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Do IPOs Affect the Prices of Other Stocks? Evidence from Emerging Markets

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We show that the introduction of a large asset permanently affects the prices of existing assets in a market. Using data from 254 initial public offerings (IPOs) in 22 emerging markets, we find that portfolios that covary highly with the IPO experience a decline in prices relative to other portfolios during the month of the issue. The effects are stronger when the IPO is issued in a market that is less integrated internationally and when the IPO is bigger. This evidence is consistent with the idea that shocks to asset supply have a significant effect on asset prices. (*JEL* G12, G14, G15)

Classical asset pricing models focus on investors' preferences (e.g., risk aversion) to explain the behavior of securities prices. Changes in asset supply, on the other hand, are typically considered to be of second-order importance. In many models, the potential effects of supply are basically assumed away by taking the case where supply is either fixed (e.g., Lucas, 1978) or perfectly elastic (e.g., Cox, Ingersoll, and Ross, 1985). There has been a recent theoretical interest in relaxing these extreme assumptions to understand the price impact of changes in the relative supply of risks (see, for example, Cochrane, Longstaff, and Santa-Clara, 2008). However, only a few papers have explored whether supply is relevant empirically. In terms of the level of supply, Hong, Kubik, and Stein (2008) document that market-to-book ratios across the United States are negatively associated with a measure of the state's relative asset supply (the ratio of each state's total book equity to total personal income). Most other papers study changes in supply and, in particular, the price effect of equity issues. For example, Baker and Wurgler (2000) show that the market price level

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tends to fall after periods of active issuance. Similarly, Ofek and Richardson (2000) show that an increase in supply through the expiration of initial public offering (IPO) lockups lowers the prices of recent IPOs. There is also evidence of supply effects in the fixed-income market. In an event study, Newman and Rierson (2004) show that a very large bond issuance of Deutsche Telekom depressed the prices of the bonds of other European telecommunications firms.

We extend the analysis of supply effects by studying the impact of IPOs on the prices of *other* assets in the market of issuance. In particular, we conduct event studies over 254 IPOs in 22 emerging markets, and we show that these IPOs permanently affect the entire cross section of prices in their markets. We show that portfolios that covary highly with the newly added asset experience a decline in prices relative to other portfolios during the month of the issuance. Securities that are closer to the IPO in terms of style (i.e., similar size and book-to-market ratios) also see their relative prices decline. These effects are larger when the supply shock is bigger (i.e., when the IPO is large relative to the market, and when the market is more segmented), providing confirmation of the supply mechanism. The magnitudes are considerable: a strategy that takes a long position in the portfolio with the lowest covariance with the IPO and a short position in the portfolio with the highest covariance with the IPO yields approximately 70 basis points over the month of issuance.

Our approach provides a relatively clean experiment for measuring the effect of supply on asset prices, and it has four main advantages. First, we focus on supply shocks instead of differences in the level of supply across market segments. This allows us to better control for unobservable differences across segments (e.g., cultural or institutional differences), provided that these are stable in short periods of time. Second, we examine the simultaneous effect on the entire cross section of prices in the market, instead of focusing only on the aggregate response (as in Baker and Wurgler, 2000) or one asset class within a market. In this way we are able to better control hard-to-measure, time-varying conditions that simultaneously affect all assets. In other words, by going into the cross section we can control for the average price change during the time of the shock, which can be driven by variables different from the nature of the shock itself (e.g., variables that explain why a market is "hot" or "cold" in one particular moment). Third, we link the cross-sectional effect of the supply shock to various measures of substitutability to the asset that is increasing its supply. For identification of the supply effect, we do not need to assume that a particular IPO carries no new information about the fundamentals of the rest of the assets in the market. We just need this information to be uncorrelated with the various measures of substitutability that we use. Finally, we consider a number of countries with various degrees of integration to international markets, different levels of market capitalization, and volume. This allows us to test whether the supply effect depends on the size of the issue relative to the market of reference or the pool of potential investors. In this respect, our focus on emerging markets comes from the need to have relatively large supply shocks. Because of their sheer size, a single IPO cannot have a significant effect in larger and more developed markets, but the mechanism described in this paper is also applicable to IPO waves or periods of active issuance and repurchase.

The next sections present a discussion of different theoretical approaches (Section 1), and a description of the methodology and the data (Section 2). The results follow in Section 3. We then conclude.

1. The Effect of New Issues on the Price of Other Assets

A change in asset supply cannot have an impact on prices in a world of flat asset demands. However, the underlying assumption behind flat and stable asset demands is that changes are small. As Scholes (1972, p. 182) puts it: "The corporation, which issues additional claims to finance investment, adds to the stock of assets that must be held; but this addition is assumed to be a small percentage of assets. At the time of a new issue there should be no effect on the market price ...." Starting with Shleifer (1986), the subsequent literature on demand curves for stocks has disputed the idea of flat demands, even for small changes, based on the absence of close substitutes and limits to arbitrage.[1] We focus on large changes in supply, which can have an effect regardless of whether there are limits to arbitrage or not.

In what follows, we rationalize the effect of supply changes on asset prices under three different families of models. We focus on the common prediction across models, namely that the covariance of a stock with the new asset (the IPO) affects the direction and magnitude of the repricing. A high and positive covariance with the IPO implies that the IPO is a "good substitute" for the stock, and therefore implies that the price of the stock should be hit harder as the new asset enters the market. These models are essentially models of relative pricing, in which the new asset affects prices because it redefines the portfolio of reference.

We comment only briefly on other ancillary predictions that each model makes that could allow us to distinguish between them in the data. While we explore some of these differences in the empirical part, we are more interested in documenting the basic fact than in providing a definitive test for the different models.

We assume throughout this discussion that capital markets are segmented by country as we define relevant markets as national equity markets. There is plenty of evidence suggesting that emerging markets are not perfectly

[1] More recent papers in this literature include Wurgler and Zhuravskaya (2002) and Barberis, Shleifer, and Wurgler (2005), who study the demand curve for stocks in the context of index additions. Kaul, Mehrotra, and Morck (2000) and Greenwood (2005) study index redefinitions. Loderer, Cooney, and Van Drunen (1991) study the price effects of stock offerings in regulated firms. We focus on cross elasticities—a quantity change in one asset affecting the price of another asset—while the literature on demand curves for stocks is exclusively focused on own-price elasticities.

integrated to international capital markets (see Bekaert and Harvey, 2003, for a survey).

1.1 Frictionless model: the capital asset pricing model

Assume that there is a representative agent with CRRA (constant relative risk aversion) preferences in each market. Under other standard assumptions and the absence of frictions, Merton (1980) shows that the market risk premium can be written as

$$E(r_m) - r_f = \gamma\sigma_m^2, \tag{1}$$

where the parameter γ is the coefficient of relative risk aversion of the representative investor, and σ_m^2 is the variance of the market return. The CAPM (capital asset pricing model) holds in each market and therefore the expected excess return on asset i is equal to the beta of the asset times the local risk premium:

$$E(r_i) - r_f = \beta_i[E(r_m) - r_f] = \gamma\,\sigma_{im}. \tag{2}$$

The second equality in Equation (2) is obtained by using the definition of market beta, $\beta_i = \sigma_{im}/\sigma_m^2$, where σ_{im} is the covariance of asset i and the market return.

Now assume that a new asset, the IPO, is introduced in the market. The market initially has $i = 1, \ldots, n$ assets, so the IPO is asset $n + 1$. We refer to the market with n assets as market 0, and to the market with $n + 1$ assets as market 1. The weight of asset i in market 0 is denoted by $\omega_{i,0}$ (analogously for market 1). We assume that the number of shares Q_i is constant and, therefore, any change in the market weight comes from a change in price. With the introduction of the IPO, the covariance on the right-hand side of Equation (2) changes, and consequently expected returns change. Assuming, for simplicity, that the risk-free rate stays constant, we can express the change in expected returns as

$$\Delta E(r_i) = \gamma\omega_{\text{ipo}}\sigma_{i,\text{ipo}} - \gamma\sum_{j=1}^{n}(\omega_{j,0} - \omega_{j,1})\sigma_{ij}. \tag{3}$$

Equation (3) has two opposing terms. In order to simplify the interpretation, first consider the case of an asset that has zero covariance with the original n assets, but a nonzero covariance with the IPO. In market 0, the expected return on this asset is the risk-free rate—the asset has no systematic risk. The change in expected return on this asset corresponds only to the first term in Equation (3) since all the other covariances are zero. The sign of the change is given by the sign of the covariance with the IPO. If the covariance with the IPO is positive, then the asset receives a risk premium in market 1; if the covariance is negative, then the asset receives a risk discount because it is a good hedge against the fluctuations of the IPO. The magnitude of the effect is influenced by the weight of the IPO in the market, ω_{ipo}, and by the price of risk given by the investor's risk aversion.

The second term in Equation (3) tends to offset the effect of the first term. The first term is the direct effect of the IPO, while the second term is the indirect effect because it depends on how the other preexisting assets in the market also respond to the IPO. The intuition is the following. From the first term we know that an asset that covaries positively with the IPO receives a higher expected return, a lower price, and consequently a lower weight in the market portfolio (*ceteris paribus*). Therefore, assets with positive IPO covariance see their market weight decline because of the first term in Equation (3). But the decrease in market weight leads mechanically to a lower covariance of these assets with the new market and a lower risk premium, dampening the previous increase in risk premium. The second term in Equation (3) captures this dampening effect. The indirect effect of the IPO is likely to be of second order except for extreme cases, which occur when the market's share of an asset gets close to 100% (see Cochrane, Longstaff, and Santa Clara, 2008).[2] We focus on the direct impact of $\sigma_{i,\text{ipo}}$ throughout the paper, so, if anything, the second term in Equation (3) biases our empirical strategy against finding a result.

The case of the entire market illustrates the linear dependence of changes in expected returns with respect to the IPO covariance:

$$\Delta E(r_m) = \gamma\omega_{\text{ipo}}\left[\sigma_{m,\text{ipo}} - \sigma_m^2\right] = \gamma\omega_{\text{ipo}}\sigma_m^2[\beta_{\text{ipo}} - 1]. \tag{4}$$

This equation shows that in this model, the average effect of the IPO on the market is not necessarily negative, but that the effect depends on whether the IPO has a market beta above or below 1. In other words, the change in the *composition* of the market is crucial and not simply the change in the *size* of the market. For instance, the market premium does not change if the IPO beta is equal to 1, which is to say that there is no price change if the market grows in a balanced way by perfectly replicating itself. In general, size is relevant in this model, but to determine the magnitude of the effect and not the sign. Market segmentation can also be understood as another way of varying the relative size of the IPO. In a less segmented market, the relevant market capitalization includes foreign assets, which amounts to say that ω_{ipo} shrinks. In the extreme case of a fully integrated market where the world market is the reference for the CAPM (Karolyi and Stulz, 2003), any IPO necessarily has a negligible size and therefore the change in expected returns in Equation (4) is zero.[3]

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[2] In terms of CAPM betas, this point can be understood as follows. In general, a positive IPO covariance increases the systematic risk of a stock and therefore its beta. However, as an asset grows and becomes the entire market, its beta has to eventually converge to 1. Therefore we could observe stocks with betas higher than 1 that experience a fall in beta even if they have a positive covariance with the IPO. The examples in Cochrane, Longstaff, and Santa-Clara (2008) suggest that this convergence happens only in cases where the asset represents more than 70% of the market, which makes this concern not empirically relevant, at least in our sample. The median market share of industry portfolios in our sample is 3%; the 95th percentile of the distribution of market share is only 36%.

