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Anticipated vs. Actual Synergy in Merger Partner Selection and Post-Merger Innovation

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Past research has primarily focused on what happens after a merger. This research attempts to determine whether anticipated benefits from the merger actually accrue. We characterize the effects of observed variables on whether pairs of firms merge, vis-à-vis roommate matching, and then link these factors to post-merger innovation (i.e., number of patents). We jointly estimate the two models using Markov Chain Monte Carlo methods with a unique panel data set of 1,979 mergers between 4,444 firms across industries and countries from 1992 to 2008. We find that similarity in national culture and technical knowledge has a positive effect on partner selection and post-merger innovation. Anticipated synergy from subindustry similarity, however, is not realized in post-merger innovation. Furthermore, some key synergy sources are unanticipated when selecting a merger partner. For example, financial synergy from higher total assets and complementarity in total assets and debt leverage as well as knowledge synergy from breadth and depth of knowledge positively influence innovation but not partner selection. Furthermore, factors that dilute synergy (e.g., higher debt levels) are unanticipated, and firms merge with firms that detract from their innovation potential. Overall, the results reveal some incongruity between anticipated and realized synergy.

Data, as supplemental material, are available at https://doi.org/10.1287/mksc.2016.0978.

Keywords: merger; innovation; synergy; roommate-matching model; empirical models; Markov Chain Monte Carlo (MCMC) methods

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1. Introduction

Corporate mergers have become a popular strategic option for firms to grow and acquire new resources to meet the rapidly changing demands of a competitive global marketplace. Given the enormous volume of mergers and their steep financial costs (global merger activity hit $3.5 trillion in 2014 alone), a wealth of academic research has been dedicated to examining whether mergers are, in fact, successful and, if so, what drives their success. For example, the literature is replete with work on the financial outcomes of mergers (e.g., Fuller et al. 2002, Ghosh and Ruland 1998, Santos et al. 2008, Swaminathan et al. 2008). Other work has focused on how mergers influence operations and management outcomes, including productivity, turnover, and compensation (e.g., Bertrand and Capron 2015, Duchin and Schmidt 2013, Gupta and Gerchak 2002). Further work has examined the effect of mergers on innovation (e.g., Ahuja and Katila 2001, Makri et al. 2010, Prabhu et al. 2005). While informative, past work is largely limited to an understanding of what happens *after* a merger has been announced or has already occurred. This leaves us with little knowledge of what leads two firms to choose one another and whether such decision factors are relevant or possibly harmful to post-merger performance.

The notion of *whom to merge with* is a game of matching wherein any two firms in a consideration set have a probability of merging based on an iterative process of who is available and which pair will create the highest anticipated synergy. Ultimately, the hope is that anticipated synergy will result in actual synergy after the merger (Bena and Li 2014, Shleifer and Vishny 2003). Thus, each firm can decide whether to enter a merger with a given firm, and vice versa, or to not engage in a merger.

In reality, however, anticipated synergy (which leads to partner selection) may not result in actual synergy (or positive post-merger performance). Firms may be attracted to certain characteristics in another firm despite them having no influence on post-merger performance. Firms may also overlook promising characteristics when selecting a merger partner and, instead, pay attention to other, nonrelevant factors.

Even more, firms could be attracted to another firm's characteristics that might harm the firm after the merger. Thus, the question arises: Are firms choosing the right partners based on the right criteria to improve post-merger performance?

In this paper, we examine how cultural, financial, and knowledge fit characteristics between firms influence (a) whether two firms merge and (b) post-merger innovation. Innovation is our outcome of interest for several reasons. Without continuous innovation, customers will lose interest in a firm's products and services, and sales will decline (Hauser et al. 2006). Accordingly, building a base of new ideas and inventions for innovation is necessary for prosperity and survival and can be a beneficial way to create a positional advantage (Day and Wensley 1988, Hult and Ketchen 2001). This notion is heavily reinforced in the marketing literature (e.g., Borah and Tellis 2014, Mishra and Slotegraaf 2013, Moorman and Miner 1997, Moorman and Slotegraaf 1999, Prabhu et al. 2005, Sood and Tellis 2009, Sorescu et al. 2007, Wind and Mahajan 1997). Innovation, however, is often difficult to continuously engender in-house, especially in high-technology markets, making mergers a powerful way to gain new ideas and products (Prabhu et al. 2005). Our aim is to characterize the degree to which firms are using partner selection to increase their innovative potential.[1]

We address this issue using a unique panel dataset of cultural, financial, and knowledge fit characteristics between 4,444 firms (3,958 firms that were involved in a merger and 486 firms that did not merge) from 1992 to 2008 across four high-technology industries in 45 countries. Using roommate matching (Gale and Shapley 1962), we derive the anticipated synergy function from the merger, which is specified in terms of observed variables (cultural, financial, and knowledge fit) between firms. The post-merger innovation outcomes (number of patents) are also modeled using the same set of variables, and both models are jointly estimated using Bayesian methods. We also capture the influence of factors that are unobservable, yet idiosyncratic, to the merging pairs (e.g., operational synergy, management changes) and which are likely to influence partner selection and post-merger innovation.

This paper makes several contributions to the marketing literature. A review of the literature across disciplines reveals that a majority of the work on mergers concentrates on post-merger performance but overlooks the important stage of *whom to merge with* (i.e., partner selection). To our knowledge, the few papers that have examined partner selection have ignored post-merger performance and/or have viewed partner selection rather singularly, not taking into account the joint decision between two firms to enter a merger, and thus, ignoring the principles of matching in equilibrium.

Furthermore, past work on post-merger performance has concentrated heavily on financial and managerial outcomes, including abnormal returns, investor quality, asset growth, and C-suite turnover. However, in truth, many post-merger outcomes relate to building new goods and services and should be topics of further study. Thus, this work is in direct response to the call for further research on marketing innovation by Hauser et al. (2006); we focus on what firms are doing to achieve the goal of innovating more.

Our primary contribution is bringing to light the nonobvious incongruence between partner selection and post-merger innovation. To our knowledge, past research has not viewed in this way the merger stages of whom to merge with and post-merger performance. By assuming that one of the goals of the two firms that are merging is innovation, one would expect firms to select merger partners that help them to innovate. Yet we identify several examples in which firms might be overlooking key synergy sources, paying attention to the wrong sources, and failing to avoid sources of synergy dilution. We categorize our findings based on the degree of congruency between the effects of cultural, financial, and knowledge fit on partner selection and post-merger innovation. Congruence implies that the effect of these variables on partner selection and on post-merger innovation are both positive, both negative or both neutral. Incongruence occurs when the variables affect partner selection but not innovation, or vice versa, or when the effects are in the opposite direction (e.g., a positive effect on partner selection but a negative effect on innovation). We summarize our findings using the following four broad categories:

- *The Right Fit*: Firms' anticipated synergy can, in fact, lead to realized post-merger synergy. For example, knowledge and cultural similarity positively affect partner selection and post-merger innovation, illustrating that, in terms of these factors, firms are indeed choosing partners that increase their innovation potential.
- *Missing Out*: Key synergy sources are unanticipated. For example, financial synergy from higher total assets and complementarity in total assets and debt leverage as well as knowledge synergy from breadth and depth of knowledge positively influence post-merger innovation but not partner selection.
- *Failure to Translate*: Anticipated synergy does not always lead to realized synergy. For example, firms merge based on industry similarity even though it has no apparent impact on innovation.
- *Synergy Dilution*: Because sources of synergy dilution are unanticipated, firms select firms that detract

[1] Consistent with marketing research (e.g., Bahadir et al. 2008, Prabhu et al. 2005, Sorescu et al. 2007), management (e.g., Hitt et al. 1990, Makri et al. 2010, Zollo and Singh 2004), and finance (e.g., Rhodes-Kropf et al. 2005, Rhodes-Kropf and Robinson 2008, Shleifer and Vishny 2003), we do not distinguish between mergers and acquisitions and refer to this activity as "mergers" throughout the paper.

from their innovation potential. For example, higher combined debt leverage is neutral on partner selection but has a negative effect on innovation.

Overall, six of the nine variables in our model showed evidence of firms possibly neglecting post-merger innovation when deciding whom to merge with.

We next provide a brief background of the literature and discuss our conjectures in Section 2. Following that, we present our data and method in Section 3. Subsequently, we provide a description of our empirical model in Section 4. We then present the results of our estimation in Section 5. Finally, we discuss the implications of this work in Section 6 and end with the limitations and directions for future research in Section 7.

2. Background and Conjectures

2.1. The Merger Literature

The merger process involves several stages and decisions, including whether to merge, whom to merge with, when to merge, deal characteristics, post-merger integration, and post-merger outcomes. Our paper focuses on the empirical investigation of two stages of the merger process: whom to merge with (partner selection) and post-merger outcomes. Accordingly, we restrict our literature review to empirical papers in marketing, management, finance, and banking that have investigated these two stages. In Table 1, we summarize the literature across three dimensions: (1) whether the outcome is innovation-related, (2) whether the paper uses the principles of matching, and (3) whether the focus is on one stage (whom to merge with *or* post-merger outcomes) or two stages (partner selection *and* outcomes).[2]

If we look at the empirical papers across disciplines that address partner selection or post-merger outcomes, or both, four things are noteworthy. First, most of the work on mergers is outside of marketing. This could be because mergers are typically thought to be driven by financial and managerial motives, not marketing objectives. We know, however, that marketing resources are used to drive mergers (Sorescu et al. 2007) and that mergers are significant for post-merger marketing outcomes (Capron and Hulland 1999, Prabhu et al. 2005).

