{\mathbf{e}_i'\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1} - \operatorname{var}(\mathbf{e}_i'\mathbf{v}|\mathbf{y})}{\sqrt{\operatorname{var}(\mathbf{e}_i'\mathbf{v}|\mathbf{y})}\sqrt{\operatorname{var}((\mathbf{1} - \mathbf{e}_i)'\mathbf{v}|\mathbf{y})}}
$$

According to Equation C.1, the first term in the numerator is independent of the level of index investment. From Theorem 6.2, applied to the portfolio $\mathbf{e}_i$, we conclude that the numerator decreases as we increase $|\mathcal{I}|$. We also know that the denominator is positive, and Theorem 6.2 (applied to $\mathbf{e}_i$, then separately applied to $\mathbf{1} - \mathbf{e}_i$) implies that the denominator is increasing. In summary, we can formally write the correlation as

$$
\frac{N(\mathcal{I})}{D(\mathcal{I})}
$$

where we have shown that $N(\mathcal{I})$ decreases with $|\mathcal{I}|$ and that $D(\mathcal{I})$ is positive and increases with $|\mathcal{I}|$. Let $\mathcal{I}_1$ and $\mathcal{I}_2$ be such that $|\mathcal{I}_1| < |\mathcal{I}_2|$. We have

$$\frac{N(\mathcal{I}_1)}{D(\mathcal{I}_1)} \underset{\substack{\uparrow \\ 0 < D(\mathcal{I}_1) < D(\mathcal{I}_2) \\ 0 < N(\mathcal{I}_1)}}{>} \frac{N(\mathcal{I}_1)}{D(\mathcal{I}_2)} \underset{\substack{\uparrow \\ N(\mathcal{I}_1) > N(\mathcal{I}_2)}}{>} \frac{N(\mathcal{I}_2)}{D(\mathcal{I}_2)}$$

which shows that the correlation decreases.

■

Proof of Theorem 6.6. Let $\mathbf{x} \in R^n$. Our goal is to examine $\operatorname{var}(\mathbf{x}'\mathbf{p})$.

We have

$$\begin{aligned} \operatorname{var}(\mathbf{x}'\mathbf{p}) &\underset{(6)}{=} \operatorname{var}(p_f\mathbf{x}'\mathbf{f}) = \operatorname{var}(p_f\mathbf{x}'(\boldsymbol{\mu}_{\mathbf{v}|\mathbf{y}} - \bar{\rho}\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1})) \\ &= \operatorname{var}\left(E[p_f\mathbf{x}'(\mathbf{v} - \bar{\rho}\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1})|\mathbf{y}]\right) \end{aligned} \tag{C.8}$$

The law of total variance, applied to the random variable $p_f\mathbf{x}'(\mathbf{v} - \bar{\rho}\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1})$, states that

$$\begin{aligned} \operatorname{var}\left(p_f\mathbf{x}'(\mathbf{v} - \bar{\rho}\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1})\right) &= E\operatorname{var}\left(p_f\mathbf{x}'(\mathbf{v} - \bar{\rho}\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1})\middle|\,\mathbf{y}\right) + \operatorname{var}\left(E[p_f\mathbf{x}'(\mathbf{v} - \bar{\rho}\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1})|\mathbf{y}]\right) \\ &\underset{(C.8)}{=} E\operatorname{var}\left(p_f\mathbf{x}'(\mathbf{v} - \bar{\rho}\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1})\middle|\,\mathbf{y}\right) + \operatorname{var}(\mathbf{x}'\mathbf{p}) \\ &= Ep_f^2\operatorname{var}\left(\mathbf{x}'(\mathbf{v} - \bar{\rho}\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1})\middle|\,\mathbf{y}\right) + \operatorname{var}(\mathbf{x}'\mathbf{p}) \\ &= Ep_f^2\operatorname{var}\left(\mathbf{x}'\mathbf{v}|\,\mathbf{y}\right) + \operatorname{var}(\mathbf{x}'\mathbf{p}) \\ &= \operatorname{var}\left(\mathbf{x}'\mathbf{v}|\,\mathbf{y}\right)Ep_f^2 + \operatorname{var}(\mathbf{x}'\mathbf{p}) \end{aligned}$$

where the last equality arises because $\operatorname{var}(\mathbf{x}'\mathbf{v}|\,\mathbf{y})$ is a scalar, and therefore can be taken outside the expectation.