[3] We are implicitly assuming in this discussion that the IPO creates a new source of wealth in the economy. The IPO has the potential to affect other asset prices because it redefines what the market is. This is in contrast with

1.2 Downward-sloping demand curves for stocks

Demand curves for stocks are flat in a frictionless benchmark such as the CAPM. They are downward sloping if there are frictions that restrict arbitrage, indicating that the market has a limited capacity to bear risks and adjust to shocks (De Long et al., 1990; Shleifer, 1986; and Shleifer and Vishny, 1997). Here we present a reduced-form model with downward-sloping demands to motivate the key prediction. We do not explicitly model the frictions that limit the risk-bearing capacity of the market. For simplicity we keep the representative agent framework, although the standard practice in the behavioral literature is to consider models with heterogeneous agents—some of them rational and others affected by cognitive biases. We cannot do full justice to the richness of behavioral models in this short discussion.

In contrast to the first section, assume that the representative agent has CARA (constant absolute risk aversion) preferences, which is a standard assumption in the literature with downward-sloping demands. Following the portfolio analysis of Grossman and Stiglitz (1980), in equilibrium the price of asset i is

$$P_i = \mu_i - \gamma \sum_{j=1}^{n} Q_j \sigma_{ij}, \tag{5}$$

where μ_i is the expected dividend of the asset.[4] The slope of the demand curve in this case is $\partial P_i / \partial Q_i = -\gamma \sigma_i^2$. As the IPO enters the market, the change in price is given by

$$\Delta P_i = -\gamma Q_{\text{ipo}} \sigma_{i,\text{ipo}}. \tag{6}$$

In the case of CARA preferences, it is easier to work with prices instead of expected returns, but the implications of Equation (6) are analogous to those of Equation (3). The price of a stock with a positive covariance with the IPO falls, and this effect is magnified by risk aversion and the size of the IPO. Despite the fact that demands are downward sloping, the repricing of stocks follows a similar intuition as in the CAPM because both models are models of relative pricing. Any stock is priced in comparison to the rest of the stocks in the market. The portfolio of reference changes when the new stock enters the market, and the covariance with the IPO measures the impact on each particular asset. The effect of the IPO covariance is therefore a property of a broad class of models that use relative pricing and not only of the CAPM.

an asset in zero net supply, i.e., an asset that does not create new wealth, in which case the relative prices of risky assets remain unchanged (Willen, 2005). However, even an asset in zero net supply can affect relative prices if we add frictions, for example, if the owners of the firm going public are liquidity constrained before the IPO. If these owners are not able to invest freely in other assets before the IPO, the risk to which they are exposed is not fully reflected in market prices. Going public and the consequent alleviation of liquidity constraints for these investors most likely change equilibrium prices.

[4] There is a slight abuse of notation because we use σ_{ij} to represent the covariance between returns in the first section and the covariance between payoffs in this section.

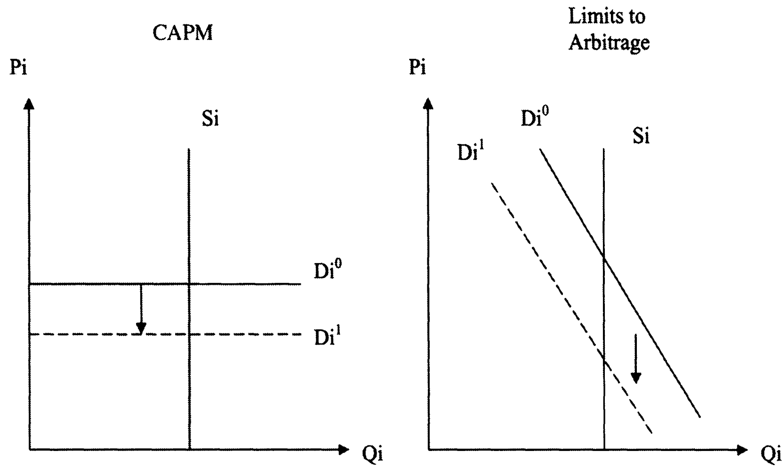

Figure 1
Change in demand for asset *i* when a new asset enters the market in different models.

Figure 1 illustrates a fall in demand for an individual stock in the CAPM and in the model with downward-sloping demands. The IPO shifts the position of the demand in the CAPM, but the demand remains flat. For a given price (expected return), the market demands zero or infinite of that stock. In the case of limits to arbitrage, the IPO also shifts the whole demand curve as the market is redefined, but the demand continues to be downward sloping. In other words, the IPO affects the position of the demand curve in both models, leaving the slope of the demand unaffected.

The market reaction to the IPO is the same as in Equation (6) except for substituting $i = m$. Therefore, the effect on the market is most likely negative. Only if the IPO has a negative covariance with the market—which is not common in empirical applications—the effect on the market is positive. This is almost a direct implication of the limited capacity to bear risk that is assumed in this model.

We have focused so far on covariances, which can be rationalized within both classes of models. However, the behavioral literature also argues that investors use "styles" to allocate their wealth and therefore to price assets. For example, Barberis and Shleifer (2003) suggest that investors classify assets using easily observable characteristics such as belonging to the S&P 500 Index or the book-to-market ratio of the stock. We can imagine that investors rebalance their portfolios as an IPO enters the market in order to maintain their desired exposure to different styles. In this process, assets that have a style similar to the style of the IPO are substituted away more strongly than other assets. For example, if there is a downward-sloping demand for "growth" (low book-to-market), a growth IPO can crowd out and lower the price of other growth stocks as we move along the demand curve for growth. In the tradition of the behavioral literature, the downward-sloping demand can be the result of the interaction of biased investors, who judge assets in comparison to their asset class, and fully rational arbitrageurs, who price assets based on fundamentals. Frictions such as performance-based contracts (Shleifer and Vishny, 1997) and short horizons (De Long et al., 1990) prevent arbitrageurs from driving prices back to fundamentals when style investors buy or sell assets as the IPO enters the market.

With frictionless arbitrage, no change in price is observed on the issuance date if agents have rationally anticipated the IPO. In a model with limits to arbitrage, the effects are probably still seen at issuance. For instance, there is no certainty about the issuance when management announces plans to do it or files for it; rather, the probability of issuance grows slowly in time and reaches its peak only on the actual date of listing.[5] This implies that there is a substantial risk to the arbitrage strategy of selling short stocks with high IPO covariance and buying stocks with low IPO covariance, which deters arbitrageurs from pursuing it and affecting prices before the date of issuance (De Long et al., 1990; and Shleifer and Vishny, 1997). A similar logic is applied by Ofek and Richardson (2000) to argue that the response to anticipated expirations of IPO lockups is evidence in favor of downward-sloping demands (see also Hong, Scheinkman, and Xiong, 2006).

Empirically, we expect a negative market reaction to equity issues according to the model with downward-sloping demands, while the market reaction is ambiguous according to the CAPM. These market-wide predictions are independent of the cross-sectional heterogeneity that both models predict (i.e., some prices falling less than others or even increasing). The evidence on market timing—the fact that periods of active issuance precede periods of low market returns—in the United States (Baker and Wurgler, 2000) and in the same database that we use in this paper (Henderson, Jegadeesh, and Weisbach, 2006) suggests that the market reaction is mostly negative, in favor of a model with downward-sloping demands.

1.3 Price pressure

The previous models coincide in that the effect of the IPO comes from a *permanent* change in the demand for a stock in contrast to *transitory* price pressure (Harris and Gurel, 1986). The idea of price pressure is that during the period surrounding the IPO, investors need to finance their acquisition of the new stock by selling other stocks, and that market makers are only willing to take the stocks at a discount. It is possible that the degree of the discount is correlated with the IPO covariance if investors sell similar stocks to finance the acquisition of the new asset. However, as investors build up liquidity again, they buy back the shares previously sold and prices rebound to their original level. Therefore, if the initial effect is due to a liquidity shortage, we should

[5] For example, in the United States, there were 885 IPO withdrawals between 1998 and 2006.

observe larger price *increases* in those stocks with a high IPO covariance in the period that follows the IPO.

The price pressure hypothesis has the unique prediction of price reversal following the main event, or to be more precise, following the abnormal volume produced by the event. This has been the key differentiating prediction in other applications such as index additions (see, for example, Kaul, Mehrotra, and Morck, 2000).

2. Event Study around IPO Dates

IPOs do not go unnoticed in emerging markets. In contrast, the sheer size of these transactions attracts the attention of all big investors such as pension funds and international funds. IPOs are focal points, particularly if they are listed alone during the month, and they can stir the whole market. We therefore conduct an event study around the date of listing of new issues.

We focus on emerging markets for two reasons. First, these markets are small and imperfectly integrated with international markets, making IPOs relatively bigger shocks. For example, the average IPO in our sample is equivalent, relative to the capitalization of its national market, to 25 times the IPO of Google in the United States.[6] IPOs are even bigger relative to volume traded in emerging markets due to limited liquidity and free-float. Second, by making cross-market comparisons, we explore variations of the basic test as the institutional setting changes. This second layer of tests improves the empirical identification and reduces concerns about omitted variables bias.

A crucial element of our experimental design is that we study the change in price of the existing stocks in the market, and not of the company going public.[7] Equity distributions are plagued with asymmetric information, as noted by Myers and Majluf (1984) and many other papers that followed. We focus on *other* stocks precisely as a way to circumvent these signaling issues. We think it is reasonable to assume that the IPO does not signal relevant information about the future cash flows of other firms listed in the market, perhaps with the exception of close competitors to the firm going public. If credit constraints are important, it can be argued that a change in capital structure, due to an IPO for example, conveys information about firms in the same product market (Chevalier, 1995; and Phillips, 1995). However, when thinking of firms outside the group of close competitors, the IPO most probably does not reveal a great deal of information about cash flows that market participants do not already know. Arguing that the IPO has signaling power implies that managers or owners of the firm going public have valuable information about *all* of the other firms in the market that investors do not have. We think that informational

6 The IPO of Google, in August of 2004, had proceeds of $1.67 billion. The joint capitalization of the NYSE and NASDAQ was approximately $16 trillion at the time.

7 For the effect of issues on the same company, see the survey by Ritter (2003).

asymmetries of this type are too strong to be a general description of IPOs. Therefore, we interpret the changes in prices that we observe as coming from changes in expected returns rather than new information about future cash flows.

2.1 Data sources

Stock prices come from the Emerging Markets Database (EMDB). We use dollar prices as of the end of the month. We do not use daily data because many stocks are traded only sporadically in emerging markets, and thus too often we observe zero daily returns.[8] We define the market return as the value-weighted return on the EMDB stocks in the country during the month. We form 17 value-weighted industry portfolios in each country following the industrial classification of Fama and French (1997).[9] Not all countries have 17 industries in every date. Forming portfolios is necessary to correct for the unbalanced nature of the panel with individual stocks since the number of stocks listed on the EMDB varies substantially across countries and across time.[10] Working with individual stocks would give unequal weight to certain events or countries. Also, as is standard in the asset pricing literature, we work with portfolios instead of individual assets in order to minimize measurement errors in variables such as covariances or betas. Having said that, the median number of stocks in the portfolios that we form is 4 (the 25th percentile of the distribution is 2; the 75th percentile is 9) and therefore we are not too far from working with individual stocks.