Second, few papers focus on the decision of whom to merge with. Erel et al. (2012) examine partner selection but model it as a binary outcome instead of modeling how firms choose one another based on a matching game. In their working papers, Akkus et al. (2016) and Uetake and Watanabe (2013) use matching games to model partner selection using data from the banking industry but ignore the consequences of this decision (i.e., post-merger outcomes).

Third, based on Table 1, the majority of papers on mergers focus exclusively on post-merger performance. A wealth of papers, primarily in finance and management, focus on noninnovation-related outcomes, such as abnormal returns, investor quality, excess value, and management turnover. Several papers examine post-merger innovation, although few consider marketing contexts and variables. While Prabhu et al. (2005) examine the influence of knowledge on new product creation, they, along with the others discussed in this section, do not consider earlier stages in the merger process.

Fourth, scant research has jointly examined the stages of partner selection and post-merger performance, and post-merger innovation in particular. In Table 2, we present a comparison of our paper to the set of papers that examine partner selection and performance, and provide details on the variables and models used in each paper. The few papers that have examined partner selection and post-merger performance have modeled the two stages in isolation, not jointly (e.g., Bena and Li 2014, Karolyi and Taboada 2015, Sorescu et al. 2007). Furthermore, they view partner selection from the perspective of one firm's choosing another for acquisition or a group of firms' engaging in mergers (or not). We view the process of merging very differently. Specifically, using the principles of matching, we examine how the characteristics of two firms interact in determining the equilibrium of the merger market, instead of focusing on only one firm's selection criteria. We allow firms to choose one another, or choose no one, based on an iterative process of who is available and which pairing provides the highest expected synergy. Park (2013) views partner selection similarly, although he focuses on post-merger asset growth, and not innovation.

In sum, to our knowledge, there is no paper that uses the principles of matching for partner selection and examines post-merger innovation. This paper attempts to address this gap.

2.2. Drivers of Anticipated Synergy

The drivers of mergers and post-merger outcomes are vast and spread across marketing, managerial, financial, and operational motives. Given that it is nearly impossible to examine all of these factors in a single framework, we focus on a few key areas that are likely to influence partner selection based on their proven effects on post-merger innovation, i.e., the environment in which innovations can be created and the level of resources available for creation.

The cultural environment, which stems from country (Johnson and Tellis 2008) and industry (Kor and Sundaramurthy 2009) affiliations, has an impact on a firm's

[2] There is a noteworthy group of theoretical papers on various stages of the merger process (e.g., Jovanovic and Rousseau 2002, Shleifer and Vishny 2003, Trautwein 1990). Given our focus on the empirical examination of mergers, we chose not to include these papers in our literature review.

Table 1 Select Empirical Literature on Whom to Merge with and Post-Merger Outcomes

Stages covered	Use of matching principles	Post-merger outcomes considered: Innovation outcomes	Post-merger outcomes considered: Noninnovation outcomes	Post-merger outcomes considered: None
One stage: Whom to merge with	No	n/a	n/a	Erel et al. (2012)[b]
	Yes	n/a	n/a	Akkus et al. (2016)[b], Uetake and Watanabe (2013, wp)[b]
One stage: Outcome	No	Prabhu et al. (2005)[a], Sorescu et al. (2007)[a], Hitt et al. (1991)[c], Ahuja and Katila (2001)[c], Cassiman et al. (2005)[c], Cloodt et al. (2006)[c], Makri et al. (2010)[c]	Capron and Hulland (1999)[a], Bahadir et al. (2008)[a], Swaminathan et al. (2008)[a], Fuller et al. (2002)[b], Santos et al. (2008)[b], Golubov et al. (2012)[b], Duchin and Schmidt (2013)[b], Harrison et al. (1991)[c], Capron (1999)[c], Ahuja and Katila (2001)[c], Gupta and Gerchak (2002)[c], Bertrand and Capron (2015)[c], Karolyi and Taboada (2015)	n/a
	Yes	n/a	n/a	n/a
Two stages: Whom to merge with and outcome	No	Sorescu et al. (2007)[a], Bena and Li (2014)[c]	Karolyi and Taboada (2015)[b]	n/a
	Yes	*Our paper*	Park (2013)[b]	n/a

Notes. n/a, Not applicable; wp, working paper; a, marketing journal; b, finance and banking journal; c, management journal.

innovation potential. In addition, a firm's resources, including its financial standing (Rhodes-Kropf and Robinson 2008) and the type of knowledge it houses (Prabhu et al. 2005, Sorescu et al. 2007), affect its ability to create new goods and services. For a firm that is seeking a merging partner to increase its innovation potential, comparing potential candidates' cultures and resources to its own is critical in deciding which firm will be a good strategic fit. Hence, the likely effects of similarities, differences, and combinations of culture and resources on post-merger innovation come to bear in the merger partner selection process.

Table 2 Comparison of Select Empirical Papers on Both Partner Selection and Performance

Title, Author, Year	Dependent variable	Independent variable	Model	Findings
Regulatory arbitrage and cross-border bank acquisitions—Karolyi and Taboada (2015)	*Cross-border acquisition and abnormal returns*	*Bank regulation indices*	Cross-sectional regression	Quality of bank regulation increases cross-border acquisitions and abnormal returns.
Why some acquisitions do better than others: Product capital as a driver of long-term stock returns—Sorescu et al. (2007)	*Target selection, target deployment, long-term abnormal returns*	*Product capital, target selection, and deployment*	OLS regression	Product capital affects performance through acquirers' superior selection and deployment of targets' innovation potential.
Understanding merger incentives and outcomes in the mutual fund industry—Park (2013)	*Whom to merge with and asset growth*	*Size ratio, distribution channel, public status, proportion of funds*	Two-sided matching game	Firms acquire others to achieve economies of scale in marketing and distribution. Some firms are eager to acquire but are poor at managing post-merged organizations.
Corporate innovations and mergers and acquisitions—Bena and Li (2014)	*Whether the firm is an acquirer or target and innovation*	*Technological and product overlap*	Conditional logit regression and difference-in-differences regression.	Synergies obtained from combining innovation capabilities are important drivers of acquisitions and innovation output.
This paper	*Whom to merge with and innovation*	*Cultural, financial, and knowledge fit and unobserved idiosyncratic fit.*	Two-sided matching game	There is a large mismatch between what causes two firms to merge and what leads to post-merger innovation.

Next we discuss how cultural, financial, and knowledge strategic fit between firms influence partner selection and post-merger innovation. Our goal is to identify consistencies and discrepancies between the effects of these characteristics on the two stages to identify what firms should and should not focus on when deciding whom to merge with. Because our focus is determining whether the effects of the chosen variables are consistent between the two stages, we refrain from making formal hypotheses but discuss the likely direction of the effects.

2.3. The Impact of Cultural Fit on Partner Selection and Innovation

There is considerable support for the role of national culture in influencing a firm's ability to innovate (e.g., Chandrasekaran and Tellis 2008, Johnson and Tellis 2008). In the context of mergers, cultural similarity/distance between two firms is an important factor to consider. The tendency of firms to interact with firms in countries similar to their own is well documented. For example, cultural distance has a negative impact on how well partners in a joint venture interact over the cultural divide (Johnson and Tellis 2008). Cultural barriers tend to limit collaboration and organizational learning (Barkema et al. 1996), lowering the partnered firms' ability to generate new ideas and, ultimately, innovate. It is conceivable, then, that firms will be more likely to merge with culturally similar firms to avoid some of the pitfalls associated with cultural distance and its potentially negative impact on innovation.

Likewise, belonging to a particular industry can shape a firm's culture and, therefore, its ability (and need) to innovate. Industries, and subindustries in particular, are characterized by idiosyncratic opportunities, threats, competitive conditions, technology, and regulations. For example, while pharmaceutical and biotechnology are considered high-technology industries, cultural differences between both types of firms abound. Pharmaceutical firms tend to operate in a high-stakes vertical culture of research and development, patent cliffs, and blockbuster chasing. By contrast, biotechnology firms, although similarly characterized by heavy research and development (R&D) investments, have a more casual and egalitarian culture (Lyman 2009). Greater industry relatedness between two firms results in a smoother post-merger integration process and, therefore, better deployment of the merged firm's innovations (Singh and Montgomery 1987). Thus, we conjecture that two firms in the same subindustry will be more likely to merge in the hope of innovating more after the merger than will two firms from different subindustries.

2.4. The Impact of Financial Fit on Partner Selection and Innovation

A firm's financial resources affect its attractiveness in the merger market, as a firm's financial standing directly influences its ability to create new goods and services. A firm's preference for resources can be grouped into two classes, i.e., one in which the firm seeks to increase the amount of an attribute (i.e., a higher mean) and one in which the firm seeks to increase the complementarity of an attribute (i.e., larger variance) (Rao et al. 1991). We examine the impact of the mean and variance of total assets and debt leverage between potential pairs of firms on whether they merge and, if so, their post-merger innovation. Total assets and debt leverage indicate the health of a firm (Mintz and Currim 2013) and dictate the degree to which the merged entity will have access to financial resources to innovate.

It is easy to imagine that the higher the total assets of the merged firm, the more it can innovate because it has access to more cash and investments. A more useful point to consider is the degree of variance between two firms' assets. Imagine, for example, that Firm A ($6 million in total assets) is considering merging with Firm X ($5 million), and that firm B ($3 million) is considering merging with Firm Y ($8 million). Both merged pairs create combined total assets of $11 million, but the dispersion is greater between the B:Y pair than between the A:X pair. Greater assets dispersion can allow for an easier integration of the two firms (Ramaswamy 1997) and deployment of assets (Rhodes-Kropf and Robinson 2008, Shleifer and Vishny 2003), which increases the ease with which innovations can be created. Thus, we conjecture that the higher the average total assets and the greater the difference in total assets, the better the innovation potential of the merged firm and the more likely that the B:Y pair will be chosen among alternatives.

