Structural Recombination and Innovation:
Unlocking Internal Knowledge Synergy through Structural Change

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Structural Recombination and Innovation

ABSTRACT

This paper examines how structural recombination of business units within a firm impacts subsequent firm innovation. We argue that structural recombination is a means for firms to unlock the potential for internal knowledge recombination, redrawing the firm’s internal boundaries to bring together complementary knowledge resources. Structural recombination may thus be beneficial to subsequent firm innovation, especially where there are substantial untapped synergies between the firm’s knowledge resources. Specifically, we argue that structural recombination will have a positive effect on firm innovation where there is unexploited relatedness between the firm’s knowledge resources, and where the firm has high quality, general purpose knowledge. Results from a 20-year panel of 71 firms operating in the U.S. medical sector confirm these arguments, with structural recombination having a positive effect on innovation for firms with unexploited knowledge relatedness and those with high quality knowledge resources. The study thus highlights the role of structural recombination in realizing untapped knowledge synergies within the firm, and provides a contingent view of the effects of structural recombination on firm innovation.

Key words: recombination, innovation, reconfiguration, structure, knowledge based view, contingency theory
INTRODUCTION

Innovation, or the creation of new knowledge, is central to the role of organizations. As proponents of the Knowledge Based View (KBV) of the firm have argued, not only are knowledge resources a key source of the firm’s competitive advantage (Grant, 1996a; Liebeskind, 1996), but the creation, transfer and integration of knowledge is an important reason firms exist (Kogut and Zander, 1992; Grant, 1996b). By creating social communities of action, firms reduce the cost of communicating and coordinating knowledge, thus enabling not only the transfer and integration of specialized knowledge, but also the creation of new knowledge through the combination of existing knowledge to generate new capabilities (Kogut and Zander, 1992; Grant, 1996a, 1996b). This ‘combinative capability’ of the firm (Kogut and Zander, 1992) is critical to the success of innovation, which is inherently a recombinative process (Ahuja, 2000; Fleming, 2001; Katila and Ahuja, 2002; Fleming and Sorenson, 2004). Firms may gain competitive advantage by spanning intra-organizational boundaries (Rosenkopf and Nerkar, 2001) and recombining knowledge within the firm (Argyres, 1996; Hargadon and Sutton, 1997; Galunic and Rodan, 1998). Such recombination may be especially valuable for multi-business firms, who may be able to realize knowledge synergies across businesses (Markides and Williamson, 1994; Cardinal and Opler, 1995), recombining knowledge across units to generate valuable innovations (Miller, Fern and Cardinal, 2007).

This kind of intra-organizational knowledge sharing has been the subject of considerable study, with a substantial body of work studying the transfer of knowledge between units within an existing structure (Tsai, 2002; Hansen and Lovas, 2004, Tortoriello et al., 2011). While treating the structure of the organization as given and studying inter-unit knowledge transfer is certainly valuable and important, it may not provide a complete picture of intra-firm knowledge recombination. A substantial body of prior literature suggests that organizational knowledge may be sticky (Von Hippel, 1994; Szulanski, 1996), so that the transfer of knowledge across epistemic intra-organizational boundaries may prove difficult (Brown and Duguid, 2001), and the recombination and transformation of internal knowledge may encounter semantic and pragmatic difficulties (Carlile and Rebentisch, 2003; Carlile, 2004). Inter-unit transfer of knowledge may therefore be insufficient in realizing the full value of internal knowledge
synergies. Moreover, treating organizational structure as given ignores the reality that organizations can and do restructure their businesses (Porter, 1987; Bowman and Singh, 1989; Galunic and Eisenhardt, 1996; Brown and Eisenhardt, 1997; Karim and Mitchell, 2004), and that such restructuring may be a means for firms to redeploy and reconfigure their resources (Garud and Nayyar, 1994; Capron, Dussauge and Mitchell, 1998; Capron and Mitchell, 1998; Eisenhardt and Brown, 1999; Karim, 2006).

Our study seeks to address these issues, complementing work on inter-unit knowledge transfers by examining the effect of structural change on firm innovation. While prior studies have focused on intra-firm knowledge recombination through the transfer of knowledge within an existing structure, we examine the potential for such knowledge recombination through changes in the organizational structure, specifically by the merging together of business units, which we refer to as structural recombination (Karim 2006). Examining the effect of structural recombination on innovation is important not only because it complements work on knowledge recombination within an existing structure, but because the received literature offers contradictory perspectives on the effect of such changes in structure on innovation. On the one hand, as discussed above, work in the dynamic capabilities tradition suggests that structural recombination may be an important means by which firms recombine their knowledge resources to develop new capabilities (Eisenhardt and Brown, 1999; Karim and Mitchell, 2004), as well as a means of integrating knowledge from external sources in a post-acquisition context (Puranam and Srikantan, 2007; Puranam, Singh and Chaudhuri, 2009). On the other hand, work on structural change more generally has found evidence for a negative and disruptive effect (Bowman et al., 1999; McKinley and Scherer, 2000), including a negative effect of structural change on new product innovation (Puranam, Singh and Zollo, 2006; Karim, 2009).

In the current study, we argue that by dissolving boundaries between units, structural recombination enables the recombination of internal knowledge resources, helping to realize untapped knowledge synergies within the firm. More specifically, we predict that structural recombination will have a positive effect on innovation for firms with untapped internal knowledge synergies, i.e. for firms that have high quality, general purpose knowledge resources that are related in unexploited ways.
These arguments are tested on a sample of 71 firms from the U.S. medical sector, using panel data from 1978-1997 that combine a detailed record of the evolution of business units with information on firm patenting. Our results show that the impact of structural recombination is strongly contingent on the firm’s existing knowledge resources. Consistent with the idea that structural recombination will help realize untapped knowledge synergies, the effect of structural recombination on innovation is positive where firms have knowledge resources that are related in unexploited ways and are of high quality.