The left-hand side, $\operatorname{var}(p_f\mathbf{x}'(\mathbf{v} - \bar{\rho}\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1}))$, is independent of the specific partition of investors into indexers and nonindexers because each element inside the variance operator is independent. Indeed, p_f is independent (see Theorem 6.1), $\mathbf{x}$ is an arbitrary vector of scalars, $\mathbf{v}$ is exogenous and hence independent, and finally $\boldsymbol{\Sigma}_{\mathbf{vv}|\mathbf{y}}\mathbf{1}$ is independent because the right-hand side of Equation C.1 is independent of the specific partition.

Also, Ep_f^2 is positive and independent of the level of index investment. Therefore, var$(\mathbf{x}'\mathbf{p})$ decreases as we increase $|\mathcal{I}|$ if and only if var$(\mathbf{x}'\mathbf{v}|\mathbf{y})$ increases as we increase $|\mathcal{I}|$. Thus, the proof follows from Theorem 6.2.

■

D Proof of Theorem on Large Economy

Proof of Theorem 8.1. To prove the theorem, we need to compute the unconstrained optimal portfolio of an indexer, given the equilibrium prices. For the rest of the proof, we fix $k_0 \in \mathcal{I}$. Let m be such that $m \geq k_0$ so that the investor is part of the mth economy.

In the mth economy (see Equation 13)

$$\mathbf{y}^m = \begin{bmatrix} \frac{1}{|\mathcal{NI}^m|} \sum_{k \in \mathcal{NI}^m} \mathbf{s}_k^m \\ \\ \frac{1}{m} \mathbf{g}' \sum_{k=1}^{m} \mathbf{s}_k^m \end{bmatrix}_{(n+1)\times 1} = \begin{bmatrix} \mathbf{v} + m^{1/2} \frac{1}{|\mathcal{NI}^m|} \sum_{k \in \mathcal{NI}^m} \boldsymbol{\epsilon}_k \\ \\ \mathbf{g}'\mathbf{v} + m^{1/2} \frac{1}{m} \mathbf{g}' \sum_{k=1}^{m} \boldsymbol{\epsilon}_k \end{bmatrix} = \begin{bmatrix} \mathbf{v} + \frac{1}{m^{1/2}} \frac{1}{1-\pi^m} \sum_{k \in \mathcal{NI}^m} \boldsymbol{\epsilon}_k \\ \\ \mathbf{g}'\mathbf{v} + \frac{1}{m^{1/2}} \mathbf{g}' \sum_{k=1}^{m} \boldsymbol{\epsilon}_k \end{bmatrix} \tag{D.1}$$

where for the last equality we have used π^m, the proportion of index investors in the mth economy (see Equation 15).

Because the equilibrium prices $(p_f^m, \mathbf{p}^m)$ are informationally equivalent to $\mathbf{y}^m$ (Corollary 5.2), the information available to the k_0th investor is the pair $(\mathbf{s}_{k_0}^m, \mathbf{y}^m)$. Thus, the optimal unconstrained portfolio is

$$\mathbf{x}_{k_0} = \frac{1}{\rho_{k_0}} \text{var}^{-1}(\mathbf{v}|\mathbf{y}^m, \mathbf{s}_{k_0}^m) \left(E[\mathbf{v}|\mathbf{y}^m, \mathbf{s}_{k_0}^m] - \frac{1}{p_f^m} \mathbf{p}^m \right)$$