Debt is an indication of a firm's financial obligations. In particular, the amount of debt relative to the firm's assets, its debt leverage, indicates the proportion of assets funded by debt. The higher the debt ratio, the higher the degree of leverage and financial risk and the lower the degree of financial flexibility. A highly leveraged firm may focus entirely on reducing debt (Scherer 1988) and not on innovation. However, greater differences in debt leverage between two firms might make their joining more attractive, especially for the more leveraged firm. Even for the less leveraged firm, having some debt is good because it is a much less expensive form of financing than equity (Berman and Knight 2009). These arguments imply that greater (average) debt leverage between two firms would be detrimental for innovation, thus lowering the chance of a merger, but that higher variance would be preferred, thus increasing the chance of a merger.

2.5. The Impact of Knowledge Fit on Partner Selection and Innovation

A firm's ability to create knowledge is a key driver of its ability to innovate (Griliches 1984). There are several ways to consider combinations of knowledge between firms, including their depth, breadth, and similarity (Prabhu et al. 2005). *Depth* refers to the amount of in-field knowledge a firm has. *Breadth* is the range of fields over which the firm has knowledge. Finally, *similarity* is the extent of overlap in the fields of knowledge between the two firms that are considering merging.

Developing depth in key fields enables firms to produce new knowledge in those and related fields (Bierly and Chakrabarti 1996, Hamel and Prahalad 1994, Prabhu et al. 2005). This suggests that, when considering a partner to merge with, a firm will view favorably another firm that will have greater combined depth of knowledge after the merger. In addition, much of the literature suggests that breadth of knowledge is helpful for innovation (Bierly and Chakrabarti 1996, Cohen and Levinthal 1990, Henderson 1994, Henderson and Cockburn 1994). Several researchers have pointed out the importance of integrating knowledge across different fields, especially in technically complex industries (Henderson and Cockburn 1994, Pisano 1994, Volberda 1996). The broader a firm's existing knowledge, the greater its ability to combine knowledge in related fields in a more complex and creative manner (Bierly and Chakrabarti 1996, Kogut and Zander 1992, Reed and DeFillipi 1990). Thus, a merger that results in broader and deeper knowledge becomes more attractive.

Knowledge similarity can be crucial to the ability of the merged firm to absorb the knowledge and use it for innovation (Mowery et al. 1996). Prior research has largely championed a positive effect of knowledge similarity on the ability to absorb and exploit the knowledge of another to innovate (e.g., Cohen and Levinthal 1990, Henderson 1994, Henderson and Cockburn 1994, Lane and Lubatkin 1998). This suggests that firms will choose one another when there is greater similarity between their knowledge bases, with the hope of increasing their post-merger innovation.

In sum, we conjecture that firms will select partners based on expectations of how cultural, financial, and knowledge fit characteristics will affect post-merger innovation. In other words, we expect the effects of these variables of the two stages to be congruent. Specifically, we conjecture that national and subindustry similarity will have a positive effect on partner selection and post-merger innovation. Furthermore, we expect that higher average total assets and variance in total assets and debt leverage will have a positive effect on both stages, although average debt leverage is expected to negatively affect both stages. Finally, we anticipate that greater knowledge breadth, depth, and similarity will have a positive impact on partner selection and post-merger innovation.

3. Data and Method

3.1. Empirical Context and Data

Through our methodological approach, we attempt to jointly estimate the likelihood of two firms' merging (among thousands of firms) and the innovativeness of the merged firms. We constructed a unique data set of merger activity, culture, and resource information, and patent activity from multiple sources. Although the innovation potential of the merged firm is a well established motivation for merging, we recognize that not all mergers occur for the sake of innovation. As a result, measuring the outcome of a merger as a function of innovation alone might lead to inconsistencies between partner selection and post-merger outcomes. We address this concern in several ways. First, we focus on high-technology firms, for which merger activities for the express purpose of gaining innovation are prevalent. Such industries are characterized by high levels of market and technological uncertainty, making popular the use of mergers as a method of gaining knowledge and resources (John et al. 1999, Rindfleisch and Moorman 2001, Wind and Mahajan 1997). Second, many of our independent variables relate directly to innovation and have a natural theoretical and empirical link to this outcome, as discussed in Section 2. Third, we include a control variable that measures the primary motivation for the merger (innovation-related or not). Fourth, we control for unobserved factors that influence why two firms have merged; this allows us to examine those that pertain more closely to our focus.

Similar to past research (e.g., Sorescu et al. 2007, Swaminathan et al. 2008), we collected data on merger deals from the Securities Data Corporation (SDC) Thompson Platinum Mergers and Acquisitions database. SDC Platinum provides complete histories of the deals, including their announcement dates and other material terms and conditions of the deal. We collected data on 1,979 mergers and 486 nonmergers for 4,444 firms (541 private and 3,903 public) between January 1992 and December 2008.[3] The firms span 45 countries; the top four most prevalent countries are the United States, the United Kingdom, Canada, and France. The merger deals fall broadly into the high-technology industries of biotechnology (15% of our sample), computers (53%), electronics (19%), and communications (13%), each of which has several subindustry classifications. The sample period ended in 2008 to ensure that we could estimate the innovation model with at least three years of information.

[3] The 4,444 firms are not necessarily unique because firms could have participated in multiple mergers during the sample period or chosen not to merge. For our analysis, each matching market is treated independently and, as a result, firms' appearing in different markets do not affect our matching estimation.

Unlike previous research, which heavily relies on data from public firms, our data set covers a broader range, including private firms, as long as the independent variables were available for them. We believe that our approach is especially meaningful given that many high-technology deals involve relatively small, private firms.

3.1.1. Merger Choice Set Construction. One challenge in assessing whether two firms *match* is that researchers do not observe the choice alternatives for a given firm, while the realized match itself is known to the researcher (i.e., we know which firms actually merged). Knowledge of the matched pair says little about which other firms were considered for the same deal. In theory, the choice set should contain all firms that exist around the time that the firm is considering looking outside to gain resources, which includes thousands of firms. However, in reality, it is unlikely that a firm would truly consider all firms for a given deal, nor is it feasible to include all of them in the model estimation.

Given these limitations, we constructed the choice sets, or markets, for each merger using a combination of heuristics and random sampling. Because the true consideration set is unknown to researchers, at the very least, we can assume that any firm that merged in the same year and in the same industry was a firm under consideration. We created markets of 100 firms or fewer, which included firms in the same industry that merged in the same year, plus firms that chose not to merge (i.e., stay-alone firms). The constructed markets ranged from 12 to 100 firms, with an average of 55 firms and a standard deviation of 25. Because the potential number of matches $[n \times (n+1)/2]$ grows quickly with the number of firms in each market (n), making estimation increasingly burdensome, we split the high-volume years into two or three markets to ensure that each market had fewer than 100 firms. In total, we created 81 markets (biotechnology firms comprised 20%; computers, 39%; electronics, 21%; and communications, 20%). We tested different sizes of the market by altering the time period of the available merging partners and found the results to be robust to alternative definitions of the constructed market.

To construct the set of stay-alone firms, we randomly sampled six from the pool of firms that excluded the matched pairs.[4] Although there are many candidates (most firms do not participate in a merger in any given year), it is difficult to create a truly random sample among the nonmerged firms because the complete sample of all of the high-technology firms (public and private) in 45 countries over 16 years is enormous. To work around this, we took our existing sample of all firms involved in the merger (3,958, or $1{,}979 \times 2$), kept the unique ones, and split them by four industry categories. Next, we focused on a particular industry, removed the matched firms, and randomly drew a single firm from the pool. If all of the independent variables were available for this firm, we retained it as a stay-alone option for that market; if not, we made another draw from the pool. We repeated the same drawing process to create a set of six stay-alone firms for all 81 markets. A very similar method of random sampling to construct a choice set has been widely used in the choice modeling literature for situations in which the true consideration set is not observable and possible alternatives are too numerous (e.g., Feather 2003, McFadden 1977, Parsons and Kealy 1992, Parsons and Needelman 1992, Train 2003, Train et al. 1987, Yu et al. 2016).

Although we cannot mathematically prove that a random selection of stay-alone firms will yield consistent estimates in the roommate-matching model, we conducted a simulation with varying sizes of firms (30, 40, 50, and 60) in a market and six additional firms (or outside options) being considered for a merger through random draws. We recovered the true values of the parameters quite well. The results of this simulation are included in Web Appendix A (available as supplemental material at https://doi.org/10.1287/mksc.2016.0978).

3.2. Variable Definitions

3.2.1. Dependent Variables. The first dependent variable is whether a merger took place between each pair of firms in each constructed market. It took on a value of 1 if the pair merged and a value of 0 if the pair did not merge. The second dependent variable is innovation, measured by the number of patents created by the merged firm. Patent data are widely used across disciplines, including in the marketing literature, to measure innovation (e.g., Chandy et al. 2006, Prabhu et al. 2005, Sorescu et al. 2007). Patents have significant strength as a measure of innovation for several reasons: (1) Patents are directly related to innovativeness, and they are granted only for nonobvious improvements or solutions with discernible utility (Walker 1995); (2) They represent an externally validated measure of technological novelty (Griliches 1990); (3) They confer property rights on the assignee and, therefore, have economic significance (Kamien and Schwartz 1982, Scherer and Ross 1990); (4) They correlate well with other measures of innovative output, such as new products (Comanor and Scherer 1969), invention counts (Achilladelis et al. 1987), and corporate technological strength (Narin et al. 1987); and (5) They are comparable across industries, allowing us to use multi-industry data.[5] We measured the number of new patents created

[4] Our case is slightly more complex than a one-sided choice model, as it involves a two-sided matching game, where each side has a choice.