These findings contribute to the literature on firm innovation and the knowledge based view of the firm, highlighting the role of structural change in enabling the recombination of knowledge resources within the firm (Kogut and Zander, 1992, 1996; Grant, 1996a). Our study thus complements the substantial body of research that has looked at the transfer of knowledge between units (Hansen and Lovas, 2004; Miller et al., 2007) by recognizing that organizational structure is not static, and suggesting that the redrawing of intra-organizational boundaries to enable knowledge recombination is an important alternative to knowledge transfers across such boundaries (Rosenkopf and Nerkar, 2001), and a means to achieve the transformation of knowledge within the firm (Carlile and Rebentisch, 2003; Carlile, 2004).

Our study also contributes to the literature on dynamic capabilities in general, and organizational design in particular. While work in the dynamic capabilities tradition has argued for the role of internal reconfiguration in helping organizations adapt to changing conditions (Capron et al., 1997; Brown and Eisenhardt, 1999; Galunic and Eisenhardt, 2001; Karim and Mitchell, 2004), studies of organizational restructuring have generally found a negative effect of such changes (Bowman et al., 1999; McKinley and Scherer, 2000), including a largely negative effect of organizational reconfiguration on innovation (Karim, 2009). Our study resolves this apparent contradiction by highlighting the contingent nature of the impact of structural recombination. Our study suggests that structural recombination both disrupts the firm’s existing routines and enables the creation of new knowledge combinations, so that the effect of structural recombination is positive only where unrealized potential for knowledge recombination exists. By providing a contingent view of structural recombination, our study goes beyond the average effect of structural change on subsequent innovation (Karim, 2009) to consider the heterogeneity of firms’
outcomes from structural recombination. In addition, our study complements work on knowledge integration in the post-acquisition context (Puranam and Srikanth, 2007; Puranam et al., 2009), showing that structural recombination may be valuable in recombining internal knowledge resources in addition to enabling the integration of external knowledge.

THEORY & HYPOTHESES

Innovation, the limits of intra-organizational knowledge transfer, and structural recombination

The creation of new knowledge is a fundamental purpose of organizations (Kogut and Zander, 1992, 1996; Grant, 1996b). By establishing social communities with shared identity, norms, sequences and patterns, organizations lower the costs of communication and coordination of knowledge, creating a shared knowledge context that enables the development of new knowledge and capabilities (Kogut and Zander, 1992, 1996; Grant, 1996b, Hoopes and Postrel, 1999). This knowledge then becomes the source of the firm’s competitive advantage, since the creation, integration and transfer of knowledge is more easily accomplished within firm boundaries than through the market (Kogut and Zander, 1992; Grant, 1996a, 1996b; Leibeskind, 1996).

A key element of organizational knowledge creation is the recombination of existing knowledge resources to create new knowledge and capabilities (Kogut and Zander, 1992; Grant 1996b). Innovation has been widely recognized as a recombinant process (Ahuja, 2000; Fleming, 2001; Fleming and Sorenson, 2004), and a substantial body of literature has studied the recombination of knowledge resources within the firm, with firms developing new capabilities by spanning intra-organizational boundaries (Hargadon and Sutton, 1997; Galunic and Rodan, 1998; Argote and Ingram, 2000; Rosenkopf and Nerkar, 2001). Such intra-organizational knowledge sharing may be especially important for diversified firms, which stand to benefit from realizing knowledge synergies across businesses (Markides and Williamson, 1994; Cardinal and Opler, 1995; Miller et al., 2007).

While the importance of intra-organizational knowledge sharing has been widely recognized, the focus of prior research has been on studying the transfer of knowledge between units in a given structure,
and the factors that influence these transfers (Hansen and Lovas, 2004). Thus researchers have examined the role of gatekeepers (Tushman and Katz, 1980), integration routines (Iansiti, 1995), formal and informal linkages (Hansen, 1999; Tsai, 2000, 2002; Hansen and Lovas, 2004), internal absorptive capacity (Tsai, 2001; Jansen et al., 2005), the nature of knowledge (Zander and Kogut, 1995; Szulanski, 1996), knowledge relatedness (Hansen, 2002; Hansen and Lovas, 2004) and the structure of internal networks (Reagans and McEvily, 2003; Fleming, Mingo and Chen, 2007; Tortoriello et al., 2011) as determinants of the extent of knowledge transfer between units. These studies all take the boundaries between units as given, and focus on the ways in which knowledge is transferred across these boundaries.

While examining intra-firm knowledge transfer in this way is both important and valuable, it may not provide a complete picture. There are many reasons why transfers of knowledge between units may be inadequate to fully realizing the knowledge synergies within the firm. First, to the extent that divisional boundaries are epistemic, i.e. they define unique communities of practice, each with their own distinct interpretive schemes and cognitive frames, the transfer of knowledge across these boundaries may be difficult (Dougherty, 1992; Fiol, 1994; Brown and Duguid, 2001). Intra-organizational boundaries will result in individuals within a division developing shared identity, perspective and experiences making it difficult for knowledge to cross these boundaries (Kogut and Zander, 1996).

Second, intra-organizational knowledge transfer may also be compromised by pragmatic and political barriers within the firm (Argyres, 1996; Carlile, 2004; Kellogg, Orlikowski and Yates, 2006). Divisions within an organization will be in competition with each other (Galunic and Eisenhardt, 1996; Tsai, 2002) and may be reluctant to share knowledge if doing so would compromise their own performance (Porter, 1987) or rob them of credit (Hargadon and Bechky, 2006), or if relations between units are arduous (Szulanski, 1996). Different divisions may also have different goals and incentives, making it difficult for them to work towards a common solution (Carlile and Rebentisch, 2003; Carlile, 2004).

Third, transfers of knowledge between units may only be helpful in realizing certain kinds of knowledge synergies. While knowledge transfers may be helpful in sharing knowledge that is codifiable and teachable (Zander and Kogut, 1995), they may be less valuable in transmitting knowledge that is tacit
and causally ambiguous, and therefore sticky (von Hippel, 1994; Szulanski, 1996). Recombinations of tacit knowledge may require extensive socialization (Nonaka, 1994) with constant face to face interaction to enable moments of creativity (Hargadon and Bechky, 2006) that may be hard to achieve across intra-organizational boundaries. The nature of the innovative or recombinant process may also play a role in determining the effectiveness of inter-unit transfers. Where the dependence between the knowledge resources is sequential (Thompson, 1967; Van de Ven et al., 1976), a unilateral, one-time transfer of knowledge from one unit to the other may be sufficient. But where reciprocal or team interaction (Thompson, 1967; Van de Ven et al., 1976) is called for, successful innovation may require collective problem solving (Carlile, 2004), which in turn may require rich communication and concurrent development (Cardinal et al., 2011), and may be hard to achieve through inter-unit transfers.