The IPO data come from Thomson Financial's SDC Platinum.[11] We start with all common equity primary IPOs. We then restrict the sample to the issues where the firm is listing in its home market. The sample excludes events initiated by firms already listed (firms issuing either a new class of stock or in other markets). IPOs are considered as events only if the amount is larger than \$20 million, which leaves out data of debatable quality and retains issues more likely to have a material impact on prices. We use IPOs that are issued in a month in which no other IPO larger than \$20 million is listed in the same market in order to keep the identification of the events as clean as possible. Simultaneous events would make inference hard since we

[8] Lesmond (2005, Table I) reports that stocks in emerging markets have up to 50% of zero-return days in a quarter, that is, it can occur that a stock is traded in only half of the potential trading days in a quarter.

[9] The definition and returns associated with these industry portfolios in the United States can be found on Ken French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). We match SDC's SIC and EMDB's GICS classification to the classification used by Fama and French (1997). We also perform tests with Fama-French's 48-industry classification and obtain similar results. The panel looks more unbalanced in that case because of missing industries in some countries and periods.

[10] For example, Chile has 35 stocks in the EMDB in 1990 and 48 in 2000. Korea has 78 stocks listed in 1990 and 162 in 2000.

[11] Henderson, Jegadeesh, and Weisbach (2006) provide a comprehensive study of this dataset, including all types of equity issues and debt issues.

are studying the effects of IPOs on the other stocks in a market.[12] From the SDC we keep the issuance date, the dollar proceeds of the IPO, and the issuing firm's country and industry. The announcement date of the IPO is not available.

After matching the EMDB and SDC data, we end up with 254 IPOs in 22 different emerging markets, corresponding to the 1989–2002 sample period. The main restriction for not studying earlier years is the start of the SDC database. The IPOs are evenly distributed across years, but we observe a higher concentration of IPOs in Asia. This is not surprising since financial markets are deeper and more integrated there (Bekaert and Harvey, 1995). Approximately one-third of the IPOs are in the financial industry (banks, insurance companies, and others). Table A1 in the Appendix provides a more detailed description of the sample and summary statistics.

2.2 Basic regression

The regression that we estimate is of the following type:

$$R^c_{i,t} = a + b\sigma_{i,\text{ipo}} + \varepsilon^c_{i,t}, \tag{7}$$

where the dependent variable is the abnormal return on industry portfolio i in country c during the month t of issuance of an IPO in the country. For each event (IPO) we have at the most 17 return observations corresponding to the 17 industry portfolios. We then stack returns from all events, which vary across time and countries. The vector a represents a set of IPO fixed effects. The main explanatory variable measures the covariance of returns between industry portfolio i and the IPO. We allow residuals $\varepsilon^c_{i,t}$ to be correlated across industries and through time in the same country (i.e., we cluster residuals by country).

We measure abnormal returns in two ways. First, we simply subtract the market return, which we call the market-adjusted return. Given the IPO fixed effects, running the regressions with market-adjusted returns or raw returns is equivalent. Second, we compute the return in excess of a market-model return estimated with data from month $t-30$ to month $t-7$. We lose approximately 10% of the observations with the second method because it requires a longer time series for each industry. For this reason, and because of the methodological issues with in-sample covariances (see the next section), our preferred measure is the market-adjusted return.

We concentrate on the within-market variation by including IPO fixed effects that absorb the market-wide fluctuation (or any change in the risk-free rate). Being able to control for unobserved characteristics constitutes a major advantage of our empirical design, because the results are robust to omitted variables that vary along any combination of the country, time, and IPO-industry dimensions. By focusing on the cross section of prices rather than the market

[12] The total number of IPOs in the SDC sample of emerging markets is 7,668. From these, 6,938 are local IPOs. Imposing the restriction of more than $20 million in proceeds leaves us with 1,443 events. Finally, 254 IPOs are listed alone in a given month and country.

price level, we remain silent about the market timing of equity issues (Baker and Wurgler, 2000; and Henderson, Jegadeesh, and Weisbach, 2006). The need to control for country unobservables is critical given the evidence on cross-country differences in valuations (La Porta et al., 2002) and IPO underpricing (Ljungqvist, 2007), and the fact that these differences are not fully explained by the literature.

2.3 Proxy for the IPO covariance

The main obstacle to run the regression in Equation (7) is that the covariance with the IPO is not observable before the firm goes public. A critical issue in this regression is to find an appropriate proxy for this variable. One natural candidate is the historical covariance between an industry and the industry of the IPO, which is almost always observable before the IPO. However, on top of being noisy due to the lack of a long time series and the dramatic changes in market structure, using an in-sample covariance would defeat the purpose of the experiment. Our whole approach hinges on the idea that changes in the composition of a market change asset prices and the comovement of returns. Covariances have embedded in them the characteristics of the segment where they are traded, which makes any in-sample covariance not a good proxy for the true, unobservable, and forward-looking covariance present in the model. The structure of the market affects the dynamics of returns as shown, for example, by Bekaert and Harvey (2000) and Henry (2000), who study how stock prices react when an emerging market opens up to foreign investors. In a similar vein, Barberis, Shleifer, and Wurgler (2005) show that stocks added to the S&P 500 exhibit changes in their degree of comovement with other stocks inside and outside the index.

In terms of the econometrics of regression (Equation (7)), the problem with in-sample covariances is that they are endogenous, or that they are correlated with the error term in the regression. Another example, this time from the corporate finance literature, can illustrate the potential correlation between $\varepsilon_{i,t}^{c}$ and the covariance computed with local data. Firms are usually organized in diversified conglomerates in emerging markets because of the poor development of financial intermediaries. A high covariance between firms can reflect the existence of these internal capital markets (Lamont, 1997). In such a case, an IPO can signal the alleviation of financial constraints for an entire set of firms within a conglomerate, and therefore cause a simultaneous change in prices in all of them. The key point here is that the IPO can signal new information about the future cash flows of these related firms, like in the model of Myers and Majluf (1984), and therefore it does not represent a pure supply shock that only affects discount rates. The extent of these internal capital markets is the omitted variable hidden in the error term and correlated with the local covariance. Unfortunately, measuring these interfirm links is virtually impossible, at least for a broad sample like the one we study.

Our approach is to use an out-of-sample proxy for the IPO covariance, which we argue is more reasonable to assume to be uncorrelated with the error term. We compute the covariance of returns between each pair of industries in U.S. monthly data from 1974 to 2003. Table A2 in the Appendix presents the 17 × 17 covariance matrix with the 153 different covariances. By construction, these estimated covariances do not vary with the institutional setting and the equity composition peculiar to each emerging market, which makes them more robust to misspecification and less prone to measurement error.

The covariance has to be a forward-looking measure of substitutability between assets since it speaks about the future distribution of returns. Therefore, our assumption is that the covariance structure observed in the United States is a good forward-looking benchmark. The United States is a well-diversified, internationally integrated market, and with relatively more active arbitrageurs. It is natural to assume that markets tend to behave more like this benchmark as they develop.

However, the question remains how good this proxy is for the unobservable covariance between the IPO and the other stocks in a market. In order to give some support for our proxy, we construct historical interindustry covariances in each market. These are highly correlated with the U.S. covariance structure: the average rank correlation is 0.45, and in all but three of the countries in our sample, we strongly reject the hypothesis that the ranking of the two measures is independent. Given that we exploit within market, cross-asset variation, we just need the ranking of the interindustry covariances to be relatively stable across countries. In fact, in some tests we use the interindustry ranking instead of the magnitude of the covariance. This shields our results against potential misspecification. For instance, Morck, Yeung, and Yu (2000) show that stocks in less developed markets tend to be more correlated, leading mechanically to higher covariances (*ceteris paribus*). However, even if all covariances are higher in some markets, our variable is valid as long as the ranking of comovement across industries does not change dramatically.

Table 1 provides the highest and lowest covariances for some industries in our U.S. data. As can be expected, the highest covariance is always for the same industry. Machinery, for example, is highly correlated with itself, steel, and consumer durables, but not too correlated with food and utilities. Food, on the other hand, is highly correlated with industries such as retail and textiles. Our comparison of covariance structures across countries suggests that similar patterns can be observed in emerging markets, despite the large differences between the industrial structure of the United States and other markets. For example, food tends to be more correlated with retail than with machinery. These comparisons also emphasize the advantages of working with industry portfolios instead of individual assets. It is more reasonable to assume a stable covariance structure at the level of industries than at the level of individual firms, resulting in less measurement error and a better proxy.

Table 1
Highest and lowest return covariances for selected industries

Industry	Highest covariances (17–13)	Lowest covariances (5–1)
Machinery	Machinery	Banks
	Steel works	Consumer products
	Consumer durables	Oil
	Everything else	Food
	Construction	Utilities
Food	Food	Machinery
	Retail	Steel works
	Textiles	Mining
	Construction	Utilities
	Consumer products	Oil
Banks	Banks	Mining
	Construction	Food
	Textiles	Consumer products
	Transportation	Oil
	Retail	Utilities

This table shows the five industries with the highest and lowest covariances with food, machinery, and banks (financial industry). The ranking follows the covariances in monthly excess returns of U.S. industrial portfolios between 1973 and 2004. The industry definitions correspond to the 17 groups of SIC Codes defined on Ken French's website.

Another issue is whether our proxy for the IPO covariance provides enough variability for a given industry across events (IPOs). We study this issue in Table 2, which shows the dispersion of covariance rankings in our sample. First, we assign to every industry in each event a ranking between 1 (lowest) and 17 (highest) based on the covariances in U.S. data. We then summarize the ranking of a particular industry across all events in our sample. In a perfect

Table 2
Summary statistics for ranking of IPO covariance by industry

Industry	Average ranking	Median ranking	Minimum ranking	Maximum ranking	No. of observations
Food	4.7	4	1	17	249
Mining	5.9	5	3	17	181
Oil	3.0	2	1	17	150
Textiles	13.1	15	6	17	204
Consumer durables	12.5	12	8	17	121
Chemicals	8.0	8	6	17	211
Consumer products	4.3	3	2	17	149
Construction	15.0	15	12	17	245
Steel works	11.5	13	3	17	167
Fabricated products	9.7	9	7	17	65
Machinery	12.9	13	1	17	197
Automobiles	8.3	8	5	17	170
Transportation	11.9	11	9	17	199
Utilities	1.9	1	1	17	111
Retail	11.7	12	3	17	184
Banks	10.4	8	5	17	252
Everything else	9.1	7	2	16	250

We assign a ranking between 1 and 17 to the industry portfolios in the market for each IPO in our sample. The ranking follows the ordering of covariances with the IPO industry according to the returns of U.S. industrial portfolios between 1973 and 2004. The highest covariance corresponds to ranking 17. We then summarize the ranking of an industry across all IPOs in the sample. IPOs cover the time period 1989–2002 in 22 emerging markets. Other details on the selection of IPOs are in the text.

experiment we would expect the average ranking to be 8.5, indicating that the industry is half the time in the low-covariance group and half the time in the high-covariance group. In our sample, 10 out of 17 industries have an average ranking in the range close to 8.5. Within each industry, there is a substantial variation as also shown by the minimum and maximum ranking. All industries, except for one, take the top position (highest covariance) at least once. Also, 9 out of 17 industries take at some point a position among the bottom three covariances. Therefore, even though some industries have a higher average ranking than others (construction vs. utilities, to take the two extremes), it is not the case that industries are permanently in the high- or low-covariance group. For the majority of industries, the ranking changes substantially depending on the IPO that has been listed in the market.

Despite the advantages of the proxy for the IPO covariance that we propose, we also check the robustness of our results by using in-sample covariances. On top of the historical country-specific covariances, we also compute time-varying country-specific covariances, which are specific to each event in the sample. When we run regressions on in-sample covariances, we instrument them with the U.S. covariances in order to account for endogeneity (i.e., dependence on local conditions) and to reduce measurement error.