[5] Some empirical research has used longer-term measures of innovation, such as first-stage R&D products (Prabhu et al. 2005),

by the merged firm for the first three years following the merger.

3.2.2. Independent Variables.

Focal Variables. We measured the cultural fit between the pairs of firms using two indicators: *national cultural distance* and *subindustry similarity*. For national cultural distance, we used data on Hofstede's (1991) four cultural dimensions, i.e., power distance, individualism-collectivism, masculinity-femininity, and uncertainty avoidance. Following Johnson and Tellis (2008) and Kogut and Singh (1988), we collapsed the cultural dimension scores into a single measure by taking the Euclidean distance of the four dimensions as follows: $CD_{ij} = \sqrt{\sum_{S=1}^{4}(D_{is} - D_{js})^2}$, where CD_{ij} is the country distance score between firm i's headquarter country and firm j's headquarter country; D_{is} is the score on dimension s for host country i; and D_{js} is the score on dimension s for host country j. Following past research (e.g., Sorescu et al. 2007), we measured subindustry similarity using a dummy variable that takes the value of 1 if the last two digits of the Standard Industrial Classification Code of the two firms are the same, and 0 otherwise.

We measured the financial fit variables using data collected from Compustat. We used the logarithm of the firm's stated total assets due to skewed distribution of this variable. Debt leverage was measured by dividing the firm's total debt by its total assets. Following Rao et al. (1991), we computed the average and differences between pairs of firms, thereby creating four measures of financial fit, i.e., *average total assets*, *difference in total assets*, *average debt leverage*, and *difference in debt leverage*.

We captured knowledge fit using measures of the combined past patent activity between firms in the consideration set, a good indicator of a firm's technical knowledge (Prabhu et al. 2005). To do so, we needed to identify the specific fields in which the firm has knowledge. The U.S. Patent Office classifies patents that relate to their field of use into specific patent classes. Therefore, it was possible to identify the technical fields in which a firm had knowledge by coding the classes in which it held patents (see Prabhu et al. 2005 for a detailed description of this methodology). *Depth of knowledge* was measured as the average number of approved patents per patent class for the pairs of firms in the year before the potential merger. *Breadth of knowledge* was measured as the total number of patent classes covered by the two firms' approved patents in the year before the potential merger. *Similarity of knowledge* was measured as the number of patent classes shared by two firms, divided by the total number of patent classes owned by the two firms combined in the year before the potential merger.

Control variables. We included industry dummies to control for industry-specific effects (one fewer than the number of industry categories). We included the stated *reason for the merger* as related to innovation or not, using data from the SDC Platinum database. SDC Platinum codes merger deals into 20 purpose categories. Two researchers separately judged the merger purpose codes and classified them as related to innovation (which took on a value of 1) or unrelated (which took on a value of 0). Innovation-related reasons included "obtain competitors' technology/strategic assets" and "allow to offer new products and services." Unrelated reasons included "concentrate on core businesses/assets," "expand presence in new geographical regions," and "increase shareholder value." The merger purpose codes existed for deals after 2000 but were frequently missing for deals before that year. To fill in the gaps, a research assistant read through popular press articles and coded the purpose of the merger. Finally, we included the *lagged number of new patents*, measured as the combined number of new patents for the two firms in the year before the potential merger to control for firms' patent-creation abilities before the merger. We list the variables, how they were operationalized, and their expected direction of effect on partner selection and post-merger innovation in Table 3.

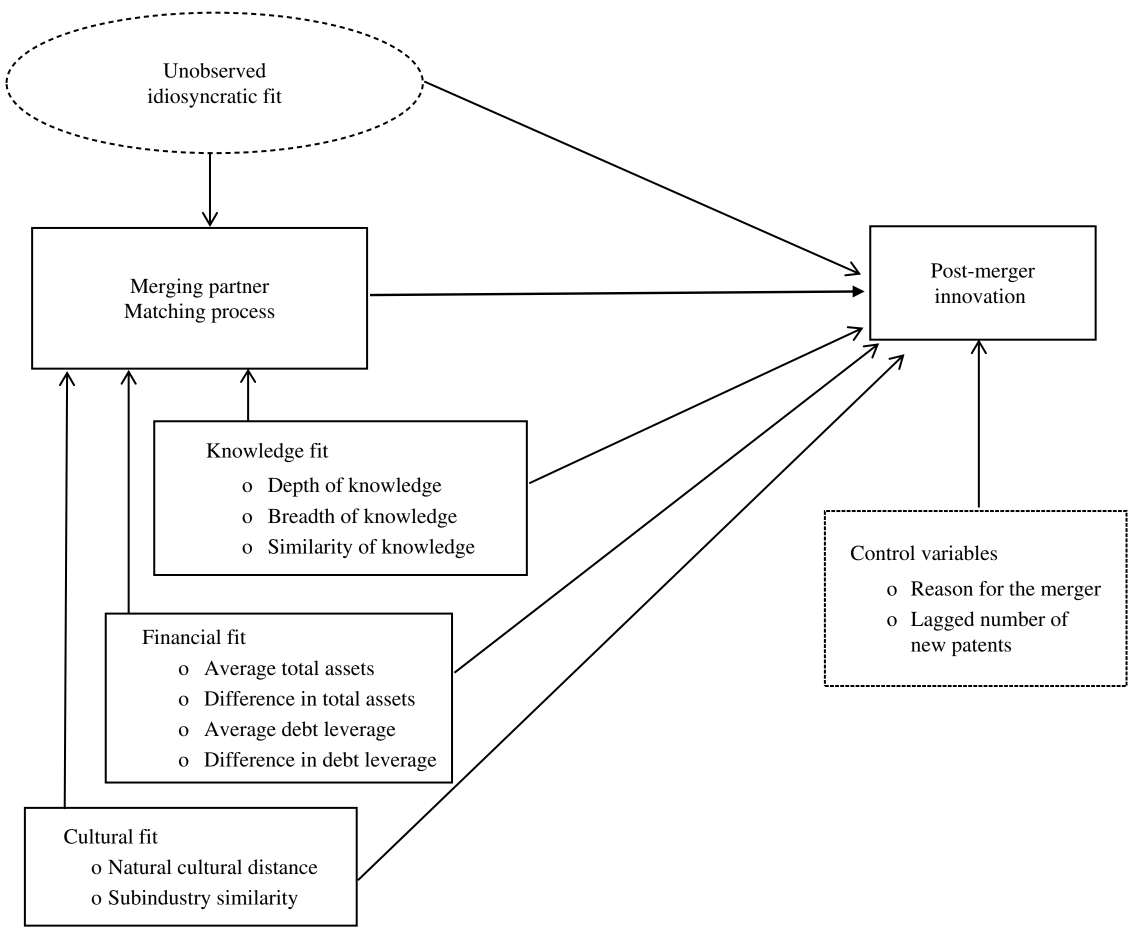
Unobserved factors. Although the cultural, financial, and knowledge aspects of strategic fit between two firms control for key firm characteristics, they alone are unlikely to explain anticipated synergy and why two firms merge. Factors such as operational synergy (Gupta and Gerchak 2002), complementary business offerings, supply channels, sales force distribution, client mix, and risk propensity (Ramaswamy 1997, Rao et al. 1991) are important to decisions of whom to merge with but are difficult to measure. Moreover, for competitive reasons, such idiosyncratic fit between firms is not disclosed to outsiders (Hitt et al. 1991). As a result, researchers are left with an incomplete understanding of what causes two firms to merge. In addition, while we attempted to gather relevant information on what has an impact on a firm's innovativeness, we may have fallen short in certain areas, especially when it is well known that merger integration is murky, at best, with much information not privy to researchers. For these reasons, we capture *unobserved idiosyncratic fit*, which affects both stages but is not observable to the researcher. Ignoring this strategic fit will lead to bias in the estimation. We describe how we captured unobserved idiosyncratic fit in Section 4. Figure 1 presents our variables and conceptual framework.

patent citations (Valentini 2012), and commercialized products (Chandrasekaran and Tellis 2008). These measures are more readily available and suitable for a small sample, single industry study. Given the significantly larger sample required for modeling matching for firms across a diverse set of industries and countries in our study, it was not feasible to adopt these additional measures.

Table 3 Variable Definition and Operationalization

Variable	Expected sign on partner selection and innovation	Operationalization
Focal variables		
National cultural distance	−	Euclidean distance of the four culture dimensions from two participating firms' countries.
Subindustry similarity	+	1 if the two firms' first two digits of the SIC code match, 0 otherwise.
Average total assets	+	Average of the total assets of the two firms.
Difference in total assets	+	Squared difference in the total assets of the two firms.
Average debt leverage	−	Average of the debt leverage (total debt/total assets) of the two firms.
Difference in debt leverage	+	Squared difference in the debt leverage (total debt/total assets) of the two firms.
Depth of knowledge	+	Average number of approved patents per patent class for the two firms in the year prior to the potential merger.
Breadth of knowledge	+	Number of patent classes covered by the two firms' approved patents in the year prior to the potential merger.
Similarity of knowledge	+	Number of patent classes shared by the two firms divided by the total number of patent classes owned by the two firms in the year prior to the potential merger.
Control variables		
Reason for the merger		1 if the stated merger incentive from news release is innovation-related, 0 otherwise.
Lagged number of new patents		Number of new patents created by two firms in the year prior to the merger.
Dependent variables		
Merger match		Whether two firms merged or stayed alone.
Post-merger innovation		Number of new patents in the first, second, and third year after the merger.