Finally, even where knowledge can be successfully transferred across units, it is not clear that such a transfer is always optimal – as Grant (1996b) puts it, “transferring knowledge is not an efficient approach to integrating knowledge” (pp. 114). Maintaining knowledge links between units is costly (Hansen, 2002), both in the sense that it uses up managerial time and resources, and because these links may constrain the ability of individual divisions to adapt to changing conditions. Faced with these costs, firms may prefer to adopt loosely coupled or modular structures (Orton and Weick, 1990; Sanchez and Mahoney, 1995), in order to stay flexible (Grant, 1996; Galunic and Eisenhardt, 2001).

None of this is to suggest, of course, that transfers of knowledge across intra-organizational boundaries are not valuable. There is ample evidence to show that such intra-organizational transfers do positively impact firm knowledge creation (Tsai, 2001; Miller et al., 2007). Our point is only that while intra-organizational transfers may be an important means of realizing some of the potential synergies between organizational knowledge resources, they may be unable to realize all such synergies. Beyond a certain point, organizations will face a paradox of transfer: the very factors that enable the firm to create, integrate and transfer knowledge within its firm boundary in a way that is superior to the market (Kogut and Zander, 1992, 1996; Grant, 1996b) will also limit the firm’s ability to transfer and recombine this knowledge across its internal boundaries amongst business units.
If transfers of knowledge across intra-organizational boundaries prove inadequate, what other means can firms use to fully realize their potential knowledge synergies? One solution may be to alter their structure, dissolving boundaries between units, and reshuffling activities from one unit to the other, thus removing the constraints that limit the transfer of knowledge (Brown and Eisenhardt, 1999; Galunic and Eisenhardt, 2001). Knowledge is more easily shared within units than between them (Tushman and Katz, 1980; Brown and Duguid, 2001), even when activities within a unit are distant from each other (Hansen and Lovas, 2004), and prior research has shown that having fewer divisional boundaries helps enable greater and wider exploration (Argyres, 1995, 1996; Argyres and Silverman, 2004). Structural recombination, or the merging together of business units within a firm, may therefore enable the recombination of knowledge resources within the firm, bringing knowledge resources that were previously separated closer together by removing the internal boundaries between them.

The effect of structural recombination on innovation

Based on the discussion above, we are now in a position to define hypotheses. To begin with, we consider the main effect of structural change on innovation. More specifically, and in line with our theoretical argument for the recombination of knowledge resources within the firm, we focus on the innovation consequences of a particular type of structural change, which we refer to as structural recombination to distinguish it from other studies. Structural recombination are changes in business units as their resources and market activities are reorganized by merging units together, generally through the absorption of one unit into another unit or the formation of a new business unit by combining existing units. Units may have different origins, being either internally developed, acquired or the result of a recombination.

As discussed above, we believe that recombining units in this way will create the potential for

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1 Karim (2006, 2009, 2012) used the general terms ‘reorganization’ and ‘reconfiguration’ when referring to the addition, deletion, and recombination of business units, or their underlying resources and activities. To remain consistent with these papers, and to more specifically highlight that our interests are in business units that are being recombined, we use the term ‘structural recombination’.
innovation through successful recombination of existing knowledge (Ahuja, 2000; Fleming, 2001; Katila and Ahuja, 2002; Nerkar, 2003; Fleming and Sorenson, 2004), specifically the recombination of knowledge resources within the firm (Galunic and Rodan, 1998; Rosenkopf and Nerkar, 2001; Katila, 2002). This is consistent with both the dynamic capabilities literature that sees organizational reconfiguration more generally as a means of revitalizing firm capabilities (Brown and Eisenhardt, 1997; Galunic and Eisenhardt, 2001; Karim and Mitchell, 2004), as well as work on organizational structure and innovation which argues that fewer divisional boundaries will result in greater exploration (Argyres, 1995, 1996; Argyres and Silverman, 2004). It is also consistent with work on post-merger innovation which has argued for the importance of structural integration in enabling the recombination of knowledge (Puranam and Srikanth, 2007; Puranam, Singh and Chaudhuri, 2009). Thus

**Hypothesis 1a: Structural recombination will have a positive effect on firm innovation.**

While our arguments so far focus on the positive effects of structural recombination in creating new knowledge and capabilities, it is important to consider that such changes in structure may also prove costly or disruptive (Miller, 1982; Nadler and Tushman, 1997; Bowman et al., 1999; McKinley and Scherer, 2000). Changes in organizational structure may disrupt the organizational routines (Cyert and March, 1963; Nelson and Winter, 1982; Puranam, Singh and Zollo, 2006), communities of practice (Brown and Duguid, 1991, 2001; Orr, 1996), social relationships (Dougherty and Bowman, 1995; Dess and Shaw, 2001) and organizational climate (Burton and Obel, 1998) within which organizational knowledge is situated (Glynn, Lant and Milliken, 1994; Fisher and White, 2000), causing a depletion of the firm’s existing knowledge. Changes in structure may be especially harmful to the firm’s tacit knowledge (Nelson and Winter, 1982; Kogut and Zander, 1992; Nonaka, 1994), since such knowledge may be lost when individuals are moved out of their existing positions (Nixon et al., 2004; Guthrie and Datta, 2008). Such disruptions of the firm’s existing routines and relationships may in turn compromise future firm learning (Fisher and White, 2000).

In addition to damaging the firm’s existing knowledge, structural recombination may also lead to
increased conflict and uncertainty, further suppressing firm innovation. Changes in organization structure are associated with increased conflict over incompatible organizational goals and allocation of resources, as well as greater complexity, uncertainty and ambiguity (Child, 1972; Galunic and Eisenhardt, 1996, 2001; Luscher and Lewis, 2008), so that organizational creativity may be inhibited by a negative and stressful environment (Amabile and Conti, 1999), and firms risk falling prey to ‘post-restructuring drift’ (Johnson, Hoskisson and Margulies, 1990).