3. Empirical Results

3.1 Asset prices fall as the covariance with the IPO increases

Table 3 presents results for the basic regression. The fixed effects are not reported, although it is worth mentioning that the average raw return during the month of an IPO is −0.30% with a standard error of 0.70%. Despite being negative, the average effect is not statistically significant.

In the month of the IPO, the coefficient of the IPO covariance is negative and significant at the 5% level with both definitions of abnormal returns. The coefficient in the regression with market-adjusted returns implies that a one-standard-deviation increase in the IPO covariance makes relative prices fall by 0.40%. In order to put this number in perspective, consider, for example, that HML (the book-to-market factor of Fama and French, 1993) gives an average premium of 0.40% per month. An alternative way of quantifying these magnitudes is to use the IPO covariance ranking of each industry as the explanatory variable. Using the ranking is also a way of controlling for possible nonlinearities that might be present in the data. The results in Table 3 indicate that moving one place closer to the IPO in the ranking makes prices fall by 5.9 basis points (3.8 basis points when using market-model abnormal returns).

The fact that we find an effect during the month of issuance contradicts a frictionless model where the effect is concentrated around the date of announcement of the IPO that is typically well in advance of the actual date of issuance. Unfortunately, the SDC does not include announcement dates in

Table 3
The effect of an IPO on the stock returns of other firms: basic evidence

	Month relative to IPO					
	Previous month		Month of IPO		Following month	
	Dependent variable: market-adjusted return					
Covariance with IPO industry	−2.38		−6.75**		−2.41	
	(3.83)		(3.28)		(3.51)	
Covariance rank		−3.16		−5.92**		−2.59
		(3.82)		(2.40)		(2.43)
No. of observations	3084	3084	3105	3105	3084	3084
No. of IPOs	253	253	254	254	254	254
R^2	0.14	0.14	0.12	0.12	0.13	0.13
p-value covariance coefficient > IPO month	13%	21%			8%	10%
	Dependent variable: market-model abnormal return					
Covariance with IPO industry	−2.72		−5.49**		1.88	
	(3.53)		(2.28)		(2.37)	
Covariance rank		−3.21		−3.87		1.25
		(3.82)		(2.53)		(2.49)
No. of observations	2708	2708	2725	2725	2739	2739
No. of IPOs	242	242	243	243	244	244
R^2	0.25	0.25	0.24	0.24	0.24	0.24
p-value covariance coefficient > IPO month	25%	44%			1%	5%

This table shows the results from the following regression:

$$R^c_{i,t} = a + b\sigma_{i,\text{ipo}} + \varepsilon^c_{i,t}$$

In the top panel of the table, the dependent variable is the return of industry i in country c in excess of the local market return during a month (market-adjusted returns). In the lower panel, the abnormal return is computed with a market model estimated between months $t-7$ and $t-30$. The local market is defined as the value-weighted sum of all stocks in that country and month reported in the EMDB database. Results are shown for month t, which is the month of the IPO, and for months $t-1$and $t+1$. The independent variable is the covariance between industry i and the industry of the IPO. This covariance is estimated with monthly industrial returns from U.S. stocks between 1973 and 2004. The industry definitions correspond to the 17 groups of SIC Codes defined on Ken French's website. The results are also shown using the rank of the covariance of each industry with a given IPO industry. The covariance rank ranges from 1 to 17. The coefficient on the covariance rank is multiplied by 10,000, so it is interpreted as basis points lost (or gained) when moving up one place in the ranking. The IPO fixed effects (a in the equation above) are not reported. Details on the selection of IPOs are provided in the text. Returns in the dependent variable are truncated at the 1% and 99% levels. Robust standard errors clustered by country are reported below the coefficients. Significance (two-sided): ***1%, **5%, *10%.

Table 4
Average returns for portfolios formed using the IPO covariance

	Average return in month relative to IPO		
	Previous month	Monthz of IPO	Following month
Portfolio with low IPO covariance	0.15% (848)	0.15% (861)	0.29% (852)
Portfolio 2	−0.31% (744)	0.15% (748)	0.27% (738)
Portfolio 3	−0.44% (653)	−0.33% (659)	0.20% (649)
Portfolio with high IPO covariance	−0.29% (839)	−0.51% (837)	−0.29% (845)
Low-high	0.44%	0.66%	0.00%
p-value	21%	5%	98%

This table shows average market-adjusted returns for four portfolios formed using the ranking of IPO covariance. Portfolio "low" includes industries with ranking between 1 and 5; portfolio 2 includes industries with rankings between 6 and 9; portfolio 3 includes industries with rankings between 10 and 13; and portfolio "high" includes industries with rankings between 14 and 17. Returns are shown for the month of the IPO, the month previous to the IPO, and the month following the IPO. The number of industries in each case is reported in parentheses. Industries are weighted equally in each portfolio. The last line shows the p-value of the test that the return on portfolios "high" and "low" is the same during that month.

order to study this issue in more detail, but this evidence is suggestive of the existence of limits to arbitrage.[13]

We find relatively large price changes, but these imply small changes in expected returns. This can be seen with the Gordon growth formula for the dividend-price ratio: $D/P = E(r) - g$. Assume that the D/P ratio is 4%. For given dividends, a change in prices of 40 basis points implies a change of only 1.6 basis points in expected returns. A back of the envelope calibration of our model shows that these are plausible magnitudes. Take the first term in Equation (3) and consider the effect of a one-standard-deviation increase in the IPO covariance. Assume that the risk aversion coefficient is 100, consistent with the equity premium evidence, and that the IPO has the average size in the sample (0.25% of the country's market capitalization; see Table A3). Multiplying these terms gives that the change in expected returns is 1.5 basis points per month. We do not perform tests with long-horizon returns precisely because changes in expected returns are small and tests would most probably lack power. The variance of returns is simply too large relative to the size of the effect that we document.

Table 4 shows profits from trading around IPOs using portfolios sorted on the IPO covariance. We divide industries into four portfolios according to the IPO covariance and we compute the equally weighted return of investing in each portfolio around the events in our sample. If we buy the portfolio with low IPO covariance and short the portfolio with high IPO covariance, we earn a significant difference of 66 basis points over the month of these IPOs (p-value $= 5\%$).

[13] Newman and Rierson (2004) document price effects both at announcement and issuance in their study of bond issues.

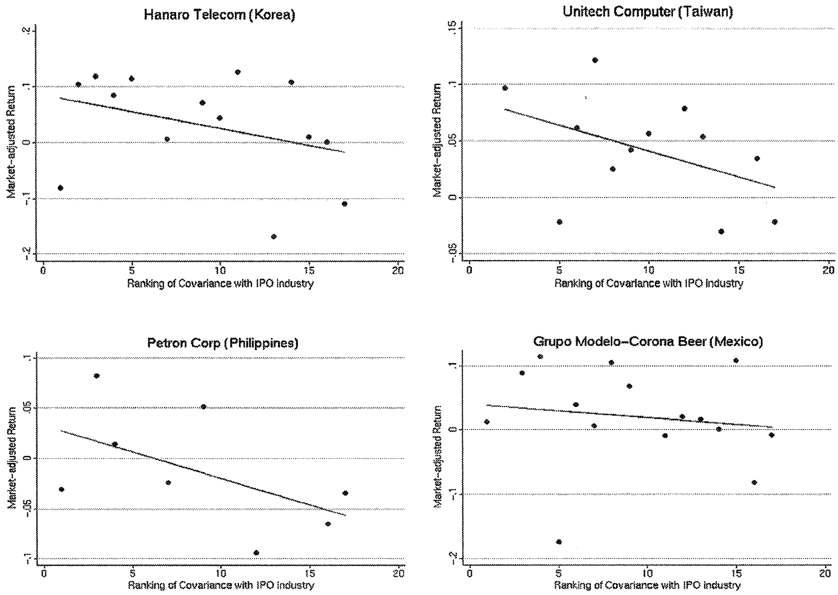

Figure 2
Industry returns according to the ranking of covariance with the IPO (selected IPOs).

Figure 2 shows the basic stylized fact in the data behind these results. The figure presents industry returns in different markets in the month of four particular IPOs: Corona in Mexico (food), Unitech in Taiwan (machinery), Petron in the Philippines (oil), and Hanaro in Korea (telecom). Industries are ranked from 1 to 17 according to the U.S. covariance with the IPO industry (with 1 being the industry with the lowest covariance). Since these IPOs are in different industries, the ranking changes across IPOs. For instance, food occupies ranking 17 in the IPO of Corona in Mexico, and it occupies ranking 2 in the IPO of Unitech in Taiwan. The relationship between returns and the covariance ranking is negative, although the slope is not always the same. Later on we relate these differences in the slope to IPO characteristics (e.g., size) and market characteristics (e.g., segmentation).

Figure 3 repeats Figure 2, but now using data from all IPOs in the sample. For each IPO, we compute the market-adjusted return on the industries in the country during the month of the issue. We then rank industries from 1 to 17 according to the U.S. covariance with the IPO industry. Finally, we average returns for each ranking position across all IPOs. These returns are plotted against the ranking, alongside a regression line. This figure shows a strong negative relationship between returns and the covariance with the IPO industry. It is clear from this figure that the effect does not come from a few outliers. Figure 3 also shows that the effect is not derived from the difference between the same industry of the IPO and the other industries. The same-industry data

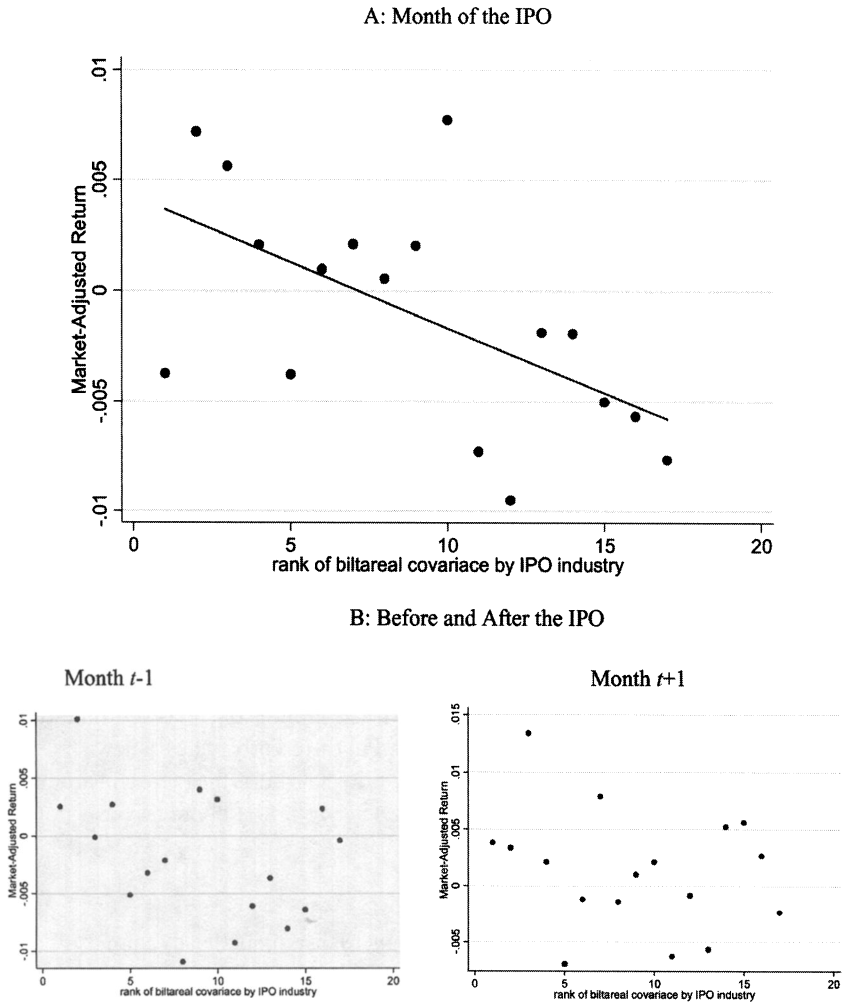

Figure 3
Industry returns according to the ranking of covariance with the IPO (average across IPOs): (A) month of the IPO and (B) before and after the IPO.

points (almost always corresponding to position 17 in the ranking) can be discarded and a similar relationship holds. If we exclude the same-industry data points from the regression with market-adjusted returns in Table 3, we obtain an even larger coefficient on the IPO covariance of −7.24, with a t-stat of −2.59 ($N = 2872$, $R^2 = 14\%$).