Figure 1 Theoretical Framework



4. Empirical Model

We developed a two-stage model: The first stage concerns the matching of firms into merged pairs (with the option of staying alone); the second stage provides an evaluation of the innovation outcome of the merger based on the matching process. The two stages are connected through an unobserved error term, which captures the unobserved idiosyncratic fit. This jointly estimated two-stage model reduces endogeneity bias by capturing the effect of unobservable variables that would improperly be attributed to the included variables (see Sorensen 2007 for more details on this method). Our empirical merger-outcome model has two parts: (i) the anticipated synergy function in matching and (ii) a function for the innovation outcome.

4.1. Roommate-Matching Model: Whether Two Firms Merge

Next we briefly describe the setup of the roommate matching game (Roth and Sotomayor 1992). (Greater detail is provided in Web Appendix B.) For n firms, we denote the set of possible matches as M_n. The anticipated synergy function in the roommate matching model is given by

$$V_{ij} = \begin{cases} Q_i\lambda + \eta_{ij}, & \text{when } i = j \\ W_{ij}\beta + \eta_{ij}, & \text{when } i \neq j \end{cases}, \tag{1}$$

where V_{ij} is the valuation of each potential match, $ij \in M_n$, W_{ij} is a vector of observed characteristics for firm i and firm j, and β is the vector of parameters to be estimated. Here, Q_i is a vector of observed characteristics for firm i for its self-match (i.e., not merging with any firm and staying alone) and λ is the corresponding parameter vector. The variables used in the stay-alone model include nondyadic variables, such as a single firm's total assets, debt leverage, and breadth and depth of knowledge. The term η_{ij} contains factors that affect the matching process but which are unobserved in the data and to the researcher. We assume that η_{ij} follows i.i.d. standard normal distribution. Using the equilibrium conditions in the roommate matching game, we derived the likelihood function for each market; the joint likelihood for all M_n markets for the observed matching results in these markets. Given that the matching results can be modeled as a discrete choice model, we can recover parameters of the V_{ij} function up to scale and level. The scale is normalized by setting the variance of the error term η_{ij} to one. We estimate the parameters λ and β using maximizing likelihood methods.

The selection in the first stage of our model determines whether to participate in a merger and with whom (or to stay alone). As described in Web Appendix B, both merger participants try to maximize their expected synergy by evaluating various available partners. This results in a complex and intertwined marketwide optimization problem. For a market of size n, there are $[n \times (n+1)/2]$ potential matching outcomes and only $n/2 \sim n$ number of final matches (or nonmatches). The input factors for all of the unrealized matches (as illustrated in the example in Web Appendix B) serve as first-stage controls: These factors affect the first-stage matching decisions but not the innovation outcome for the merged pairs. We allow the unobserved idiosyncratic fit error term from the first stage to enter the second stage for the merged pairs. This process is quite similar, but not equivalent to, the selection issues described by Heckman (1979).

4.2. Outcome Model: Post-Merger Innovation

The second part of the merger model is a regression equation for the innovation outcome.[6] For each $ij \in M_n$ let

$$Y_{ij} = X_{ij}\alpha + \varepsilon_{ij}, \tag{2}$$

where X_{ij} contains observed characteristics and α contains the parameters to be estimated. The outcome vector, Y_{ij} represents firms' counts of new patents in the three years ($t = 1, 2, 3$) after the merger deal.[7]

$$\begin{aligned} y_{ijt} &= X_{ijt}\alpha + \varepsilon_{ijt}, \\ \varepsilon_{ijt} &= \eta_{ij}k_t + \delta_{ijt}, \quad t = 1, 2, \text{and } 3. \end{aligned} \tag{3}$$

The error correlations in the models for Y_{ij} and V_{ij} are linked through a set of parameters, k_t: $0 < k_t < 1$, $t = 1$, 2, 3. The remaining errors are assumed to follow a multivariate normal distribution: $\delta_{ij} \sim N(0, \Sigma_Y)$, where $\delta_{ij} = (\delta_{ij1}, \delta_{ij2}, \delta_{ij3})'$. We assume that the δ_{ij}s are uncorrelated with the η_{ij}s. We did not impose any other constraints on the variance-covariance structure Σ_Y.

Therefore, the joint distribution of η_{ij} and ε_{ij} is multivariate normal and is given by

$$\begin{pmatrix} \eta_{ij} \\ \varepsilon_{ij} \end{pmatrix} \sim N\left(0, \begin{bmatrix} 1 & K^T \\ K & \Sigma_\varepsilon \end{bmatrix}\right) = N\left(0, \begin{bmatrix} 1 & K^T \\ K & \Sigma_Y + \Sigma_k \end{bmatrix}\right), \tag{4}$$

[6] Because patent counts are commonly overdispersed, we conducted robustness tests using alternative specifications, including a negative binomial model and a zero inflated model. We found that all but one of the effects are significant in both the ordinary least squares (OLS) and negative binomial models; even the one with a nonsignificant coefficient is in the same direction. From Akaike information criterion (AIC) and Bayesian information criterion (BIC) model fit measures, we found that the zero inflated model had a slight improvement in AIC compared to the negative binomial model, but with a considerable deterioration in BIC. Thus, it was unclear whether this additional specification was an improvement. We therefore chose to use the standard OLS method due to its relative simplicity compared to the other specifications, as well as its ability to produce robust results.

[7] The outcome measure can theoretically be tracked for any number of years. While synergy may not have been fully realized in shorter time periods, additional external factors come into play, adding noise to the outcomes in longer time periods. After balancing these competing factors, we chose three years as a reasonable time period.

where $K = (k_1, k_2, k_3)'$,

$$\Sigma_k = \begin{pmatrix} k_1^2 & k_1k_2 & k_1k_3 \\ k_1k_2 & k_2^2 & k_2k_3 \\ k_1k_3 & k_2k_3 & k_3^2 \end{pmatrix}, \quad \text{and}$$

$$\Sigma_Y = \begin{pmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} \\ \sigma_{12} & \sigma_2^2 & \sigma_{23} \\ \sigma_{13} & \sigma_{23} & \sigma_3^2 \end{pmatrix}.$$

The error terms are assumed to be independent of X, W, and Q. The estimated coefficient α in the innovation outcome function reflects the influence of the cultural, financial, and knowledge fit variables (i.e., the market sorts out, resulting in pairs of matched firms and stay-alone firms: See Web Appendix B for more details). The covariance Σ_ε among the error terms K captures the effect of unobserved synergies between i and j, which affect the matching and innovation stages. The estimates K and Σ_ε will reveal the unknown strength and duration of the effect of the unobserved synergy on the innovation outcome.

4.3. Parameter Identification and Model Estimation

When Firm A merges with Firm B, no other firms can merge with Firm A or Firm B, thereby affecting the available options for other firms in the matching market and leading to sorting in the market. Matching and sorting, which are two fundamental properties of our model estimation and identification, solve the endogeneity problem in the innovation outcome analysis. Endogeneity arises when firms self-select to participate in a merger, and we (as researchers) observe only the effect of the merger on the matched pairs. This is problematic because the merger action is not random. Our inclusion of the first-stage matching process and stay-alone option, however, controls for the endogeneity problem. Because of sorting and interaction, the presence of other firms (and more generally their characteristics) affects whether two firms merge and, if not, whether they pursue other firms or decide to stay alone. The assumption for identification, therefore, is that the characteristics of the firms in each market are exogenously given and independent of the error terms in the model (Sorensen 2005). In other words, the set of potential matching pairs, Mn, is a super-set of the merged pairs and the unmatched pairs, which enter the matching game inequality conditions and serve as exclusion restrictions for model identification. Please refer to Web Appendix B for more information on the exclusion restrictions.

In our joint specification of the roommate matching model and the outcome function, the parameters to be estimated include the matching stage synergy parameters, λ and β, the outcome function parameter, α, the error correlation parameters k_t, and the variance covariance matrix, Σ_Y of the outcome errors (the error component that is not correlated to the matching errors). It is important to acknowledge that the firms in our context interact bidirectionally, such that their merger decisions cannot be analyzed in isolation, as is the case with choices modeled using probit estimation. Thus, the likelihood function does not factor into a product over the likelihood of each firm's action. All error terms must be simultaneously integrated to evaluate the likelihood function of our roommate-matching model. The dimensionality of this integral runs into the thousands and presents several technical challenges. To address this problem, we adopted a Bayesian method of estimation, which uses the Markov Chain Monte Carlo (MCMC) method to circumvent the integration problem (see Sorensen 2007 for a description of this procedure). The model is estimated from iterated simulations of the posterior distribution. Albert and Chib (1993) and Tanner and Wong (1987) show that treating latent variables as parameters significantly simplifies simulation of the resulting augmented posterior distribution, and the MCMC procedure using Gibbs sampling (Gelfand and Smith 1990, Geweke 1999) can simulate this distribution. We specify the prior and posterior distributions of all of the parameters in the appendix.

5. Results

5.1. Summary Statistics

The summary statistics of the potential pairs, matched pairs, stay-alone firms (or nonmergers), and innovation outcome measures are shown in Table 4. A comparison of Panels 4.1 and 4.2 indicates that matched firms are culturally more similar than are the potential pairs and have greater depth, breadth, and similarity of knowledge. Furthermore, the number of patents is greater among the merged pairs than among the potential pairs, suggesting that firms might be merging to innovate or that innovation occurs as a consequence of merging. A comparison of Panel 4.3 with Panels 4.1 and 4.2 further suggests that the breadth and depth of knowledge for stay-alone firms are higher than those of potential pairs but are lower than those of the matched pairs. It appears that firms tend to avoid deals that will dilute their knowledge resources.