Thus, while structural recombination may benefit the firm by enabling the creation of new knowledge through recombination, this benefit may be offset by the disruption of the firm’s existing knowledge and capabilities, causing innovation to decline (Karim, 2009). We therefore offer the competing hypothesis:

*Hypothesis 1b: Structural recombination will have a negative effect on firm innovation.*

**Structural recombination and the potential for internal knowledge recombination**

Our discussion so far suggests that structural recombination has two competing effects: on the one hand, it enables the realization of untapped knowledge synergies within the firm, providing a boost to firm innovation; on the other hand, it disrupts the firm’s existing knowledge and capabilities, causing innovation to suffer. While the previous section sets these effects up as competing hypotheses, the logic of the argument suggests that whether structural recombination is beneficial or harmful to subsequent innovation will depend upon the extent of untapped knowledge synergies within the firm. Where significant untapped synergies exist, structural recombination is likely to have a positive effect; where it does not, the effect of structural recombination will be primarily disruptive. This is similar to arguments in the literature on post-acquisition integration: targets with strong potential synergies with the parent are usually integrated, whereas those that are acquired for their stand-alone resources are best left autonomous (Datta & Grant, 1990; Pablo, 1994; Zollo & Singh, 2004; Puranam and Srikanth, 2007; Puranam, Singh and Chaudhuri 2009; Zaheer, Castañer and Souder, 2012).

We therefore propose a contingent view of the effect of structural recombination, with its effect on innovation depending upon the extent to which there are untapped knowledge synergies within the firm.
The extent of untapped knowledge synergies within the firm will, in turn, depend upon two factors: the potential for internal knowledge recombination, i.e. the extent to which knowledge within the firm is amenable to being recombined; and the value of internal knowledge recombination, i.e. the extent to which such recombinations are likely to be valuable. In what follows, we discuss these two aspects and their moderating effect on the impact of structural recombination in more detail.

**Potential for internal knowledge recombination**

To begin with, the extent of internal knowledge synergies, and therefore the effect of structural recombination, will depend upon the extent of relatedness between the knowledge resources of the firm. It is only where knowledge resources in different parts of the firm are related that the recombination of these resources will yield valuable synergies. If the distinct knowledge resources of the firm are unrelated to each other, then bringing them together through structural recombination will yield little benefit. Rather, bringing together disparate knowledge may only amplify the disruptive effect of structural recombination (Argote and Ingram, 2000).

The importance of relatedness has its roots in the notion of firms as ‘coherent diversifiers’ (Teece et al., 1994), maximizing the value from internal complementarities by entering into lines of business that are related, in that they share common technological or market characteristics. Studies have shown that firms tend to diversify their technologies in coherent ways, “filling all the possible ‘technological gaps’ between [patent] classes” (Breschi et al., 2003, p.86), and that such coherence has a positive effect on firm innovation performance (Nesta and Saviotti, 2005). In addition, technological relatedness or coherence has been shown to be critical to achieving performance improvement through process management (Benner and Veloso, 2008) and realizing technology synergies from mergers (Cassiman et al., 2005; Makri et al., 2010).

There are several reasons why technological relatedness will enhance the potential for internal knowledge synergy. First, the greater the relatedness between the knowledge resources of the firm, the greater the value of innovation from the recombination of this internal knowledge (Teece et al., 1994;
Argyres, 1996; Cassiman et al., 2005; Benner and Veloso, 2008; Makri et al., 2010). Second, greater relatedness between internal knowledge resources will lower the coordination and communication costs between different units within the firm, enabling them to work together more easily (Tushman, 1978; Teece et al., 1994; Argyres, 1996; Breschi et al., 2003; Nesta and Saviotti, 2005). As several studies have pointed out, intra-firm knowledge sharing is critically dependent on the existence of shared language (Dougherty, 1992), frames (Fiol, 1994), coding schemes (Zander and Kogut, 1995) and mental models (Galunic and Rodan, 1998) within the firm, and greater technological relatedness implies the existence of these common elements linking the knowledge of different units. Third, greater knowledge relatedness may also ameliorate the disruptive effects of structural change. Individuals in related knowledge spaces may already have informal ties from being members of a shared community of practice (Brown and Duguid, 1991), and the formation of new ties may be easier given shared language and understanding.

Relatedness between the firm’s knowledge resources, and the synergy associated with such relatedness, is a necessary but not a sufficient condition for the positive effect of structural recombination on innovation. To the extent that these potential synergies are already being exploited within the existing organizational structure through the sharing of knowledge across internal boundaries, structural recombination may not be required. Instead, as prior literature has suggested, the potential synergies between the firm’s knowledge resources may be realized through knowledge transfers between units (Tsai, 2002; Hansen and Lovas, 2004; Miller et al., 2007). Structural recombination is only likely to have a positive effect on innovation when internal synergies are not being exploited within the existing structure, i.e. the firm has a set of related knowledge resources, but the connections between these resources are not being exploited, possibly because knowledge is unable to transcend internal boundaries. It is in the presence of such unexploited knowledge relatedness that structural recombination can help unlock the potential for internal knowledge recombination by redrawing the boundaries of the firm. Thus,

**Hypothesis 2:** The relationship between structural recombination and innovation will be more positive, the greater the unexploited relatedness between the knowledge resources of the firm.
The firm’s internal knowledge may be more amenable to recombination not only if its knowledge is in related areas, as discussed above, but also if the knowledge itself is capable of being applied more generally. Other things being equal, the more general the firm’s knowledge resources, the wider the range of domains in which they may be useful, and therefore the greater the potential for internal knowledge recombination. If the firm’s knowledge resources are highly specialized to their individual domains, then it may be difficult to recombine them with knowledge resources from other domains, even if the other domains are related. Conversely, if the firm’s knowledge resources are more general, i.e. they are capable of being used more generally than the resources of other firms, then it may be possible to leverage them across even seemingly distant knowledge domains.