We plug in the above equilibrium prices (Theorem 4.1) and rearrange as follows:

$$\mathbf{x}_{k_0} = \frac{\bar{\rho}^m}{\rho_{k_0}} \operatorname{var}^{-1}(\mathbf{v}|\mathbf{y}^m, \mathbf{s}^m_{k_0}) \operatorname{var}(\mathbf{v}|\mathbf{y}^m)\mathbf{1} + \frac{1}{\rho_{k_0}} \operatorname{var}^{-1}(\mathbf{v}|\mathbf{y}^m, \mathbf{s}^m_{k_0}) \left(E[\mathbf{v}|\mathbf{y}^m, \mathbf{s}^m_{k_0}] - E[\mathbf{v}|\mathbf{y}^m]\right) \tag{D.2}$$

We define $\mathbf{y}^m_{k_0}$ to be as in Equation D.1, except that k_0 is "treated" as a nonindexer.

$$\mathbf{y}^m_{k_0} := \begin{bmatrix} \dfrac{1}{|\mathcal{NI}^m|+1} \displaystyle\sum_{k \in \mathcal{NI}^m \bigcup \{k_0\}} \mathbf{s}^m_k \\ \\ \dfrac{1}{m}\mathbf{g}' \displaystyle\sum_{k=1}^{m} \mathbf{s}^m_k \end{bmatrix}_{(n+1)\times 1} = \begin{bmatrix} \mathbf{v} + \dfrac{1}{m^{1/2}} \dfrac{1}{1-\pi^m+1/m} \displaystyle\sum_{k \in \mathcal{NI}^m \bigcup \{k_0\}} \boldsymbol{\epsilon}_k \\ \\ \mathbf{g}'\mathbf{v} + \dfrac{1}{m^{1/2}}\mathbf{g}' \displaystyle\sum_{k=1}^{m} \boldsymbol{\epsilon}_k \end{bmatrix}_{(n+1)\times 1} \tag{D.3}$$

In the technical lemma presented at the start of Appendix C, we proved that $\mathbf{\Sigma_{vv|y}1}$ does not depend on the partition of investors (see Equation C.1). Thus, $\operatorname{var}(\mathbf{v}|\mathbf{y}^m_{k_0})\mathbf{1} = \operatorname{var}(\mathbf{v}|\mathbf{y}^m)\mathbf{1}$, which implies

$$\operatorname{var}^{-1}(\mathbf{v}|\mathbf{y}^m_{k_0}) \operatorname{var}(\mathbf{v}|\mathbf{y}^m)\mathbf{1} = \mathbf{1} \tag{D.4}$$

We note that the pairs $(\mathbf{y}^m, \mathbf{s}^m_{k_0})$ and $(\mathbf{y}^m_{k_0}, \mathbf{s}^m_{k_0})$ are informationally equivalent: Given either pair, we can compute the other pair. Now, according to our main theorem (Theorem 5.1), $\mathbf{y}^m_{k_0}$ satisfies (GR); thus,

$$\begin{aligned} E[\mathbf{v}|\mathbf{y}^m, \mathbf{s}^m_{k_0}] &= E[\mathbf{v}|\mathbf{y}^m_{k_0}, \mathbf{s}^m_{k_0}] = E[\mathbf{v}|\mathbf{y}^m_{k_0}] \\ \operatorname{var}(\mathbf{v}|\mathbf{y}^m, \mathbf{s}^m_{k_0}) &= \operatorname{var}(\mathbf{v}|\mathbf{y}^m_{k_0}, \mathbf{s}^m_{k_0}) = \operatorname{var}(\mathbf{v}|\mathbf{y}^m_{k_0}) \end{aligned} \tag{D.5}$$