In comparing innovative output, we find that, on average, the number of new patents declines in the first year after the merger compared to the year before; however, the level picks up again in the second and third years. It appears that the integration disturbance (or adaptation) is most severe in the first year after the merger, whereas anticipated synergy transitions into realized synergy from the second year onward. Overall, we see some model-free evidence of matching and associated merger outcomes.

Table 4 Summary Statistics

	Potential pairs ($N = 144{,}246$) Panel 4.1		Merged pairs ($n = 1{,}979$) Panel 4.2	
Variable	Mean	SD	Mean	SD
National cultural distance	20.42	27.97	8.65	20.43
Subindustry similarity	0.21	0.41	0.42	0.49
Average total assets	9.67	3.58	9.69	3.79
Difference in total assets	2.72	2.07	2.45	1.71
Average debt leverage	1.09	1.94	1.03	0.79
Difference in debt leverage	0.47	1.88	0.40	0.66
Depth of knowledge	0.76	5.47	5.51	32.59
Breadth of knowledge	1.32	9.84	8.39	35.14
Similarity of knowledge	0.01	0.08	0.05	0.17
Reason for the merger			0.12	0.33
Lagged number of new patents			52.45	324.06

	Stay-alone firms ($n = 4{,}444$) Panel 4.3			Innovation outcome ($n = 1{,}979$) Panel 4.4	
Variable	Mean	SD	Variable	Mean	SD
Average total assets	4.92	2.49	*New patents in Year* 1	46.40	299.91
Average debt leverage	0.55	1.63	*New patents in Year* 2	58.35	424.14
Depth of knowledge	1.77	5.25	*New patents in Year* 3	61.25	462.36
Breadth of knowledge	2.57	11.88			

5.2. Model Fit

We compare the fit of the joint model, which captures the effects of unobserved idiosyncratic fit, with the fit of the two models estimated separately. The log-likelihood for the joint model is 4,952 and, for the separate model estimation, is 4,593. Given that a higher log-likelihood indicates better fit, we can see that the joint estimation outperforms an estimation of the two models separately. This could be largely driven by the fact that the separate models fail to control for unobserved idiosyncratic fit. In addition, we compare a null model in which all of the parameters are set to zero to the full jointly estimated model with the cultural, financial, knowledge, and control variables using the Bayes factor.[8] The log (Bayes factor) is 358.48, indicating that the joint estimation model has a significant advantage over a null model that fails to account for the effect of observed and unobserved variables. Furthermore, the three correlation factors (k values) that link the matching and innovation outcome functions are all positive and significant. Thus, it becomes clear that the unobserved idiosyncratic fit does, in fact, play a significant role in partner selection and post-merger innovation and, as a result, needs to be captured by researchers and included in similar estimations. Without its inclusion (i.e., without jointly estimating the models), the estimates for the observed variables would be biased and their effects on innovation overstated.

[8] In Bayesian estimation, the Bayes factor is the most commonly used measure to compare two alternative model specifications. It is the ratio of the marginal likelihood between the two alternative models. Because the Bayes factor automatically punishes the model for the inclusion of additional parameters, a model with more explanatory variables does not necessarily result in a higher Bayes factor over another model with fewer explanatory variables. According to Jeffreys (1961), when the Bayes factor is greater than 100 and the log (Bayes factor) is greater than 4.6, the model advantage is decisive.

5.3. Parameter Estimates Contrasting Matching and Innovation Stages

As can be seen in Table 5, in terms of cultural fit, national cultural distance has a negative effect on the likelihood of merging ($\beta = -0.02$, $p < 0.05$) and a negative effect on post-merger innovation ($\alpha = -0.01$, $p < 0.05$). This confirms past research (e.g., Johnson and Tellis 2008) on the negative effect of cultural distance on post-merger outcomes. Furthermore, this result demonstrates a consistency between the two stages, suggesting that firms are choosing merger partners that are culturally similar, as this is likely to increase post-merger innovation. Subindustry similarity has a positive effect on the likelihood of merging ($\beta = 0.71$, $p < 0.05$) but no effect on innovation ($\alpha = 0.01$, $p > 0.10$). This result counters past research (e.g., Singh and Montgomery 1987) on the positive effect of subindustry similarity on integration and post-merger performance. Thus, while firms seem to favor similar partners, such similarity does not translate into realizable gains in innovation.

In terms of financial fit, average total assets has no effect on the likelihood of merging ($\beta = -0.06$, $p > 0.10$) but has a positive effect on innovation ($\alpha = 0.03$, $p < 0.05$). Similarly, difference in total assets has no effect on the likelihood of merging ($\beta = 0.04$, $p > 0.10$) but

Table 5 Estimation Results

Joint model				
	Merger outcome (V)	Innovation outcome (Y)		
		Year 1	Year 2	Year 3
Variable	β	$\alpha 1$	$\alpha 2$	$\alpha 3$
National cultural distance[a]	−0.02*	−0.01*	−0.01*	−0.01*
Subindustry similarity	0.71*	0.01	−0.01	−0.02
Average total assets	−0.06	0.03*	0.03*	0.03*
Difference in total assets	0.04	0.05*	0.05*	0.05*
Average debt leverage	0.16	−0.07*	−0.064*	−0.06*
Difference in debt leverage	−0.13	0.06*	0.058*	0.06*
Depth of knowledge[a]	0.02	0.01*	0.002*	0.01*
Breadth of knowledge[a]	−0.02	0.01*	0.002*	0.01*
Similarity of knowledge	0.87*	0.16*	0.198*	0.17*
Reason for the merger		−0.01	−0.023	−0.03
Lagged number of new patents		0.01*	0.01*	0.01*
Unobserved idiosyncratic fit (k)[b]		0.11*	0.14*	0.06*

Stay-alone model	
Variable	λ
Log (assets)	−0.05
Book leverage	0.10
Depth of knowledge	−1.62*
Breadth of knowledge	−1.33*

Note. The results are created based on 45,000 draws (5,000 burn-ins).

[a]In the innovation outcome function, the patent count variable is scaled to be comparable to the unobserved idiosyncratic fit term. The marked independent variables are also scaled so that the estimates are in the same magnitude as the rest of the variables. Industry dummies are included but are not shown to conserve space. For the same reason, the constants from the innovation outcome model are also omitted.

[b]Indicates the correlation between V and Y for three years after the merger. Significant values indicate that the unobserved idiosyncratic fit significantly affects innovation.

*Parameter estimate is significant at $p < 0.05$.

has a positive effect on innovation ($\alpha = 0.05$, $p < 0.05$). Average debt leverage has no effect on the likelihood of merging ($\beta = 0.16$, $p > 0.10$) but has a negative effect on innovation ($\alpha = -0.07$, $p < 0.05$). Finally, difference in debt leverage has no effect on the likelihood of merging ($\beta = -0.13$, $p > 0.10$) but has a positive effect on innovation ($\alpha = 0.06$, $p < 0.05$). The direction and significance of the effects of the financial fit variables on post-merger innovation confirmed our expectations and are consistent with past research (e.g., Rhodes-Kropf and Robinson 2008, Shleifer and Vishny 2003). However, we expected the same effects for partner selection and were surprised by their nonsignificance, which we subsequently discuss.

With respect to the knowledge variables, depth of knowledge between two firms has no effect on the likelihood of firms' merging ($\beta = 0.02$, $p > 0.10$) but has a positive effect on post-merger innovation ($\alpha = 0.01$, $p < 0.05$). Similarly, breadth of knowledge has no effect on the likelihood of merging ($\beta = -0.02$, $p > 0.10$) but has a positive effect on innovation ($\alpha = 0.01$, $p < 0.05$). While the positive effects of depth and breadth on post-merger innovation were expected and are consistent with past research (e.g., Prabhu et al. 2005), their null effects on partner selection are surprising, which we discuss further in Section 6. Finally, similarity of knowledge has a positive effect on both the likelihood of merging ($\beta = 0.87$, $p < 0.05$) and innovation ($\alpha = 0.16$, $p < 0.05$), revealing a congruency between partner selection and post-merger innovation.

6. Discussion

While the topic of mergers and their outcomes is hardly new, the study of upstream phenomena, including what motivates two firms to merge, is (to our knowledge) original. The work presented here focuses on partner selection and post-merger innovation in a single framework. This focus allows us to compare the effects of cultural, financial, and knowledge fit factors on both stages to identify whether anticipated synergy results in realized synergy for the merged firms. Our empirical study of thousands of mergers in several high-technology industries across many countries demonstrates that there is a large disparity between why firms merge and what helps them innovate. The consequences of this can be overlooking opportunities, paying attention to the wrong information, and lack of synergy.

Our primary contribution centers on comparing what influences partner selection and what influences post-merger innovation. We contend that positive congruence (i.e., factors that positively influence partner selection and innovation) implies that anticipated synergy is, in fact, translating into actual synergy and that firms are choosing partners that help them innovate. Negative congruence (i.e., factors that negatively influence partner selection and innovation) implies that firms might be choosing wisely in that they are less likely to merge with a firm that reduces their innovativeness. Incongruence between the two stages (i.e., factors that affect one stage but not the other or affect them both but in opposite directions) implies that firms may be overlooking important information when choosing a partner or may be paying attention to the wrong information. We summarize our findings in Table 6.