The role of knowledge generality has been discussed in the prior literature (Jaffe, Trajtenberg, and Henderson, 1993; Bresnahan and Trajtenberg, 1995) with studies highlighting the role of general purpose technologies in enabling growth (Moser and Nicholas, 2004; Maine and Garnsey, 2006), driving markets for technology (Arora et al., 2001; Gambardella and Giarratana, 2012), and increasing both the impact of a technology and the valuation of the firm that owns it (Lerner, 1994). In particular, greater generality has been linked to the realization of innovation complementarities (Bresnahan and Trajtenberg, 1995) with more general technologies being amenable to recombination across a wider range of domains, thus increasing both the likelihood of successful recombination, and the potential value of such recombinant innovation.

In line with these arguments, we expect that greater generality of firm knowledge will increase the value of internal knowledge synergies. The more general the firm’s knowledge resources, on average, the greater the likelihood that they will be amenable to recombination with other knowledge resources within the firm. Greater potential for recombination will translate into greater internal knowledge synergies, which, in turn, will make structural recombination more valuable. Thus,

Hypothesis 3: The relationship between structural recombination and innovation will be more

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Note that knowledge generality is distinct from the breadth or diversity of firm knowledge (Katila and Ahuja, 2002; Garcia-Vega, 2006) – the former measures how widely a single (average) technology of the firm can be applied, the latter the range of different technologies within the firm.
positive, the greater the generality of the firm's existing knowledge resources.

Value of internal knowledge recombination

While the arguments above focus on the potential for internal knowledge recombination, the extent of internal knowledge synergies may also depend upon the value of the combinations made possible. In particular, the potential for internal knowledge synergies may depend upon the pre-existing quality of the firm’s knowledge resources. The inherent quality of a firm’s knowledge is a critical part of its overall combinative capability (Kogut and Zander, 1992), with technologies that recombine high quality knowledge being more likely to be valuable themselves (Nelson, 1982; Weitzman, 1998). Firms with higher quality knowledge may have a superior understanding of their technology space, which in turn may aid in recombinant search, giving clear direction to their search (Gavetti and Levinthal, 2000; Fleming, 2001), and allowing them to achieve better outcomes in a more efficient manner (Fleming and Sorenson, 2004). Firms with higher quality knowledge may also have superior absorptive capacity (Cohen and Levinthal, 1990), and therefore combinative capability (Van den Bosch et al., 1999), being better able to absorb or engage with technological knowledge from other business units.

Overall, then, we expect the value of internal knowledge complementarity to be greater, the greater the quality of the firm’s existing knowledge resources. To the extent that structural recombination is a means to realizing this complementarity, it follows that the effect of structural recombination on innovation will be strongest for firms with high quality existing knowledge. Thus,

Hypothesis 4: The relationship between structural recombination and innovation will be more positive, the higher the quality of the firm’s existing knowledge resources.

METHODS & MEASURES

Data and Sample

The empirical setting for this study is the medical sector, including its three main industries of medical devices, pharmaceuticals, and healthcare service. Data was gathered from several editions of the
"Medical & Healthcare Marketplace Guide", namely those published in 1978, 1983, 1986, 1989, 1993 and 1997. The guides include information on firms operating in the U.S., and include both domestic and international firms. Information is available on each firm and its business units, along with the reconfiguration history of how units were recombined over time. There is also information at the firm level about performance and degree of diversification (outside of the medical sector). Given the complexity of this information, and the intricacies of mapping business unit evolution, we limit ourselves to a sample of firms whose names start with the letters A, B, or C. This gives us an initial sample of 250 firms that we then track from 1978 to 1997, including 181 medical device firms, 38 healthcare service firms, and 31 pharmaceutical firms. These 250 firms include a total of 866 unique business units over our study period.

The detailed information on firm organization and reconfiguration for these 250 firms is augmented with data on firm technology, by matching firms to patents filed with the USPTO using the NBER patent database (Hall et al., 2001). Patent data has been widely used in the technology literature to measure firm knowledge and innovation (Ahuja and Lampert, 2001; Fleming, 2001; Rosenkopf and Nerkar, 2001; Nerkar, 2003; Miller et al., 2007), and the richness of information available with this data allows us to construct meaningful measures of the firm’s knowledge characteristics as well as a measure of firm innovation overall. Note that the use of patent data also allows us to study innovation at a more granular level than prior work that has examined the effect of structural reconfiguration on firms’ entry into new product markets (Karim, 2009). Patent data are available for all patents granted up to 2006, allowing us to study firm innovation for a significant period of time after the structural recombination in our data.

For this study, since our main construct of interest is structural recombination, we sample on the firms that have multiple business units, are recombination-active, survive for at least two time periods (to include lagged terms), and for which patent data is available. This sampling reduces our sample from 250 firms to 71 firms. Of these remaining 71 firms, within one time period the average amount of

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recombination is 1.26 events. The firms had an average (non-logged actual value) of 14,000 employees and almost $611 million in medical sales.

Measures

**Dependent variable**

Our dependent variable for all hypotheses is firm innovation in a period. The variable ‘Innovation’ is measured as the citation-weighted patent stock of a firm at time ‘t+1’, i.e. one time period (approximately four years) after the structural recombination has been completed. Patents are counted in the year that they are applied for, though only patents that are eventually granted are included in our measure. Following Hall, Jaffe and Trajtenberg (2005) we use an annual discount rate of 15% to create a stock measure of patents. Thus, the value of patent stock in any year is the sum of the number of patents applied for in that year and the stock of patents in the previous year discounted by 15%. Moreover, because patents may vary in their value (Griliches 1990; Trajtenberg 1990; Ahuja and Lampert 2001), we weight each patent by the number of citations it receives from other patents. This is done by first adjusting the citations received by the patent by the average citations received by any patent in that same year and within that same patent class (to account for differences in citation rates across patent classes and cohorts), and then multiplying the patent by this (adjusted) number of citations. The use of citation weights is a common feature in innovation literature, as is the adjustment of citation counts to account for cohort and patent class (Hall et al., 2001; Hall et al., 2005; Kaul, 2012). In addition, weighting patents by citations means that we are closer to measuring the value of the knowledge generated by the firm. Since we observe the change in patent stock, the measure captures how innovative a firm has been during the period, or the extent of new knowledge it has created.

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4 Our analysis uses a lagged panel structure that includes the firm’s patent stock at time ‘t’ as a predictor, so that our analysis essentially predicts the change in patent stock between ‘t’ and ‘t+1’. As discussed below we also use the citation-weighted number of patents applied for between t and t+1 as an alternate dependent variable and find similar results.