As another example of the basic effect, consider the price impact of the typical IPO in transportation. Figure 4 plots market-adjusted returns against the covariance ranking as in Figure 3, but only for the IPOs in the transportation industry. For example, the returns of transportation covary significantly more with the construction industry than with the food industry (the covariances

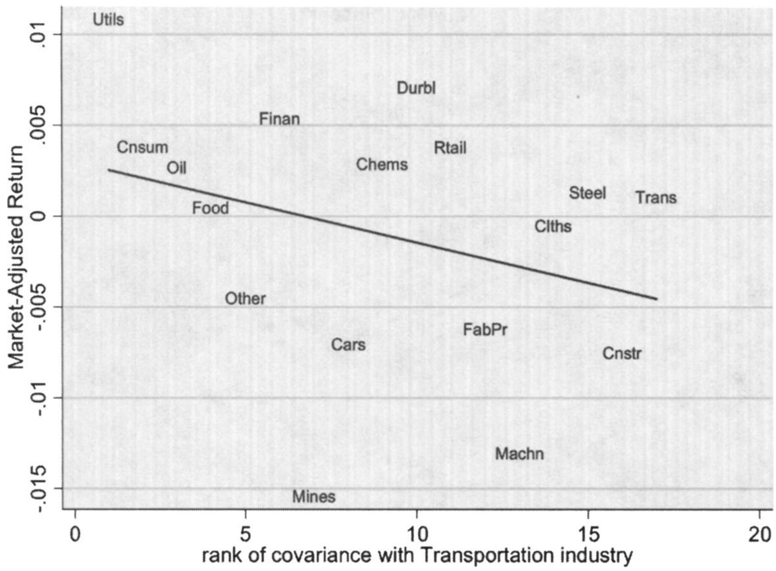

Figure 4
The average IPO in the transportation sector.

are 0.27% and 0.19%, respectively). IPOs in transportation turn out to be associated with a lower return in the construction industry relative to the food industry of approximately 50 basis points. Put differently, when a new stock in transportation is listed in the market, a portfolio that shorts the local construction industry and buys the food industry generates a return of about 50 basis points over the month of the IPO.

3.2 Before and after the IPO

It is crucial for the identification strategy to examine the dynamics of the effects just described. In particular, we want to rule out that the IPO covariance is picking up a factor that explains returns regardless of the new equity issue. For this purpose, we examine the months before and after the IPO. This horizon is comparable to other event studies in the literature on index additions. For instance, Kaul, Mehrotra, and Morck (2000) examine abnormal returns up to 6 weeks after the event. Extending the horizon beyond 1 or 2 months runs the risk of confounding the effects of the IPO with other events, especially since we study the other stocks listed in the market.

The regressions in Table 3 show that the effect of the IPO covariance is exclusive to the month of the issue. Both before and after the IPO, the covariance is not significant and the coefficients are much smaller (in magnitude) than during the month of the IPO. If we test the hypothesis that the effect is larger (in magnitude) in the month of the IPO, we obtain significant differences when comparing the month of the IPO with the month after (p-values below 10%). This implies that we reject the hypothesis of price reversal after more than a month following the IPO. In comparison, Harris and Gurel (1986) report reversals of 3/4 of the event-window abnormal return after only 29 trading days of the event (index additions in their case). When comparing with the month prior to the IPO, the p-values are around 20%. In Table 4, the trading profits between portfolios low and high are smaller and not statistically significant in months that are not the month of the IPO.

The lower panel of Figure 3 shows this result graphically. While during the month of the IPO, the coefficient on the ranking is significantly negative (at the 2% level) and explains 30% of the cross-sectional variation in average returns by ranking, it is insignificant and explains only 10% of the variation during the months before and after the issuance.

Figure 5 shows these dynamics in yet another way. For each IPO, we compute separately the market-adjusted return on industries above and below position number 8 of the ranking of IPO covariance. We then plot the entire distribution of returns for both groups of industries. The difference in means of the two distributions is quite apparent in the month of the IPO. A Kolmogorov-Smirnov test rejects the null of equality of distribution functions at the 3.5% level. The effect is not present in the months before and after the IPO (Figure 5B). For these months the test fails to reject the null at p-values of 27% and 40%, respectively.

3.3 Other factors in the cross section of stock returns

Despite the evidence on the dynamic effect of the IPO covariance, we check for the possibility that it proxies for factors that are commonly included in cross-sectional regressions of stock returns. We first consider the factors used by Fama and French (1992), which are the log of market equity (ME), the log of the market-to-book ratio (P/B), the price-earnings ratio when earnings are positive ($P/E(+)$), and a dummy for those observations with negative earnings ($E < 0$). These variables are measured 12 months prior to the IPO for each industry portfolio in each country. The P/B and $P/E(+)$ are value weighted in each portfolio. Beta—the quintessential factor—is already included in the model for abnormal returns (the dependent variable).[14]

All of the factors, except for the earnings dummy, enter the regression significantly and with the expected negative sign in Table 5. The results on the P/B ratio confirm the international evidence on the value premium presented by Fama and French (1998). The IPO covariance survives these controls in terms of magnitude and significance. Hence, a high IPO covariance is not simply an indication of a large size or high market-to-book, which are both typically associated with lower average returns.

Momentum is also a robust predictor of returns. We measure momentum as a dummy variable that takes the value of 1 when the cumulative market-adjusted return over months $t-6$ through $t-1$ is positive, or in other words, when the

[14] The results in Table 5 are the same if we use market-adjusted returns instead.

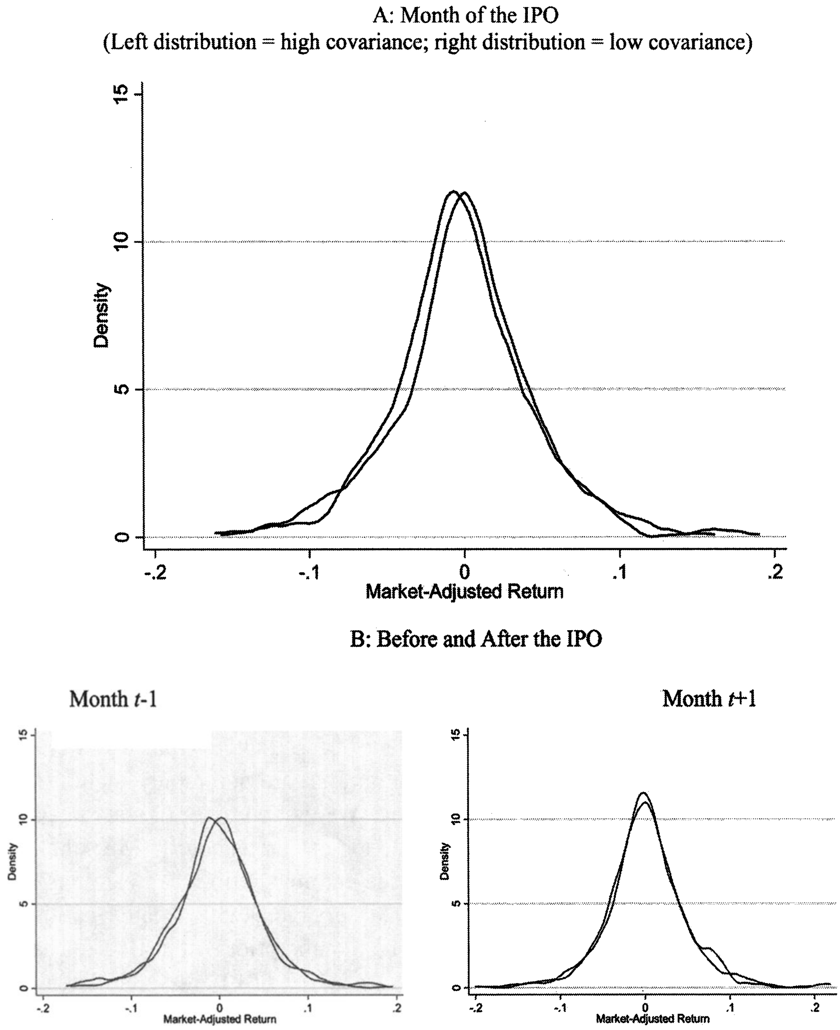

Figure 5
Distribution of returns for industries with high and low IPO covariance: (A) month of the IPO (left distribution = high covariance; right distribution = low covariance) and (B) before and after the IPO.

industry under consideration is a winner in the 6 months prior to the IPO.[15] As seen in Table 5, winners in the past 6 months earn, on average, an extra 1% during the month of the IPO. Even after including momentum, the coefficient on the IPO covariance remains significant at the 5% level and its magnitude is only slightly reduced.

[15] We also tried the original definition of momentum in Jegadeesh and Titman (1993), which goes from month $t-12$ to month $t-2$. It was less robust than the definition we use here and it does not affect the coefficient on the IPO covariance.

Table 5
The effect of an IPO on the stock returns of other firms: alternative cross-sectional factors

	Dependent variable: market-model abnormal return in IPO month				
Covariance with IPO industry	−5.454**	−5.585**	−5.572**	−5.018**	−5.205**
	(2.269)	(2.244)	(2.228)	(2.371)	(2.190)
Log(ME)	−0.002*				0.000
	(0.001)				(0.001)
Log(*P*/*B*)		−0.008***			−0.006**
		(0.003)			(0.003)
P/*E*(+)			−0.0001***		−0.0001**
			(0.0001)		(0.0001)
E <0 dummy			−0.0001		−0.001
			(0.007)		(0.008)
Momentum				0.010**	0.009*
				(0.005)	(0.005)
No. of observations	2725	2718	2725	2725	2718
No. of IPOs	243	243	243	243	243
R^2	0.236	0.240	0.238	0.238	0.245

This table shows the results from the following regression:

$$R^c_{i,t} = a + b\sigma_{i,\text{ipo}} + X^c_{i,t} + \varepsilon^c_{i,t}.$$

The dependent variable is the return of industry i in country c in excess of the market-model return. The local market is defined as the value-weighted sum of all stocks in that country and month reported in the EMDB database. Results are shown for month t, which is the month of the IPO. The set of independent variables includes the covariance between industry i and the industry of the IPO. This covariance is estimated with monthly industrial returns from U.S. stocks between 1973 and 2004. The industry definitions correspond to the 17 groups of SIC Codes defined on Ken French's website. The other independent variables, represented by $X_{i,t}{}^c$ in the equation above, include the log of the market equity (ME), the log of the price-to-book ratio (*P*/*B*), the price-earnings ratio if earnings are positive (*P*/*E*(+)), a dummy for negative earnings (E <0), and a dummy for those industries that have positive accumulated market-adjusted returns in the 6 months prior to the IPO (momentum). The first four control variables mentioned are measured 12 months prior to the IPO. The IPO fixed effects (a in the equation above) are not reported. Details on the selection of IPOs are provided in the text. Returns in the dependent variable are truncated at the 1% and 99% levels. Robust standard errors clustered by country are reported below the coefficients. Significance (two-sided): ***1%, **5%, *10%.