So the optimal unconstrained portfolio is

$$\begin{aligned}
\mathbf{x}_{k_0} &\underset{(\mathrm{D.2})}{=} \frac{\bar{\rho}^m}{\rho_{k_0}} \operatorname{var}^{-1}(\mathbf{v}|\mathbf{y}^m, \mathbf{s}^m_{k_0}) \operatorname{var}(\mathbf{v}|\mathbf{y}^m)\mathbf{1} + \frac{1}{\rho_{k_0}} \operatorname{var}^{-1}(\mathbf{v}|\mathbf{y}^m, \mathbf{s}^m_{k_0}) \big(E[\mathbf{v}|\mathbf{y}^m, \mathbf{s}^m_{k_0}] - E[\mathbf{v}|\mathbf{y}^m]\big) \\
&\underset{(\mathrm{D.5})}{=} \frac{\bar{\rho}^m}{\rho_{k_0}} \operatorname{var}^{-1}(\mathbf{v}|\mathbf{y}^m_{k_0}) \operatorname{var}(\mathbf{v}|\mathbf{y}^m)\mathbf{1} + \frac{1}{\rho_{k_0}} \operatorname{var}^{-1}(\mathbf{v}|\mathbf{y}^m_{k_0}) \big(E[\mathbf{v}|\mathbf{y}^m_{k_0}] - E[\mathbf{v}|\mathbf{y}^m]\big) \\
&\underset{(\mathrm{D.4})}{=} \underbrace{\frac{\bar{\rho}^m}{\rho_{k_0}}\mathbf{1}}_{\text{market portfolio}} + \underbrace{\frac{1}{\rho_{k_0}} \operatorname{var}^{-1}(\mathbf{v}|\mathbf{y}^m_{k_0}) \big(E[\mathbf{v}|\mathbf{y}^m_{k_0}] - E[\mathbf{v}|\mathbf{y}^m]\big)}_{\text{zero-mean random portfolio}}
\end{aligned}$$

This proves the first part of the theorem, with

$$\boldsymbol{\xi}^m_{k_0} = \operatorname{var}^{-1}(\mathbf{v}|\mathbf{y}^m_{k_0}) \big(E[\mathbf{v}|\mathbf{y}^m_{k_0}] - E[\mathbf{v}|\mathbf{y}^m]\big)$$

Our next goal is to show that $\lim_{m\to\infty} \boldsymbol{\xi}^m_{k_0} = \mathbf{0}_{n\times 1}$. To prove this, we need to perform some preliminary computations. In particular, we need to express the conditional expectations and conditional variances in terms of the primitives of the sequence of economies, specifically $\boldsymbol{\Sigma}_{\mathbf{vv}}$ and $\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}}$.

Define

$$\boldsymbol{\Sigma}_1 = \begin{bmatrix}\boldsymbol{\Sigma}_{\mathbf{vv}} & \boldsymbol{\Sigma}_{\mathbf{vv}}(\boldsymbol{\Sigma}_{\mathbf{vv}} + \boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}})^{-1}\boldsymbol{\Sigma}_{\mathbf{vv}}\mathbf{1}\end{bmatrix}$$

For a scalar π and h, define

$$\boldsymbol{\Sigma}_2(\pi, h) = \begin{bmatrix}\boldsymbol{\Sigma}_{\mathbf{vv}} + \dfrac{1}{1-\pi+h}\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}} & \boldsymbol{\Sigma}_{\mathbf{vv}}\mathbf{1} \\ \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}} & \mathbf{1}'\boldsymbol{\Sigma}_{\mathbf{vv}}(\boldsymbol{\Sigma}_{\mathbf{vv}} + \boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}})^{-1}\boldsymbol{\Sigma}_{\mathbf{vv}}\mathbf{1}\end{bmatrix}$$