There are a few results for which anticipated synergy translates into actual synergy. For example, both similarity in national culture and technical knowledge increase the chance of a merger *and* the innovativeness of the merged firm. These results suggest that firms that are interested in increasing their innovativeness are using national culture and knowledge similarity appropriately as justification for merging.

However, as Table 6 demonstrates, there is evidence of strong incongruence between what motivates a firm to merge with another and what affects post-merger innovation.

For example, we find that firms are more likely to merge if they belong to the same subindustry, despite the fact that this has no apparent effect on their innovation potential. This implies that firms might be overweighing the benefits of belonging to the same subindustry; managers should consider this when entering negotiations with firms in related businesses. This is a clear case in which anticipated synergy does not translate into actual synergy (in the form of innovation). Furthermore, in industries where innovation is a key motivator of growth, firms might be overlooking key sources of synergy when deciding whom to merge with. For example, firms' combined total assets, their ability to meet their financial obligations, and their depth and breadth of technical knowledge all positively influence post-merger innovation but are unanticipated in the partner-selection stage. Finally, we find that firms might be merging with partners that detract from their innovation potential. For example, while higher debt leverage reduces the merged firm's innovation potential, firms fail to take this into consideration when choosing a partner (i.e., the effect of higher debt leverage on partner selection is nonsignificant). Thus, we find several instances where anticipated synergy that arises from partner selection and realized synergy that arises from post-merger innovation are incongruous.

We measured post-merger innovation using a count measure of new patents for the merged firm. One

Table 6 Summary of the Findings

Variable	Effect on merging (anticipated synergy)	Effect on post-merger innovation (realized synergy)	Congruency between anticipated and realized synergy	Implication
National cultural distance	−	−	Yes	Firms avoid merging with culturally distant firms that detract from their innovation potential.
Subindustry similarity	+	NS	No	Firms merge with firms in similar subindustries, even though it has no effect on their ability to innovate.
Average total assets	NS	+	No	While higher total assets helps the merged firm innovate, this is an unanticipated source of synergy, and firms fail to choose a partner based on this factor.
Difference in total assets	NS	+	No	While differences in total assets help the merged firm innovate, this is an unanticipated source of synergy, and firms fail to choose a partner based on this factor.
Average debt leverage	NS	−	No	While higher debt leverage inhibits the merged firm's innovation, firms fail to anticipate this source of synergy dilution when choosing a partner.
Difference in debt leverage	NS	+	No	While differences in debt leverage help the merged firm innovate, this is an unanticipated source of synergy, and firms fail to choose a partner based on this factor.
Depth of knowledge	NS	+	No	While deeper combined knowledge improves post-merger innovation, this is an unanticipated source of synergy, and firms fail to choose a partner based on this factor.
Breadth of knowledge	NS	+	No	While a greater breadth of combined knowledge increases post-merger innovation, this is an unanticipated source of synergy, and firms fail to choose a partner based on this factor.
Similarity of knowledge	+	+	Yes	Firms choose partners with greater knowledge similarity, which helps them innovate and create synergy.

Note. NS, Nonsignificant effect.

may argue that patents are an inadequate measure of a firm's actual innovation as not all patents are commercialized. To counter this issue, we collected another measure of innovation, top scientist attrition, which is a measure of intellectual human capital, a resource necessary for innovation. The importance of top scientists for innovation is well established. Firms with top scientists enjoy faster technological progress and higher economic rents (Zucker and Darby 1996). Retaining top scientists is essential for a merger to succeed and to achieve its goals (Bower 2001, Pautler 2003). Following the work of Sorescu et al. (2007), we identified whether the top five scientists from each firm of the merged pair were still working for the firm up to three years after the merger. We found that the scientist retention rate was 67% one year after the merger, 54% after two years, and 47% after three years. We then regressed the top scientist retention measure on the cultural, financial, and knowledge-based fit measures and jointly estimated it with the merger model described for the number of patents. The results of this additional analysis mirror those of the patent count measure used in our primary model estimation, down to each and every effect. This illustrates that the costs of overlooking factors that influence partner selection and innovation outcomes, including patent count and talent retention, might be broader than expected.

Our findings also provide evidence that, beyond the effects of publicly observable factors, unobserved idiosyncratic fit between two firms significantly influences the merger decision and post-merger performance. Without taking these factors into account, researchers run the risk of over-crediting cultural, financial, and knowledge fit factors.

7. Limitations and Directions for Future Research

When studying knowledge and innovation, we examined the knowledge embedded in pre-merger patents and the innovation in new patents after the merger. Patents are a widely used measure of knowledge across several high-technology industries and have been used as such by marketing researchers (e.g., Dutta et al. 1999, Prabhu et al. 2005). Nevertheless, knowledge and new ideas might be embedded in other sources and innovations might be represented by other forms, especially in nontechnology-based industries. Future research would benefit from examining longer-term innovation measures, including commercialized products and services. Similarly, one aspect of culture, especially at the industry level, can be measured in more comprehensive ways than just a dummy variable of subindustry identity. Both industry and firm culture can be measured by capturing the cultural orientations of firms that operate in a certain industry as well as the cultural norms of a given firm. Furthermore, while we measured a firm's debt leverage as a ratio of debt to assets, this variable can also be operationalized as a ratio of debt to equity.

While our modeling approach accounted for the effects of unobserved idiosyncratic factors, researchers and managers alike would benefit from uncovering what, exactly, is in that *black box*. Various legal and resource constraints might prevent a firm from accomplishing a merger. Alternatively, operational and organizational synergies might motivate a firm to merge with another firm and are likely to influence post-merger outcomes. Future research might consider appending historical and survey data to better understand the influence of other pertinent factors.

The general roommate-matching game does not always have stable matching equilibrium, which is required for empirical implementation. For estimation, we followed the empirical matching literature by imposing aligned preference assumptions to ensure the existence and uniqueness of equilibrium. Specifically, we assumed that two merger participants had the same synergy expectation at the time of the merger, although we made no assumption about an even split of payoff from actual synergy. While this assumption is in accord with previous research, future research might allow for unequal synergy expectations by each firm. In addition, future researchers might consider constructing the merger choice sets (here referred to as *markets*) differently, including increasing the number of stay-alone options and testing alternative partner sets. In the same vein, exclusion restrictions can be further examined by altering the number of the stay-alone firms used in the matching stage analysis.

Supplemental Material

Supplemental material to this paper is available at https://doi.org/10.1287/mksc.2016.0978.

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Appendix. Specifications for Model Estimation

We use a Bayesian estimation method to recover the parameters in this model. Let $\theta \equiv (\beta, \vec{\alpha}', \lambda, K)$. The variance-covariance matrix Σ_Y also will be estimated. The densities defined by the model are denoted as ϕ, and the densities derived for the simulation are denoted as π.

Priors for θ: The prior distribution for θ is a normal distribution. Let the prior density be denoted as $\phi_0(\theta)$. This density is given by

$$\phi_0(\theta) \propto \exp(-0.5(\theta-\theta_0)' A_\theta(\theta-\theta_0)), \quad (5)$$

where C is a generic normalizing constant (here and below) that ensures that the densities integrate to 1, and $\theta_0 = (\beta_0, \vec{\alpha}_0', \lambda, K)$. The matrix A_θ is the inverse of the covariance matrix of the prior distribution, and in each estimated specification, it is 10 times the identity matrix. Furthermore, increases in the prior variance leave the estimated parameters largely unchanged. Corresponding to the parameters, the covariance matrix is decomposed into A_β^{-1}, A_α^{-1}, A_λ^{-1}, and A_k^{-1}.

Priors for Σ_Y: The prior for Σ_Y is an inverted Wishart distribution: $\Sigma_Y \sim \mathrm{IW}(v_0, V_0)$. We specify $v_0 = 4$ and $V_0 = v_0 I$.

To draw the posterior distribution of θ and Σ, we use the Gibbs sampling method.

A.1. Conditional Distributions of Matching Variables

The conditional augmented posterior distribution of V_{ij} depends on whether firm i and firm j are matched. Let V_{-ij} contain all outcome variables except V_{ij}. When $ij \notin \mu_n$ and $i \neq j$, the density is simply

$$\pi(V_{ij} \mid V_{-ij}, \mu_n, W_{ij}) \propto 1[V_{ij} \le \bar{V}_{ij}] \times \exp(-0.5(V_{ij} - W_{ij}\beta)^2). \quad (6)$$

When $ij \notin \mu_n$ and $i = j$, the density is

$$\pi(V_{ij} \mid V_{-ij}, \mu_n, Q_i) \propto 1[V_{ij} \le \bar{V}_{ij}] \times \exp(-0.5(V_{ij} - Q_{ij}\lambda)^2). \quad (7)$$

When $ij \notin \mu_n$ and $i \neq j$, the outcome of the match is observed. Correlations between the error terms mean that the outcome contains additional information about the match. The conditional density is given by

$$\pi(V_{ij} \mid V_{-ij}, Y_{ij}, X_{ij}, W_{ij}, \mu_n, \theta, \Sigma_Y)$$
$$\propto 1[V_{ij} \ge \underline{V}_{ij}] \times \exp\left\{-\frac{[V_{ij} - W_{ij}'\beta - (\vec{Y}_{ij} - \vec{X}_{ij}\vec{\alpha})\Sigma_Y^{-1}K]^2}{2\cdot(1-K^T\Sigma_Y^{-1}K)}\right\}. \quad (8)$$

When $ij \in \mu_n$ and $i = j$, the density is

$$\pi(V_{ij} \mid V_{-ij}, \mu_n, Q_i) \propto 1[V_{ij} \ge \underline{V}_{ij}] \times \exp(-0.5(V_{ij} - Q_{ij}\lambda)^2). \quad (9)$$

All of these are truncated normal distributions. The first is $\mathrm{N}(W_{ij}\beta, 1)$, truncated from above at $\bar{V}_{ij}$. The second is $\mathrm{N}(Q_{ij}\lambda, 1)$, truncated from above at $\bar{V}_{ij}$. The third is $\mathrm{N}(V_{ij} - W_{ij}\beta - (\vec{Y}_{ij} - \vec{X}_{ij}\vec{\alpha})\Sigma_Y^{-1}K, (1-K^T\Sigma_Y^{-1}K))$, truncated from below at $\underline{V}_{ij}$. The fourth is $\mathrm{N}(Q_{ij}\lambda, 1)$, truncated from below at $\underline{V}_{ij}$. The expressions for the upper and lower truncation points $\bar{V}_{ij}$ and $\underline{V}_{ij}$ are the conditions (3) and (4) shown in Online Appendix B. They are the upper and lower bounds for equilibrium valuations in the Roommate Matching Model. Furthermore, μ_n (defined in Online Appendix B) represents the unique equilibrium for the roommate matching game for a market with n players.