3.4 IPO size and market segmentation

In a deep market like the United States, probably no IPO is big enough to have a significant impact on other stocks. Emerging markets, on the other hand, are much smaller in terms of total market capitalization, turnover, and number of investors. The dollar proceeds of the average IPO in our sample are \$98 million. Relative to the market of issuance, the average IPO represents 0.25% of market capitalization (see Table A1). The smallest IPO in our sample is equivalent to Google's IPO in the United States (0.01% of market capitalization). Perhaps more important is the fact that, given the prevalence of government and insider control (La Porta et al., 2000), market capitalization substantially overstates the value of stocks that are actually traded in these markets. Just to give a sense of the magnitude of the correction needed to account for this problem, the free-float market capitalization is only 14% of total capitalization in Chile. If we assume that this number is the same for all countries, then the average IPO represents just below 1% of the respective market free-float.

Table 6
The effect of an IPO on the stock returns of other firms: subsamples according to the size of the IPO

	Size of the IPO relative to the local market		
	Small	Medium	Big
Covariance with IPO industry	−4.58	−5.04	−11.14***
	(7.07)	(4.11)	(3.95)
No. of observations	1024	1025	1056
No. of IPOs	79	81	94
R^2	0.14	0.13	0.10

This table shows the results from the following regression:

$$R_{i,t}^{c} = a + b\sigma_{i,\text{ipo}} + \varepsilon_{i,t}^{c}.$$

The dependent variable is the return of industry i in country c in excess of the local market return during a month (market-adjusted returns). The local market is defined as the value-weighted sum of all stocks in that country and month reported in the EMDB database. Results are shown for month t, which is the month of the IPO. The independent variable is the covariance between industry i and the industry of the IPO. This covariance is estimated with monthly industrial returns from U.S. stocks between 1973 and 2004. The industry definitions correspond to the 17 groups of SIC Codes defined on Ken French's website. The size of an IPO is the proceeds from the IPO divided by the total market capitalization of the country in the month of the IPO (excluding the IPO itself). The sample is split into three groups (small-medium-big) according to the 33rd and 66th percentile of the IPO size. The IPO fixed effects (a in the equation above) are not reported. Details on the selection of IPOs are provided in the text. Returns in the dependent variable are truncated at the 1% and 99% levels. Robust standard errors clustered by country are reported below the coefficients. Significance (two-sided): ***1%, **5%, *10%.

When we regress returns on IPO size (excluding the fixed effects), we obtain a coefficient of −0.83 with a standard error of 0.61 ($N = 3105$, $R^2 = 0.2\%$). The direct effect of size is therefore negative, but not significant, at least in the month of the IPO. The evidence in Henderson, Jegadeesh, and Weisbach (2006), which looks more broadly at equity issues, suggests that the effect is indeed negative once we extend the horizon a little bit.

The fixed effects absorb any direct impact of size in our benchmark regression, but size should amplify the effect of the covariance as seen in Equations (3) and (6). In Table 6, we split the sample into three according to IPO size (proceeds relative to total market capitalization). The coefficient on the IPO covariance increases in magnitude as we move from small to big IPOs. In fact, the effect of the covariance is significant in the third of the sample that corresponds to big IPOs and not in the other subsamples.

A second source of variation in size comes from the segmentation of markets. Segmentation determines the extent of the demand for assets. For instance, investors from all over the world are potential participants in a perfectly integrated market. We present two alternative measures of segmentation in Table 7. These measures vary across countries and through time, as opposed to other institutional features that vary almost exclusively across countries. The decade under consideration is a period of substantial changes in segmentation, so we prefer these time-varying measures (Bekaert and Harvey, 1995).

Table 7
The effect of an IPO on the stock returns of other firms: subsamples according to market segmentation and related variables

	Market segmentation		
	Low	Medium	High
Covariance with IPO industry	−7.30	−8.03**	−14.67***
	(6.75)	(3.86)	(2.78)
No. of observations	903	801	819
No. of IPOs	71	67	66
R^2	0.10	0.08	0.16
	Market turnover		
	High	Medium	Low
Covariance with IPO industry	0.26	−15.42***	−9.84**
	(2.11)	(4.18)	(4.36)
No. of observations	1029	999	1022
No. of IPOs	85	80	86
R^2	0.16	0.14	0.08
	Developed vs. emerging markets		
	Developed	Emerging	
Covariance with IPO industry	1.38	−7.13***	
	(1.33)	(2.36)	
No. of observations	3490	1729	
No. of IPOs	283	192	
R^2	0.07	0.12	

This table shows the results from the following regression:

$$R^c_{i,t} = a + b\sigma_{i,\text{ipo}} + \varepsilon^c_{i,t}.$$

The dependent variable is the return of industry i in country c in excess of the local market return during a month (market-adjusted returns). The local market is defined as the value-weighted sum of all stocks in that country and month reported in the EMDB database. Results are shown for month t, which is the month of the IPO. The independent variable is the covariance between industry i and the industry of the IPO. This covariance is estimated with monthly industrial returns from U.S. stocks between 1973 and 2004. The industry definitions correspond to the 17 groups of SIC Codes defined on Ken French's website. Market segmentation corresponds to the IFC investable index divided by the IFC global index. Market turnover is provided by the EMDB and it is the total value of traded shares over the total market capitalization in a month. The sample is split into three groups (low-medium-high) according to the 33rd and 66th percentile of each measure. In the lower panel, return data from Datastream for companies in 37 countries are aggregated into industry portfolios with equal weights, and then split into developed and emerging markets as defined by IFC. The IPO fixed effects (a in the equation above) are not reported. Details on the selection of IPOs are provided in the text. Returns in the dependent variable are truncated at the 1% and 99% levels. Robust standard errors clustered by country are reported below the coefficients. Significance (two-sided): *** 1%, ** 5%, * 10.

Our first measure corresponds to the ratio of the investable IFC index to the global IFC index (Bekaert, 1995). This ratio, which is available at the monthly frequency, shows the fraction of market capitalization in which foreigners can potentially invest. In the top panel of Table 7, we split the sample into three according to this ratio. The coefficient on the IPO covariance increases in magnitude as we move to more segmented markets. As seen in the first column, it is not significant in well-integrated emerging markets.

The middle panel of Table 7 presents results when the sample is split according to the market turnover. Low liquidity is a deterrent to foreign investors and an important cause of segmentation (Bekaert and Harvey, 2003). As expected, the effect of the IPO covariance is strong in less liquid markets, but missing in the more liquid ones.

So far we have focused on variation in emerging markets. We also consider an out-of-sample test in the bottom of Table 7. We compare emerging markets as a whole with those markets that are more developed and well integrated according to the IFC classification. The stock-price data in this exercise come from Datastream for both groups of countries. We build 17 industry portfolios for each of 37 countries in the sample since 1990. Then we match the returns to the previous IPO dates for emerging markets and IPO dates for developed markets selected from the SDC following the same procedure. We run the main regression separately for emerging and developed markets. In the sample of emerging markets, the results are comparable in magnitude and significance to the results of the EMDB sample. There is no effect of the IPO covariance in developed markets, which is expected given the relative size of IPOs and the better international integration of these markets. We consider this only as a robustness exercise because the number of stocks in Datastream is much smaller than in EMDB, and because we can form only equally weighted portfolios since shares outstanding were not available.

3.5 Evidence on style investing

Under the style-investing hypothesis, what matters is the closeness of each asset to the IPO along the dimensions that investors use to form portfolios. We focus on two dimensions, the book-to-market ratio and size, which are familiar style labels.[16] A first obstacle that we face is that these two characteristics of the IPO are only known after or contemporaneously to the issue, and we do not want to run regressions with future or contemporaneous information because it can lead to spurious inference. Moreover, the SDC provides book-to-market ratios for only a small subset of IPOs. What we do instead is to classify the industry portfolios according to their aggregate book-to-market ratio and size relative to the industry of the IPO in the month prior to the realization of returns. We say that an industry is close to the IPO if the absolute difference in book-to-market ratios between the two industries is small (size closeness is defined in an analogous way). We are implicitly assuming that the IPO's book-to-market ratio is well approximated by its industry average. Our hypothesis is then that if the IPO comes in an industry with high book-to-market, it hits harder those stocks that also have high book-to-market. We also assume that demands for styles are country specific, as in the demand for "Korean value stocks" or "Chilean growth stocks."

[16] Teo and Woo (2004) also use categories based on size and book-to-market ratios in tests of style investing.

In Table 8, we provide support for this idea by showing that the prices of industries that are close to the IPO industry in terms of book-to-market and size fall relative to other industries. The effects are again limited to the month of the IPO, which implies that there is a permanent change in expected returns and not simply price pressure. A one-standard-deviation increase in book-to-market closeness leads to a 0.44% decline in prices, while a one-standard-deviation increase in size closeness leads to a 0.42% decline in prices. The effect of size is more robust, and in fact it makes the book-to-market variable insignificant when both are included in the regression. The IPO covariance is still significant and its coefficient is of similar magnitude when compared to our benchmark regression.

In Table 9, we see that the effects are concentrated in markets with medium and high levels of segmentation. The impact of this second class of substitutability measures is not necessarily expected to be stronger in less integrated markets since style investing can also affect international investors. However, our evidence suggests that style investing is even worse in markets dominated by local investors.

One problem with testing style investing is that the definition of a style is always debatable. For instance, following the methodology for the IPO covariance, we also tried the measure of book-to-market closeness with historical book-to-market ratios in U.S. industries. This measure was never significant in the regressions. We can argue that it is not a relevant style for the participants in these markets. Including this measure in the regressions did not affect the coefficient of the IPO covariance (results not reported).

3.6 Trading volume

Trading volume can be an important piece of information in distinguishing the price pressure hypothesis from other theories with permanent shifts in the demand for stocks. The price pressure hypothesis predicts that prices have to rebound once the abnormal volume associated with the IPO disappears. We showed that there is no reversal in prices up to 1 month after the IPO. Here we examine whether abnormal volume has effectively disappeared by that time.

The regressions with turnover are slightly different from the regressions with returns. Most importantly, there is less agreement in the literature as to what exactly constitutes abnormal turnover. Turnover has high autocorrelation, but different methods to remove the underlying trend, and to obtain the innovation in turnover, yield very different results (Lo and Wang, 2000). For this reason, we use raw turnover as the dependent variable while we control in the regression for pre-IPO turnover. We present results with pre-IPO turnover measured as the average turnover between months $t-13$ and $t-2$. We have explored other definitions (for example, turnover in month $t-2$) and the results are basically the same as those reported here.