5 Throughout this paper, we use four-digit IPC classes as our measure of patent class. To ensure consistency in classification, all patents are assigned based on their 2006 patent classes.
**Independent variables**

Our main independent variable is the extent of firm structural recombination during a period. The variable ‘Recombination’ is a count, for a firm, of the number of events in which a business unit was merged into another business unit (thus losing its original identity) for the lagged time period ‘t-1’ to ‘t’.

We measure the ‘Unexploited relatedness’ between a firm’s technologies in two steps. First, we construct a measure of the overall relatedness of the firm’s knowledge resources, as the average relatedness between each dyad of firm patents, based on the patent classes to which they belong. Relatedness between two patent classes is measured using data from the entire population of USPTO patents, and is calculated as the number of citations between the classes as a proportion of total citations by patents in either class. Mathematically,

$$\text{Knowledge Relatedness} = \frac{\sum p_i p_j r_{ij}}{\sum p_i \cdot \sum p_j} \quad \ldots(1)$$

$p_i$ is the stock of firm patents in patent class $i$

$r_{ij}$ is the relatedness of patent class $i$ and $j$ (from USPTO data)

This measure theoretically varies from 0 to 1, with higher values indicating greater overall relatedness, though in practice its range is more limited, since the relatedness between two patent classes is never 1 (this would require that patents in each class exclusively cite patents in the other class). Our measure is closely related to measures of technological coherence in the literature (Breschi et al., 2003; Nesta and Saviotti, 2005), except that we measure relatedness using the pattern of citations between classes, rather than co-classifications.

The relatedness of the firm’s knowledge resources is then adjusted for the actual sharing of

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6 For robustness, we also include the count of recombinations from ‘t-2’ to ‘t-1’. Results from this analysis (available upon request) shows no evidence of a significant effect of longer lags on innovation. We also find no evidence for a curvilinear effect of structural recombination as suggested by prior work (Karim, 2009), with the inclusion of a square term for recombination having no significant effect.

7 In line with prior literature (Hall et al., 2001; 2005) we use only the first listed patent class of the patent. While this introduces some error in measurement, we believe the extent of the imprecision is small, given the relatively large size of the patent stock of our sample firms (Benner and Waldhofgel, 2008).

8 This operationalization of the knowledge relatedness measure makes use of the fact that, by our definition, the average relatedness of a patent to all other firm patents is the same for all firm patents in a given patent class. Rather than considering each patent individually, therefore, we can simply calculate the average relatedness of each patent class in the firm to every other patent class in the firm.
knowledge between patents within the firm, which is calculated as the ratio of self-citations to total citations by the firm’s patents. This percentage of self-citations is then subtracted from overall relatedness to give our final measure of unexploited relatedness. Thus,

\[ \text{Unexploited Relatedness} = \text{Overall Relatedness} - \% \text{ self-citations} \quad \text{(2)} \]

The intuition is that this measure captures the extent to which the sharing of knowledge between the technologies within the firm falls short of or exceeds the average sharing of knowledge between these technologies in general, based on their patent classes. Thus a positive value of unexploited relatedness means that patents within the firm cite each other less than an average set of patents in the same patent classes (since knowledge relatedness is greater than percentage self-citations), while a negative value suggests that they cite each other more. In theory, this measure could vary from -1 to 1.

The variable ‘Knowledge Generality’ is calculated as the average generality of the firm’s patents, using a measure of generality developed by Jaffe, Trajtenberg and Henderson (1993). The generality of an individual patent is calculated as 1 minus the Herfindahl index of its forward citations by patent class, i.e.

\[ \text{Generality} = 1 - \sum s_i^2 \]

where \( s_i \) is the ratio of citations received by the patent from patent class \( i \) to the total citations received by the patent. This measure takes values from 0 to 1 with higher values indicating that the citations received by the patent are more widely spread across patent classes, i.e. the patent is more general in its use. These patent level generality measures are aggregated to the firm level as the average generality across the stock of the firm’s patents, using the same depreciation rate as the measure of patent stock used as the dependent variable.

The variable ‘Knowledge Quality’ is, for a firm in a given period, the average number of citations it has received per patent, where the number of citations is adjusted for the average citations in the focal patent’s year and patent class. This measure is similar to what others have used in past papers as indication of innovative impact or quality (Fleming 2001; Ahuja and Lampert 2001⁹; Rosenkopf and Nerkar 2001; Nerkar 2003; Miller et al., 2007; Makri et al., 2010), and measures the average quality of

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⁹ Ahuja and Lampert (2001) specifically examined firms’ breakthrough inventions and thus observed the top 1% of an industry’s citation-weighted patents.
the firm’s patents relative to other patents in the same year and patent class. Thus, a knowledge quality measure of ‘1’ means that the firm’s patents are, on average, neither more nor less impactful than the patents of other firms in the same technology areas. Values greater than 1 imply that the firm’s patents are, on average, of higher quality than those of other firms, while a value less than 1 implies that they are of lower quality.

**Control variables**

We include a number of controls. First, because our dependent variable is the change in patent stock, we control for the level of a firm’s patent stock at time ‘t’. This calculation of this measure is described in the dependent variable section above.

Second, we control for firm performance. One concern with our analysis is that the effect of structural recombination may vary with the performance context of the recombination. Specifically, if firms are undertaking structural change as a means of consolidating and streamlining operations in response to poor performance, then we would expect to see lower subsequent innovation than if structural recombination is undertaken in order to pursue new strategic opportunities. We therefore include a control for firm growth, measured as the (winsorized) increase in the firm’s total sales between ‘t-1’ and ‘t’, to account for the confounding effect of firm performance. Results from using a measure of firm growth based on employment rather than sales (available upon request) are similar.

In addition to controlling for growth, we try to account for the performance context of the recombination in two other ways. First, as discussed in the methods section below, we use a two-stage model to account for the endogeneity of the firm’s recombination decision. Second, as a supplementary analysis, we examine the effect of firm performance on the moderating effect of the knowledge characteristics discussed above, by examining the effects of structural recombination in high and low performance firms separately. While we do not define formal hypotheses for this analysis, our expectation is that our hypothesized effects will be stronger in high performance firms than in low performance firms.