We have

$$\operatorname{cov}(\mathbf{v}, \mathbf{y}^m) = \boldsymbol{\Sigma}_1, \quad \operatorname{var}(\mathbf{y}^m) = \boldsymbol{\Sigma}_2(\pi^m, 0), \qquad \operatorname{var}(\mathbf{v}|\mathbf{y}^m) = \big(\boldsymbol{\Sigma}_{\mathbf{vv}} - \boldsymbol{\Sigma}_1\boldsymbol{\Sigma}_2^{-1}(\pi^m, 0)\boldsymbol{\Sigma}_1'\big)$$

where, above, we have evaluated $\boldsymbol{\Sigma}_2(\pi, h)$ at $(\pi, h) = (\pi^m, 0)$. We also have

$$\operatorname{cov}(\mathbf{v}, \mathbf{y}^m_{k_0}) = \boldsymbol{\Sigma}_1, \quad \operatorname{var}(\mathbf{y}^m_{k_0}) = \boldsymbol{\Sigma}_2(\pi^m, 1/m), \quad \operatorname{var}(\mathbf{v}|\mathbf{y}^m_{k_0}) = \big(\boldsymbol{\Sigma}_{\mathbf{vv}} - \boldsymbol{\Sigma}_1\boldsymbol{\Sigma}_2^{-1}(\pi^m, 1/m)\boldsymbol{\Sigma}_1'\big)$$

where, this time, we have evaluated $\boldsymbol{\Sigma}_2(\pi, h)$ at $(\pi, h) = (\pi^m, 1/m)$.

We use those expressions to rewrite $\boldsymbol{\xi}_{k_0}^m$:

$$\begin{aligned}\boldsymbol{\xi}_{k_0}^m &= \left(\boldsymbol{\Sigma}_{\mathbf{vv}} - \boldsymbol{\Sigma}_1 \boldsymbol{\Sigma}_2^{-1}(\pi^m, 1/m)\boldsymbol{\Sigma}_1'\right)^{-1} \boldsymbol{\Sigma}_1 \\ &\times \left(\boldsymbol{\Sigma}_2^{-1}(\pi^m, 1/m)\left(\mathbf{y}_{k_0}^m - E\mathbf{y}_{k_0}^m\right) - \boldsymbol{\Sigma}_2^{-1}(\pi^m, 0)\left(\mathbf{y}^m - E\mathbf{y}^m\right)\right)\end{aligned}$$

This is a product of two terms. The first term is nonrandom, has dimensions $n \times (n+1)$, and has the finite limit:

$$\left(\boldsymbol{\Sigma}_{\mathbf{vv}} - \boldsymbol{\Sigma}_1 \boldsymbol{\Sigma}_2^{-1}(\bar{\pi}, 0)\boldsymbol{\Sigma}_1'\right)^{-1} \boldsymbol{\Sigma}_1$$

where $\bar{\pi} \equiv \lim \pi^m$.

Thus, to prove that $\lim \boldsymbol{\xi}_{k_0}^m = \mathbf{0}_{n\times 1}$ with probability one, it is sufficient to prove that with probability one

$$\lim \left(\boldsymbol{\Sigma}_2^{-1}(\pi^m, 1/m)\left(\mathbf{y}_{k_0}^m - E\mathbf{y}_{k_0}^m\right) - \boldsymbol{\Sigma}_2^{-1}(\pi^m, 0)\left(\mathbf{y}^m - E\mathbf{y}^m\right)\right) = \mathbf{0}_{(n+1)\times 1} \tag{D.6}$$

For a scalar π and h, define the matrices $A(\pi, h)$ and $B(\pi, h)$:

$$\mathbf{A}(\pi, h) := \begin{bmatrix} \frac{1-\pi}{1-\pi+h} & 0 & \cdots & 0 & 0 \\ 0 & \frac{1-\pi}{1-\pi+h} & \cdots & 0 & 0 \\ \vdots & & \ddots & & \\ 0 & 0 & \cdots & \frac{1-\pi}{1-\pi+h} & 0 \\ 0 & 0 & \cdots & 0 & 1 \end{bmatrix}_{(n+1)\times(n+1)}$$

$$\mathbf{B}(\pi, h) := \begin{bmatrix} \frac{1}{1-\pi+h} & 0 & \cdots & 0 \\ 0 & \frac{1}{1-\pi+h} & \cdots & 0 \\ \vdots & & \ddots & \\ 0 & 0 & \cdots & \frac{1}{1-\pi+h} \\ 0 & 0 & \cdots & 0 \end{bmatrix}_{(n+1)\times n}$$