A.2. Conditional Distributions of Parameters

1. *Posterior for* β: Denote $VA_{ij} = V_{ij}$ if $ij \in M_n$ and $ij \notin \mu_n$ and $VA_{ij} = V_{ij} - (\vec{Y}_{ij} - \vec{X}_{ij}\vec{\alpha})\Sigma_Y^{-1}K$ if $ij \in \tau_n$.

$$p(\beta \mid VA_{ij}, W_{ij}, \beta_0, A_\beta) \propto p_0(\beta)\cdot(VA_{ij} \mid W_{ij}, \beta),$$
$$\propto |A_\beta|^{1/2} \exp\left(-\frac{1}{2}(\beta-\beta_0)' A_\beta(\beta-\beta_0)\right)$$
$$\cdot \prod_{n=1}^{N} \prod_{(ij\in M_n)\cap(ij\notin o_n)} \exp\left(\frac{1}{2}(VA_{ij} - W_{ij}\beta)'(VA_{ij} - W_{ij}\beta)\right), \quad (10)$$

$$\beta \mid VA_{ij}, W_{ij}, \beta_0, A_\beta \sim \mathrm{N}(\bar{\beta}, \Sigma_\beta)$$
$$\Sigma_\beta = \left(\sum_{n=1}^{N} \sum_{(ij\in M_n)\cap(ij\notin o_n)} W_{ij}'W_{ij} + A_\beta\right)^{-1}, \quad (11)$$

$$\tilde{\beta} = \left(\sum_{n=1}^{N} \sum_{(ij\in M_n)\cap(ij\notin o_n)} W_{ij}'W_{ij} + A_\beta\right)^{-1}$$
$$\cdot\left[\sum_{n=1}^{N} \sum_{(ij\in M_n)\cap(ij\notin o_n)} (W_{ij}'VA_{ij}) + A_\beta\beta_0\right]. \quad (12)$$

2. *Posterior for* λ:

$$p(\lambda \mid V_{ij}, Q_{ij}, \lambda_0, A_\lambda) \propto p_0(\lambda)\cdot(VA_{ij} \mid Q_{ij}, \lambda),$$
$$\propto |A_\lambda|^{1/2} \exp\left(-\frac{1}{2}(\lambda-\lambda_0)' A_\lambda(\lambda-\lambda_0)\right)$$
$$\cdot \prod_{n=1}^{N} \prod_{ij\in o_n} \exp\left(-\frac{1}{2}(V_{ij} - Q_{ij}\lambda)'(V_{ij} - Q_{ij}\lambda)\right), \quad (13)$$

$$\lambda \mid VA_{ij}, W_{ij}, \beta_0, A_\beta \sim \mathrm{N}(\bar{\lambda}, \Sigma_\lambda), \quad (14)$$

$$\Sigma_\lambda = \left(\sum_{n=1}^{N} \sum_{ij\in o_n} Q_{ij}'Q_{ij} + A_\lambda\right)^{-1},$$
$$\tilde{\lambda} = \left(\sum_{n=1}^{N} \sum_{ij\in o_n} Q_{ij}'Q_{ij} + A_\lambda\right)^{-1} \quad (15)$$
$$\left[\sum_{n=1}^{N} \sum_{ij\in o_n} (Q_{ij}'V_{ij}) + A_\lambda\lambda_0\right].$$

3. *Posterior for* $\vec{\alpha}$: Denote $\vec{YE}_{ij} = \vec{Y}_{ij} - \eta_{ij}K$.

$$p(\alpha \mid YE_{ij}, X_{ij}, \Sigma_Y, \tau_n, \alpha_0, A_\alpha) \propto p_0(\alpha)\cdot(YE_{ij} \mid X_{ij}, \Sigma_Y, \alpha, \tau_n),$$
$$\propto |A_\alpha|^{1/2} \exp\left(-\frac{1}{2}(\alpha-\alpha_0)' A_\alpha Y(\alpha-\alpha_0)\right) |\Sigma_Y|^{-(\Sigma_{n=1}^N \mu_n/2)}$$
$$\cdot \prod_{n=1}^{N} \prod_{ij\in\tau_n} \exp\left[-\frac{1}{2}(YE_{ij} - X_{ij}\alpha)'\Sigma_Y^{-1}(YE_{ij} - X_{ij}\alpha)\right], \quad (16)$$

$$\alpha \mid YE_{ij}, X_{ij}, \Sigma_Y, \tau_n, \alpha_0, A_\alpha \sim N(\tilde{\alpha}, \Sigma_\alpha), \quad (17)$$

$$\Sigma_\alpha = \Sigma_Y \otimes \left(A_\alpha + \sum_{n=1}^{\mathrm{N}} \sum_{ij\in\tau_n} X_{ij}'X_{ij}\right)^{-1}, \quad (18)$$

$$\tilde{\alpha} = \left(A_\alpha + \sum_{n=1}^{N} \sum_{ij\in\tau_n} X_{ij}'X_{ij}\right)^{-1} \left[\sum_{n=1}^{N} \sum_{ij\in\tau_n} (X_{ij}'YE_{ij}) + A_\alpha\alpha_0\right]. \quad (19)$$

4. *Posterior for* Σ_Y:

$$p(\Sigma_Y \mid YE_{ij}, X_{ij}, \alpha, \tau_n, v_0, V_0) \propto p_0(\Sigma_Y) p(YE_{ij} \mid X_{ij}, \Sigma_Y, \alpha, \tau_n),$$
$$\propto |\Sigma_Y|^{-(v_0+3+1)/2} \mathrm{tr}\left(-\tfrac{1}{2} V_0 \Sigma_Y^{-1}\right)$$
$$\cdot |\Sigma_Y|^{-(\Sigma_{n=1}^N \mu_n/2)} \mathrm{tr}\left(-\tfrac{1}{2} S_Y \Sigma_Y^{-1}\right), \quad (20)$$

$$S_Y = \sum_{n=1}^{N} \sum_{ij \in \tau_n} (YE_{ij} - X_{ij}\alpha - n_{ij}K)'(YE_{ij}^Y - X_{ij}\alpha - n_{ij}K), \quad (21)$$

$$\Sigma_Y \mid YE_{ij}, X_{ij}, W_{ij}, \alpha_Y, \tau_n, v_0, V_0$$
$$\sim \mathrm{IW}\left(v_0 + \sum_{n=1}^{N} \mu_n, V_0 + S_Y\right). \quad (22)$$

5. *Posterior for* K: Denote $Z_{ij} \equiv Y_{ij} - X_{ij}\alpha$.

$$p(K \mid Z_{ij}, \eta_{ij}, \tau_n, \Sigma_Y, K_0, A_k)$$
$$\propto p_0(K) \cdot p(Y_{ij} \mid X_{ij}, \eta_{ij}, \tau_n, \Sigma_Y, K_0, A_k), \quad (23)$$
$$\propto |A_K|^{1/2} \exp\left[-\tfrac{1}{2}(K - K_0)' A_K (K - K_0)\right] \cdot |\Sigma_Y|^{-(\Sigma_{n=1}^N \mu/2)}$$
$$\cdot \exp\left(-\frac{1}{2} \sum_{n=1}^{N} \sum_{ij \in \tau_n} (Z_{ij}^Y - \eta_{ij}K)' \Sigma_Y^{-1} (Z_{ij}^Y - \eta_{ij}K)\right). \quad (24)$$

The vector $K \mid Z_{ij}, \eta_{ij}, \tau_n, \Sigma_Y, K_0, A_k \sim \mathrm{N}(\tilde{K}, \Sigma_k)$ is truncated below at $c(0,0,0)$ and above at $c(1,1,1)$.

$$\Sigma_K = \Sigma_K \otimes \left(A_K + \sum_{n=1}^{N} \sum_{ij \in \mu_n} \vec{\eta}_{ij}' \vec{\eta}_{ij}\right)^{-1},$$
$$\text{where } \vec{\eta}_{ij} = (\eta_{ij}, \eta_{ij}, \eta_{ij}), \quad (25)$$

$$\tilde{K} = \left(A_\alpha + \sum_{n=1}^{N} \sum_{ij \in \tau_n} \vec{\eta}_{ij}' \vec{\eta}_{ij}\right)^{-1} \left[\sum_{n=1}^{N} \sum_{ij \in \tau_n} (\vec{\eta}_{ij}' Z_{ij}) + A_K K_0\right]. \quad (26)$$

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