Table 8
The effect of an IPO on the stock returns of other firms: *B/M* and size closeness to the IPO

	Dependent variable: market-adjusted return								
	Month relative to IPO								
	Previous month			Month of IPO			Following month		
Covariance with IPO industry	−3.067 (4.163)	−3.24 (4.346)	−3.223 (4.246)	−7.177** (3.434)	−7.38** (3.726)	−6.752* (3.471)	−2.138 (3.843)	−2.05 (4.152)	−2.238 (3.989)
B/M closeness to IPO industry	−0.0003 (0.002)		−0.0004 (0.002)	−0.0035* (0.002)		−0.0034 (0.002)	0.0015 (0.002)		0.0014 (0.002)
Size closeness to IPO industry		0.0009 (0.001)	0.0008 (0.001)		−0.0026** (0.001)	−0.0024** (0.001)		0.0008 (0.001)	0.0006 (0.001)
No. of observations	2656	2669	2656	2685	2688	2685	2675	2676	2675
No. of IPOs	235	235	235	235	235	235	236	236	236
R^2	0.160	0.159	0.160	0.137	0.136	0.138	0.142	0.141	0.142

This table shows the results from the following regression:

$$R^c_{i,t} = a + b\sigma_{i,\text{ipo}} + c\ B/M\ closeness + d\ size\ closeness + \varepsilon^c_{i,t}.$$

The dependent variable is the return of industry i in country c in excess of the local market return during a month (market-adjusted returns). The local market is defined as the value-weighted sum of all stocks in that country and month reported in the EMDB database. Results are shown for month t, which is the month of the IPO, and for months $t-1$ and $t+1$. The covariance between the industry i and the industry of the IPO is estimated with monthly industrial returns from U.S. stocks between 1973 and 2004. The industry definitions correspond to the 17 groups of SIC Codes defined on Ken French's website. *B/M* (book-to-market) closeness is the negative of the log of the absolute difference between the *B/M* of industry i and the IPO industry in the month before the realization of the return. Size closeness is defined analogously. The IPO fixed effects (a in the equation above) are not reported. Details on the selection of IPOs are provided in the text. Returns in the dependent variable are truncated at the 1% and 99% levels. Robust standard errors clustered by country are reported below the coefficients. Significance (two-sided): ***1%, **5%, *10%.

Table 9
The effect of an IPO on the stock returns of other firms: *B/M* and size closeness across levels of market segmentation

	Market segmentation		
	Low	Medium	High
Covariance with IPO industry	−7.369	−2.866	−16.731***
	(9.471)	(5.489)	(3.789)
B/M closeness to IPO industry	−0.0028	−0.0038	−0.0041**
	(0.005)	(0.003)	(0.002)
Size closeness to IPO industry	−0.0022	−0.0020*	−0.0015
	(0.003)	(0.001)	(0.002)
No. of observations	807	676	715
No. of IPOs	67	60	62
R^2	0.107	0.093	0.183

This table shows the results from the following regression:

$$R^c_{i,t} = a + b\sigma_{i,\mathrm{ipo}} + c\ B/M\ closeness + d\ size\ closeness + \varepsilon^c_{i,t}.$$

The dependent variable is the return of industry i in country c in excess of the local market return during a month (market-adjusted returns). The local market is defined as the value-weighted sum of all stocks in that country and month reported in the EMDB database. Results are shown for month t, which is the month of the IPO. The covariance between industry i and the industry of the IPO is estimated with monthly industrial returns from U.S. stocks between 1973 and 2004. The industry definitions correspond to the 17 groups of SIC Codes defined on Ken French's website. *B/M* (book-to-market) closeness is the negative of the log of the absolute difference between the *B/M* of industry i and the IPO industry in the month before the realization of the return. Size closeness is defined analogously. Market segmentation corresponds to the IFC investable index divided by the IFC global index. The sample is split into three groups (low-medium-high) according to the 33rd and 66th percentile of market segmentation. The IPO fixed effects (a in the equation above) are not reported. Details on the selection of IPOs are provided in the text. Returns in the dependent variable are truncated at the 1% and 99% levels. Robust standard errors clustered by country are reported below the coefficients. Significance (two-sided): ***1%, **5%, *10%.

Table 10 shows that the IPO covariance significantly predicts higher dollar volume in the month of issuance. A one-standard-deviation increase in the IPO covariance increases monthly volume by 0.07% from a median of 4%. This evidence, taken together with the price dynamics, suggests that industries that covary highly with the IPO experience more selling pressure than other industries as investors rebalance their portfolios to accommodate the IPO. The relationship is marginally significant in the month before the IPO, but it is insignificant in the month following the IPO. The behavior of volume before the IPO can be interpreted as evidence of investors spreading their trades as the IPO approaches. Although similar patterns are observed when turnover is measured as number of shares, we do not obtain significant coefficients on the IPO covariance (p-value of 13% in the month of the IPO). Importantly, there is no evidence of abnormal volume in the month after the IPO with either measure of turnover. Overall, this evidence speaks against the price pressure hypothesis because there is no evidence of price reversal despite the fact that volume is back to normal levels.

Table 10
The effect of an IPO on the trading volume of other firms

	Dependent variable: trading volume Month relative to IPO					
	Previous month		Month of IPO		Following month	
	Dollar volume	Shares volume	Dollar volume	Shares volume	Dollar volume	Shares volume
Volume preevent	0.88***	0.88***	0.89***	0.89***	0.86***	0.86***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Covariance with	31.77*	23.89	30.11**	21.38	21.81	13.11
IPO industry	(17.16)	(16.86)	(13.39)	(13.62)	(28.59)	(27.86)
No. of observations	2927	2893	2926	2892	2923	2889
No. of IPOs	249	247	249	247	249	247
R^2	0.86	0.85	0.85	0.84	0.82	0.82

This table shows the results from the following regression:

$$V_{i,t}^{c} = a + bV_{i,\text{pre}}^{c} + c\,\sigma_{i,\text{ipo}} + \varepsilon_{i,t}^{c}.$$

The dependent variable is the log of monthly turnover in industry i in country c. For each month, we present regressions with two alternative measures of turnover. First, turnover is defined as the dollar amount traded over total market capitalization. Second, turnover is defined as the number of shares traded over total shares outstanding. We value weight firm-level measures of turnover in order to get the industry turnover. Results are shown for month t, which is the month of the IPO, and for months $t-1$and $t+1$. The first explanatory variable is the preevent turnover measured as the average turnover between months $t-13$ and $t-2$. The other explanatory variable is the covariance between industry i and the industry of the IPO. This covariance is estimated with monthly industrial returns from U.S. stocks between 1973 and 2004. The industry definitions correspond to the 17 groups of SIC Codes defined on Ken French's website. The IPO fixed effects (a in the equation above) are not reported. Details on the selection of IPOs are provided in the text. Robust standard errors clustered by country are reported below the coefficients. Significance (two-sided): ***1%, **5%, *10%.

3.7 Robustness checks

A key obstacle in our empirical strategy is that the covariance with the IPO is not observable. We have argued so far that the covariance between industries in the United States is a good proxy for this unobservable variable. An alternative is to use a covariance structure estimated in our sample of emerging markets, although this strategy raises endogeneity concerns. We present here instrumental variables (IV) regressions where the in-sample covariance is instrumented with the U.S. covariance. As pointed out by Cochrane (2001, p. 435), basic econometric theory also recommends IV to clean measurement error present in more noisy estimates of covariances or betas.

We compute several covariances in sample. First, we form portfolios that aggregate a particular industry across all emerging markets (e.g., the food industry in emerging markets). Then we compute covariances between these aggregate industry portfolios in the entire sample period. Second, we compute covariances between industries in each country, again using the entire sample period (we require at least 2 years of data for each industry). The third estimate of covariance is specific to each IPO. At the moment of the IPO, we compute covariances between the industries in that country with data of the previous 24 months. This third measure of covariance is missing if the IPO is the first firm of the industry listed in that country. The rank correlations between these measures and the U.S. covariances are high, although the in-sample covariances are significantly higher and noisier (see Table A3). For example, the average covariance in the United States is 0.002 while the average IPO-specific covariance is 0.011. The standard deviation of these estimates is 0.0005 in the United States and 0.0146 in the case of the IPO-specific covariance.

The regressions show negative and significant coefficients with the three in-sample covariance measures in Table 11. The magnitude of the coefficients is not comparable to previous tables because these are different covariances. In fact, we expected to obtain smaller coefficients because the in-sample covariances are higher than in the United States.

Table 12 presents other robustness checks that show that the results are not driven by particular features of the sample. First, we exclude the Asian markets that dominate the IPO sample—Malaysia, Taiwan, and Thailand. The coefficient on the IPO covariance becomes even stronger once we eliminate these markets, which is not surprising given that these markets are more internationally integrated. Second, we exclude the IPOs from the financial industry, which again dominate our IPO sample. The coefficient on the covariance remains of similar magnitude and significance in this case.

We also check that the industries with a low dispersion in the IPO covariance ranking are not driving the results. The concern is that the spread given by the IPO covariance is proxying for a permanent factor rather than something associated with the IPO itself (although we already showed that the dynamics

Table 11
The effect of an IPO on the stock returns of other firms: in-sample measures of interindustry covariances

	Dependent variable: market-adjusted return in IPO month		
	Covariance in all emerging markets IV	Covariance by country IV	Covariance by country and IPO IV
Covariance with IPO industry	−2.952*	−1.407***	−1.379***
	(1.543)	(0.539)	(0.530)
No. of observations	3105	3032	2922
No. of IPOs	254	247	235
R^2	0.12	0.09	0.07

This table shows the results from the following regression:

$$R = a + b\sigma + \varepsilon$$

The dependent variable is the return of industry i in country c in excess of the market return. The local market is defined as the value-weighted sum of all stocks in that country and month reported in the EMDB database. Results are shown for month t, which is the month of the IPO. The independent variable is the covariance between industry i and the industry of the IPO. This covariance is estimated in three different ways. In the first column it is estimated with returns on industry portfolios in emerging markets over the entire sample period. In the second column the covariance is estimated using returns only in the country of the IPO, again in the entire sample period. In the third column it is estimated with returns in the country of the IPO and in the 24 months prior to the IPO. These measures of covariance are instrumented with the covariance structure in monthly industrial returns from U.S. stocks between 1973 and 2004. The industry definitions correspond to the 17 groups of SIC Codes defined on Ken French's website. Details on the selection of IPOs are provided in the text. Returns in the dependent variable are truncated at the 1% and 99% levels. The IPO fixed effects (a in the equation above) are not reported. Robust standard errors clustered by country are reported below the coefficients. Significance (two-sided): *** 1%, ** 5%, * 10%.

of the effect do not support this idea). The spread given by the IPO covariance might be coming from comparing the returns on industries such as construction and utilities, which are more typically in the high- and low-covariance groups irrespective of the IPO being listed. One way to show that the results are not driven by these industries is to compute the difference between portfolios with low IPO covariance and high IPO covariance reported in Table 3 but excluding construction and utilities from the sample. In this case, the spread between low and high portfolios increases to 70 basis points and remains significant at the 6% level. We can also exclude from the basic regression the six industries with lowest dispersion in the ranking. These industries are oil, textiles, consumer products, construction, machinery, and utilities (see Table 2). The remaining industries interchange ranking positions frequently. As seen in the third column of Table 12, excluding the low-dispersion industries barely affects the coefficient on the covariance, which remains significant at the 10% level.