Third, we include several firm level controls, drawing upon prior work on the impact of structural recombination (Karim, 2009). ‘Medical Sales’ is the natural log of the monetary sales of the firm (in
thousands), and controls for firm size. ‘% Medical’ is the ratio of the firm’s medical sales to its total sales, and indicates extent of non-diversification (i.e. increasing amounts indicate activity predominantly in the medical sector). ‘Firm age’ is the number of years since the firm was incorporated. ‘Acquired Units’ is a count of the number of acquired business units at the firm; this controls for the level of a firm’s acquisition activity.

Finally, we also include a dummy variable to account for periods in which the firm does not patent at all. One concern with our analysis is that in cases where the firm does not patent, the stock of patents at t+1 is simply a mathematical function of the stock at t, i.e. the change in patent stock is the result of depreciation rather than new innovation by the firm. In a sense, this would tend to bias against our results, since we would not see an improvement in innovation in cases where the firm does not innovate at all. Nevertheless, to ensure that our results are not driven by periods where the firm does not patent, we include a dummy variable that takes the value of 1 if the firm has no patents between t and t+1 and 0 otherwise. For further robustness, we also re-run our models using only the subsample of firm-periods where firms do patent. As reported in the robustness section below, our results continue to hold in this subsample.

*** Table 1 about here ***

Table 1 provides summary statistics and correlations for our sample. While there are several significant correlations, the average VIF across our variables is 1.62 with no VIF being higher than 2.1, suggesting that multicollinearity problems are not severe (Belsley et al., 1980, Belsey 1991).

**Methodology**

Given the panel nature of our data, as well as the continuous nature of our dependent variable, we use fixed effects panel regressions (xtreg in STATA) with fixed effects for both firm and period. Since we are interested in the effect of structural recombination on subsequent innovation, and on the moderating role of pre-recombination knowledge characteristics, we use a lagged structure, predicting change in patent stock between t+1 and t as a function of structural recombination between t-1 and t, and knowledge characteristics at t-1. The basic equation represented by the model is:
Patent Stock \( t+1 \)

\[ = \alpha + \beta_1 \text{Recombination}_{t-1-t} + \beta_2 \text{Recombination}_{t-1-t} \ast \text{Knowledge Characteristics}_{t-1} \]

\[ + \beta_3 \text{Knowledge Characteristics}_{t-1} + \beta_4 \text{Patent Stock}_t + \beta \text{Controls}_t + \gamma_i + \delta_t + \varepsilon \]

\[ \ldots(3) \]

where \( \gamma_i \) is a firm fixed effect, \( \delta_t \) is a period fixed effect, and \( \varepsilon \) is an error term.

*Endogeneity correction*

One issue with this analysis is that our main explanatory variable, structural recombination, may be endogenous. In particular, firms may vary in their propensity to undertake structural recombination depending on the nature of their technological knowledge, as well as the size of their patent stock. To account for this possibility we run a first stage probit regression predicting the likelihood of recombination as a function of firm technology variables and the lagged values of the other controls in our main regression (i.e. their values prior to the structural recombination). Following Heckman (1979) we then calculate the inverse mills ratio from the predicted probability of recombination from this first stage regression, and include it as a control in our main models.

In addition to including all the independent variables from the second stage analysis, we also include a measure for the total number of units in the first stage to act as an instrumental variable. The logic for this instrument is that a firm with greater number of independent units is at greater risk for structural recombination, but that given similar size, similar number of acquired units, and similar knowledge characteristics, firms with more units will not be more or less innovative.

The results for this first stage regression are reported in Table 2. Model 1 shows the regression with all predictors except the instrumental variable, and Model 2 adds the total number of units as a predictor. A comparison of the two models confirms the strength of our instrument with the addition of total units significantly improving the fit of the prediction model (Prob (Chi-sqr) <0.05). Following Larcker and Rusticus (2010) we also test the validity of our instrument by regressing the residuals from our main (second-stage) equation on the instrumental variable. The results of this analysis (available upon request) confirm the validity of our instrument, with total units having an insignificant relation with the second
stage residuals ($F = 0.00$, $\text{Prob} > F = 0.998$).

RESULTS

Table 3 reports our main analysis. Model 1 includes only control variables, and model 2 adds our main independent variable of structural recombination. The coefficient of structural recombination is insignificant, so neither H1a nor H1b is supported.

*** Tables 2 and 3 and Figure 1a and 1b about here ***

Model 3 then examines the moderating effect of unexploited relatedness, by including the interaction between structural recombination and unexploited relatedness$^{10}$. This interaction term enters the model with a positive and marginally significant ($p = 0.053$ in a two-sided test) coefficient. Model 3 thus indicates support for H2; in the presence of unexploited relatedness, structural recombination has a positive effect on innovation. This positive moderating effect is consistent with our arguments for structural recombination being a means for firms to realize internal knowledge synergies that are not being captured through intra-firm transfer.

Model 4 then examines the moderating effect of knowledge generality. While H3 predicted a positive interaction between knowledge generality and structural recombination, the coefficient of the interaction term in Model 4 is insignificant. H3 is therefore not supported.

Next, we turn our attention to knowledge quality. Model 5 shows a positive and significant coefficient for the interaction between knowledge quality and structural recombination, implying that firms with high quality knowledge are likely to benefit from structural recombination, consistent with H4. Model 5 thus provides strong support for the idea that the knowledge recombination enabled by structural recombination will be valuable if the firm has high quality knowledge resources to recombine.

Finally, Model 6 and Model 7 show models with all three interaction terms, Model 6 showing the full set of interactions without the controls, while Model 7 shows the full model. H2 and H4 continue to be supported in these models, with the coefficient of the interaction between recombination and unexploited

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$^{10}$ To alleviate multicollinearity issues, all interactions are mean-centered.
relatedness, which was only marginally significant in Model 3, achieving significance at conventional levels once the moderating effect of knowledge quality is accounted for. The effect of structural recombination is thus seen to be positive for firms with high unexploited relatedness and high quality knowledge resources, but insignificant otherwise.