Then, from the definition of $\mathbf{y}^m$ (see Equation D.1) and the definition of $\mathbf{y}_{k_0}^m$ (see Equation

D.3), we can write

$$\mathbf{y}_{k_0}^m = \mathbf{A}(\pi^m, 1/m)\mathbf{y}^m + \frac{1}{m}\mathbf{B}(\pi^m, 1/m)(\mathbf{v} + m^{1/2}\boldsymbol{\epsilon}_{k_0})$$

where, above, we have evaluated $A(\pi, h)$ and $B(\pi, h)$ at $(\pi, h) = (\pi^m, 1/m)$. In particular, $E\mathbf{y}_{k_0}^m = E\mathbf{y}^m$, and $\mathbf{A}(\pi, 0)$ is the identity matrix.

We can now rewrite the left-hand side of Equation D.6:

$$\begin{aligned}
&\lim\Bigg(\boldsymbol{\Sigma}_2^{-1}(\pi^m, 1/m)\Big(\mathbf{y}_{k_0}^m - E\mathbf{y}_{k_0}^m\Big) - \boldsymbol{\Sigma}_2^{-1}(\pi^m, 0)\Big(\mathbf{y}^m - E\mathbf{y}^m\Big)\Bigg) \\
&\quad = \lim\Big(\boldsymbol{\Sigma}_2^{-1}(\pi^m, 1/m)\mathbf{A}(\pi^m, 1/m) - \boldsymbol{\Sigma}_2^{-1}(\pi^m, 0)\mathbf{A}(\pi^m, 0)\Big)\Big(\mathbf{y}^m - E\mathbf{y}^m\Big) && \text{(I)} \\
&\quad + \lim \boldsymbol{\Sigma}_2^{-1}(\pi^m, 1/m)\frac{1}{m}\mathbf{B}(\pi^m, 1/m)\Big(\mathbf{v} - \boldsymbol{\mu}_{\mathbf{v}} + m^{1/2}\boldsymbol{\epsilon}_{k_0}\Big) && \text{(II)}
\end{aligned}$$

Consider term II. Because $\lim_m \pi^m$ exists, for every realization of $\mathbf{v}$ and $\boldsymbol{\epsilon}_{k_0}$, the limit, as m goes to infinity, is zero. Thus, to complete the proof that $\lim_m \boldsymbol{\xi}_{k_0}^m = \mathbf{0}$ with probability one, we only need to show that the limit of term I is, with probability one, zero.

We multiply the denominator of term I by $1 = m^{1/2} \times \frac{1}{m} \times m^{1/2}$, so term I can be written as

$$\lim\Big(\boldsymbol{\Sigma}_2^{-1}(\pi^m, 1/m)\mathbf{A}(\pi^m, 1/m) - \boldsymbol{\Sigma}_2^{-1}(\pi^m, 0)\mathbf{A}(\pi^m, 0)\Big)\Big(\mathbf{y}^m - E\mathbf{y}^m\Big)$$

$$= \frac{1}{m^{1/2}} \times \frac{\big(\boldsymbol{\Sigma}_2^{-1}(\pi^m, 1/m)\mathbf{A}(\pi^m, 1/m) - \boldsymbol{\Sigma}_2^{-1}(\pi^m, 0)\mathbf{A}(\pi^m, 0)\big)}{1/m} \times \frac{1}{m^{1/2}}\Big(\mathbf{y}^m - E\mathbf{y}^m\Big)$$