The last two columns in Table 12 examine the issue of privatizations. Privatizations are particularly big IPOs not uncommon in emerging markets. However, in our sample we have only eight privatizations out of 254 IPOs. When

Table 12
The effect of an IPO on the stock returns of other firms: robustness checks

	Dependent variable: market-adjusted return in IPO month				
	Excluding major Asian markets	Excluding banks' IPOs	Excluding low-dispersion industries	Privatizations	Excluding privatizations
Covariance with	−8.77***	−7.25**	−7.75*	−50.27**	−6.14**
IPO industry	(3.24)	(3.55)	(3.99)	(22.42)	(3.06)
No. of observations	1759	2007	2049	76	3029
No. of IPOs	143	167	254	8	246
R^2	0.11	0.14	0.15	0.12	0.13

This table shows the results from the following regression:

$$R_{i,t}^c = a + b\sigma_{i,\mathrm{ipo}} + \varepsilon_{i,t}^c .$$

The dependent variable is the return of industry i in country c in excess of the market return. The local market is defined as the value-weighted sum of all stocks in that country and month reported in the EMDB database. Results are shown for month t, which is the month of the IPO. The independent variable is the covariance between industry i and the industry of the IPO. This covariance is estimated with monthly industrial returns from U.S. stocks between 1973 and 2004. The industry definitions correspond to the 17 groups of SIC Codes defined on Ken French's website. In the first column, the sample excludes those IPOs in Malaysia, Taiwan, and Thailand. In the second column, the sample excludes those IPOs of the financial industry (banks, insurance companies, and others). In the third column, the sample excludes the observations from six industries: oil, textiles, consumer products, construction, machinery, and utilities. In the fourth column, only IPOs that correspond to privatizations of government-owned companies are included. In the fifth column, the sample excludes privatizations. Details on the selection of IPOs are provided in the text. Returns in the dependent variable are truncated at the 1% and 99% levels. The IPO fixed effects (a in the equation above) are not reported. Robust standard errors clustered by country are reported below the coefficients. Significance (two-sided): ***1%, **5%, *10%.

we restrict the regression to privatizations, the effect of the IPO covariance is almost 10 times larger than in the benchmark case. This can be explained in part by the size of these transactions. It can also be because these represent cleaner experiments in terms of signaling to other industries: privatizations are usually influenced by political factors rather than future prospects about cash flows. The last column shows that the main effect is not driven purely by privatizations.

4. Conclusions

This paper shows that changes in asset supply have a significant impact on asset prices. We measure the change in supply through IPOs. The supply shock has a cross-sectional impact that is inversely related to the covariance of returns with the IPO. Selling the portfolio with the highest covariance with the IPO and buying the portfolio with the lowest covariance gives a spread of approximately 70 basis points during the month of the IPO.

We have focused on the effect of the IPO covariance throughout the paper. This effect can be reconciled with frictionless models and models of limited risk-bearing capacity. Other evidence, in particular the effect on issue dates, despite the fact that IPOs are anticipated events, the presence of style investing, and to a lesser extent the negative relationship between IPOs and market returns, points toward a model where demand curves are downward sloping and frictions are present.

Our evidence is concentrated on emerging markets in an attempt to isolate clearly identifiable supply shocks, such as IPOs, and of considerable size with respect to their reference market. We can also test whether the results rely on a particular market structure by comparing the incidence of IPOs across levels of market segmentation. The results are therefore cleaner than what they would be in a more general test of IPO effects in well-developed markets. We think, however, that the themes in this paper can be extended to more general settings.[17] In developed markets, a single IPO cannot have a material impact on all other stock prices because of its relative size. But within narrower segments, we may be able to find similar effects, for instance, among stocks included in a particular index, among ADRs of a given country, among stocks of the same style, and so on. We may also want to think about IPO waves as the relevant shock in a more developed market. IPO waves often come by industry and they can cause significant changes in the composition of the market, comparable to the IPOs studied in this paper. Merger waves and the associated repurchases of stock can also have a similar impact.

[17] In an analogous way, the literature on demand curves for stocks has focused on the rather extreme case of index additions. This provides a clean identification strategy, but it does not imply that the relevance of the discussion is limited to index additions.

Appendix

Table A1
Sample characteristics

Country	No. of observations	No. of IPOs	Year	No. of observations	No. of IPOs
Argentina	121	11	1989	7	1
Brazil	63	4	1990	45	4
Chile	54	5	1991	202	20
China	132	9	1992	149	15
Czech Republic	11	1	1993	272	25
Greece	143	12	1994	537	44
Hungary	14	2	1995	413	31
Indonesia	189	16	1996	258	18
India	191	13	1997	199	16
Korea	334	22	1998	170	13
Sri Lanka	11	1	1999	211	17
Mexico	217	16	2000	233	19
Malaysia	370	25	2001	160	12
Pakistan	51	4	2002	249	19
Philippines	96	13			
Poland	68	8			
Portugal	15	2			
Thailand	394	36			
Turkey	28	2			
Taiwan	582	50			
Venezuela	8	1			
South Africa	13	1			
Total	3,105	254		3,105	254

	IPO industry	No. of observations	No. of IPOs
1	Food	222	18
2	Mining and minerals	25	2
3	Oil and petroleum products	68	6
4	Textiles, apparel & footwear	34	3
5	Consumer durables	70	6
6	Chemicals	66	5
7	Drugs, soap, perfumes, tobacco	43	3
8	Construction and construction materials	243	21
9	Steel works, etc.	49	4
10	Fabricated products	26	3
11	Machinery and business equipment	326	26
12	Automobiles	67	6
13	Transportation	132	11
14	Utilities	65	6
15	Retail stores	63	6
16	Banks, insurance companies, and other financials	1,098	87
17	Everything else	508	41
Total		3,105	254

Table A2
Interindustry covariances of returns in the United States

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	0.0023																
2	0.0014	0.0047															
3	0.0011	0.0024	0.0030														
4	0.0020	0.0023	0.0015	0.0039													
5	0.0018	0.0022	0.0015	0.0027	0.0036												
6	0.0017	0.0025	0.0019	0.0026	0.0024	0.0031											
7	0.0019	0.0013	0.0012	0.0017	0.0020	0.0017	0.0026										
8	0.0020	0.0028	0.0018	0.0032	0.0030	0.0027	0.0019	0.0038									
9	0.0015	0.0035	0.0021	0.0028	0.0028	0.0029	0.0014	0.0032	0.0046								
10	0.0017	0.0026	0.0019	0.0026	0.0025	0.0024	0.0015	0.0028	0.0029	0.0032							
11	0.0015	0.0025	0.0018	0.0027	0.0033	0.0025	0.0019	0.0031	0.0033	0.0027	0.0049						
12	0.0015	0.0021	0.0013	0.0027	0.0027	0.0023	0.0014	0.0028	0.0028	0.0024	0.0027	0.0040					
13	0.0019	0.0025	0.0018	0.0028	0.0026	0.0025	0.0018	0.0030	0.0029	0.0027	0.0027	0.0025	0.0033				
14	0.0012	0.0011	0.0013	0.0011	0.0011	0.0011	0.0011	0.0013	0.0010	0.0012	0.0009	0.0011	0.0012	0.0018			
15	0.0021	0.0019	0.0012	0.0031	0.0027	0.0023	0.0019	0.0030	0.0023	0.0023	0.0026	0.0025	0.0026	0.0011	0.0034		
16	0.0019	0.0020	0.0016	0.0024	0.0023	0.0022	0.0018	0.0026	0.0022	0.0022	0.0022	0.0021	0.0024	0.0014	0.0023	0.0026	
17	0.0016	0.0021	0.0015	0.0024	0.0027	0.0022	0.0018	0.0027	0.0025	0.0022	0.0032	0.0022	0.0023	0.0010	0.0024	0.0021	0.0028

The table shows the covariance matrix of excess returns for 17 U.S. industries classified according to the SIC Codes on Ken French's website. The data are monthly from 1973 to 2004.

Table A3
Summary statistics

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
Covariance with IPO (United States)	3105	0.00227	0.00058	0.00087	0.00486
Covariance with IPO (all emerging markets)	3105	0.00376	0.00249	0.00062	0.02963
Covariance with IPO (by country)	3032	0.01356	0.00948	−0.00319	0.09621
Covariance with IPO (by country and IPO)	2922	0.01162	0.01468	−0.08713	0.15073
Covariance ranking with IPO (United States)	3105	9.3	4.9	1	17
Market-adjusted returns	3105	−0.00133	0.06817	−0.21106	0.21990
Market-model abnormal returns	2725	−0.00659	0.08087	−0.24746	0.24562
B/M closeness to IPO	2701	−0.25023	1.27025	−2.86383	7.38482
Size closeness to IPO	2702	−8.66322	1.76843	− 11.54057	0.14829
Log(ME)	2970	7.4388	1.7593	0.1705	11.9915
Log(*P/B*)	2960	0.8842	0.8746	− 2.1404	2.8638
P/E(+)	2970	30.096	35.861	0.000	207.350
E <0 dummy	2970	0.05758	0.23298	0	1
Momentum	3039	0.45179	0.49775	0	1
Log shares volume traded	3097	−3.2299	1.4268	−13.8179	− 0.6586
Log dollar volume traded	3097	−3.2195	1.4329	−13.8220	− 0.6636
IPO size	3105	0.0025	0.0061	0.0001	0.0521
Market segmentation (1 = least segmented)	2523	0.6172	0.3173	0	1
Market turnover	3050	0.1030	0.1105	0.0025	0.6176

Table A4
Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
Covariance with IPO (United States)	(1)	1.00																		
Covariance ranking with IPO (United States)	(2)	0.70	1.00																	
Covariance with IPO (by country)	(3)	0.19	0.11	1.00																
Covariance with IPO (all emerging markets)	(4)	0.21	0.03	0.07	1.00															
Covariance with IPO (by country and IPO)	(5)	0.03	0.07	0.29	0.04	1.00														
Market-adjusted returns	(6)	0.01	−0.04	0.02	0.01	0.04	1.00													
Market-model abnormal returns	(7)	0.03	−0.01	0.03	0.01	−0.03	0.74	1.00												
B/M closeness to IPO	(8)	0.04	0.03	0.16	0.00	−0.01	−0.06	−0.01	1.00											
Size closeness to IPO	(9)	0.00	0.01	0.12	−0.12	0.08	−0.03	−0.02	0.07	1.00										
Log(ME)	(10)	−0.07	−0.17	−0.09	0.03	−0.07	0.01	−0.05	0.00	−0.30	1.00									
Log(*P/B*)	(11)	0.01	−0.07	−0.19	0.06	−0.08	−0.02	−0.06	−0.25	−0.04	0.37	1.00								
P/E(+)	(12)	0.05	0.02	−0.05	0.05	−0.02	−0.08	−0.09	−0.08	−0.13	0.23	0.38	1.00							
E <0 dummy	(13)	−0.07	0.00	0.07	−0.03	0.10	−0.01	0.02	0.00	0.03	−0.20	−0.19	−0.20	1.00						
Momentum	(14)	−0.04	−0.03	0.11	0.00	0.12	0.11	0.05	0.07	0.01	−0.02	−0.17	−0.09	0.02	1.00					
Log shares volume traded	(15)	0.14	0.11	0.12	0.02	0.16	0.05	0.02	0.08	−0.12	0.10	−0.23	0.00	−0.06	0.12	1.00				
Log dollar volume traded	(16)	0.15	0.11	0.13	0.03	0.16	0.03	0.00	0.09	−0.12	0.10	−0.23	0.00	−0.07	0.12	1.00	1.00			
IPO size	(17)	−0.14	−0.02	0.05	0.04	0.03	0.04	−0.01	0.02	0.21	−0.22	−0.04	−0.07	0.04	0.02	−0.15	−0.15	1.00		
Market segmentation	(18)	−0.13	−0.01	0.19	0.05	0.18	0.03	−0.05	−0.03	−0.09	−0.03	−0.13	−0.09	0.14	0.19	0.02	0.02	0.00	1.00	
Market turnover	(19)	0.07	0.01	−0.02	−0.05	0.16	0.02	−0.05	0.08	−0.16	0.10	−0.31	−0.11	−0.08	0.20	0.58	0.57	−0.04	0.07	1.00

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