We have decomposed the term into a product of three terms. The limit of the first term, $\frac{1}{m^{1/2}}$, is zero. The middle term, $\dfrac{\big(\boldsymbol{\Sigma}_2^{-1}(\pi^m, 1/m)\mathbf{A}(\pi^m, 1/m) - \boldsymbol{\Sigma}_2^{-1}(\pi^m, 0)\mathbf{A}(\pi^m, 0)\big)}{1/m}$, has a finite limit equal to

$$\frac{\partial}{\partial h}\boldsymbol{\Sigma}_2^{-1}(\bar{\pi}, 0)A(\bar{\pi}, 0)$$

where $\bar{\pi} = \lim \pi^m$.[27] The limit of the third term,

$$\frac{1}{m^{1/2}}\Big(\mathbf{y}^m - E\mathbf{y}^m\Big) \underset{(D.1)}{=} \begin{bmatrix} \frac{1}{m^{1/2}}\left(\mathbf{v}-\boldsymbol{\mu}_{\mathbf{v}}\right) + \frac{1}{|\mathcal{NI}^m|}\sum_{k\in\mathcal{NI}^m}\boldsymbol{\epsilon}_k \\ \\ \frac{1}{m^{1/2}}\mathbf{g}'\left(\mathbf{v}-\boldsymbol{\mu}_{\mathbf{v}}\right) + \mathbf{g}'\frac{1}{m}\sum_{k=1}^m \boldsymbol{\epsilon}_k \end{bmatrix}$$

is zero, with probability one, thanks to the strong law of large numbers.

This completes our proof that for every $k_0 \in \mathcal{I}$, $\lim \boldsymbol{\xi}_{k_0}^m = \mathbf{0}_{(n+1)\times 1}$ with probability one.

■

E Overall Equilibrium

Let $\lambda = \{\mathcal{NI}, \mathcal{I}\}$ denote a partition of investors. In Section 5 we characterized the equilibrium prices $(p_f(\lambda), \mathbf{p}(\lambda))$ that correspond to the partition.

First, we proved that the equilibrium prices and allocations are identical to the equilibrium prices and allocations in the artificial economy. In particular, the investors' allocations are independent of the the partition and all investors hold the market portfolio.

Second, in Theorem 6.1 we showed that regardless of what the partition of investors is, the price of the risk-free asset, the return on the risk-free asset, the price of the market portfolio, and the return on the market portfolio do not depend on the partition.

Putting the two together, we find that investors' expected utilities, conditional on signals and prices, are the same regardless of the partition. Therefore, the unconditional expected

[27] Using rules for differentiation for matrices, we can compute this partial derivative. It is equal to

$$\frac{1}{(1-\bar{\pi})^2}\boldsymbol{\Sigma}_2^{-1}(\bar{\pi},0)\begin{bmatrix}\boldsymbol{\Sigma}_{\boldsymbol{\epsilon\epsilon}} & \mathbf{0}_{n\times 1} \\ \mathbf{0}_{1\times n} & 0\end{bmatrix}\boldsymbol{\Sigma}_2^{-1}(\bar{\pi},0) - \frac{1}{1-\bar{\pi}}\boldsymbol{\Sigma}_2^{-1}(\bar{\pi},0)\begin{bmatrix}\mathbf{I}_{n\times n} & \mathbf{0}_{n\times 1} \\ \mathbf{0}_{1\times n} & 0\end{bmatrix}$$

utilities are the same regardless of the partition. Thus, ex ante investors are indifferent between indexing and nonindexing.

Finally, the notion of overall equilibrium that Grossman and Stiglitz (1980) develop requires that investors be ex ante identical. If we assume, pursuant to Grossman and Stiglitz (1980), that all investors have the same coefficient of risk aversion, then for any partition λ, the unconditional expected utility of an indexer is the same as the unconditional expected utility of a nonindexer. Thus, any partition λ and the prices associated with the partition, $(p_f(\lambda), \mathbf{p}(\lambda))$, form an overall equilibrium (see Grossman and Stiglitz, 1980, section E).

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