The moderating effects of unexploited relatedness and knowledge quality are shown graphically in Figures 1a and 1b, which show the predicted effects of structural recombination at the high (upper quartile) and low (lower quartile) levels of the moderating variables, holding all other variables at their sample mean. The predicted values of innovation are based on Model 7. Thus, figure 1a shows that structural recombination has a negligible effect on subsequent innovation for firms with unexploited relatedness at the lower quartile of the distribution, but a strongly positive effect for firms with unexploited relatedness at upper quartile levels. This is consistent with H2. Similarly, consistent with H4, figure 1b shows that structural recombination leaves subsequent innovation unaffected for firms with low quality knowledge, but has a strong positive effect where knowledge quality is high.

Overall, these results highlight the contingent nature of structural recombination on innovation. They show that structural recombination has a positive effect on subsequent innovation where the firm has untapped internal knowledge synergies, i.e. where it has not fully exploited the relatedness between its knowledge resources, and where these resources are of high quality. Where such untapped knowledge synergies are absent, however, structural recombination has little effect on subsequent innovation.

Supplementary Analysis and Robustness

*** Table 4 about here ***

To further confirm and explore these results, we undertake a number of supplementary analyses, which are shown in Table 4. Panel A of Table 4 shows a number of alternate analyses, using different models and samples to ensure that our findings are robust. First, model 8 re-runs our analysis using a flow rather than a stock measure of our dependent variable, measured as the (citation-weighted) number of patents applied for between t and t+1, to confirm that our results are not skewed by our choice of a stock
variable as a dependent variable\textsuperscript{11}. Second, model 9 re-runs model 7 using a dynamic panel model (Arrelano and Bover, 1995; Blundell and Bond, 1998) rather than a fixed effects panel model, to ensure that our results are robust to alternate methods. Third, model 10 re-runs model 7 on the subsample of firms that have at least one patent between \( t \) and \( t+1 \), to ensure that our results are not biased by the inclusion of non-patenting firms. As Table 4 shows, we continue to find support for H2 and H4 across these alternate analyses. To further confirm that our results are not biased by autocorrelation, we run an Arellano Bond test for zero autocorrelation, following the dynamic panel model. Results from this test (available upon request) are unable to reject the hypothesis of no autocorrelation, with \( z \) statistics of 0.37 (\( \text{prob} > z = 0.71 \)) for first-order autocorrelation, and -0.88 (\( \text{prob} > z=0.38 \)) for second-order autocorrelation.

Panel B in Table 4 then undertakes two sets of supplementary analysis to further explore our findings. First, we examine the relationship between unexploited relatedness and knowledge quality. While our results so far show that both unexploited relatedness and knowledge quality positively moderate the impact of structural recombination on subsequent innovation, it is unclear whether they act as complements or as substitutes. In other words, is it sufficient for a firm to have either unexploited relatedness or high knowledge quality, or does it need to have both in order to benefit from structural recombination?

We explore this question in Models 11 and 12 in Table 4, by examining the moderating effect of knowledge quality in subsamples of firms with high (above median) and low (below median) levels of unexploited relatedness respectively. As Table 4 shows, the interaction between knowledge quality and structural recombination is positive and significant in the low unexploited relatedness subsample, but negative and significant in the high unexploited relatedness subsample, with the difference between them being statistically significant. We interpret this to mean that unexploited relatedness and knowledge

\textsuperscript{11} We use a fixed-effects model rather than a count model for three reasons. First, weighting by (class-adjusted) citations means that the flow measure is not an integer count but a continuous variable. Second, interaction terms in non-linear models are difficult to test and interpret (Hoetker, 2007). Third, the median number of patents for firms that did patent in our sample was 19, with a median citation count of 134, so treating our dependent variable as continuous seems like a good approximation.
quality are substitute sources of knowledge synergy, with firms benefiting from structural recombination in the presence of either high knowledge quality or high unexploited relatedness, but not both. Results from splitting the sample on the basis of knowledge quality (available upon request) are similar, showing a positive and significant effect of unexploited relatedness in the low knowledge quality subsample.

In addition to considering the relation between unexploited relatedness and knowledge quality, we also examine the difference in their moderating effect in high and low performance contexts. As discussed briefly above, we expect that the firm’s ability to profit from the realization of internal knowledge synergies following structural recombination will be higher if the structural recombination is undertaken in the context of strong firm performance. High performing firms are likely to have higher levels of organizational slack, which may buffer them from the disruptive consequences of change (Cyert and March, 1963; Bourgeois 1981) and have a positive effect on innovation (Nohria and Gulati, 1996; Chen and Miller, 2007). Structural recombinations undertaken in the context of strong performance are also more likely to be focused on the realization of new opportunities between businesses, and thus more likely to result in successful knowledge recombination. In contrast, structural recombination undertaken by firms that are struggling with performance issues are more likely to be focused on cost-cutting through restructuring and downsizing, and are likely to be associated with limited slack and dysfunctional behavior, which will tend to compromise innovation (Cameron, Whetten and Kim, 1987; Love and Nohria, 2005). We would therefore expect the role of structural recombination in unlocking internal knowledge synergies to be stronger in high performance contexts.

This prediction is tested in models 13 and 14 of Table 4, with performance being measured using a measure of productivity calculated as sales per employee\(^{12}\). Consistent with our expectations, the coefficients of the interaction terms corresponding to H2 and H4 are positive and significant in the strong performance case, but insignificant in the weak performance case, with the difference between the two subsamples being significant in both cases. Therefore, H2 and H4 are supported where structural recombination is undertaken in the context of strong performance, but not when it is undertaken in

\(^{12}\) Results from measuring performance as the sales growth of the firm are similar.
response to weak performance. This supplementary result is only preliminary, given that our measures of firm performance are fairly crude, but it suggests that the use of structural recombination in unlocking internal knowledge synergies may be further contingent upon the firm’s prior performance. It also provides further support for our main argument that structural recombination is a means to unlocking untapped knowledge synergies, with the effect of unrealized coherence and technological impact being strongest precisely where our theory would predict.

**CONCLUSION**

The findings of this study provide strong support for the argument that structural recombination is an important means by which firms realize untapped knowledge synergies within the firm. In cases where such untapped internal synergies exist, i.e. where the firm has high quality knowledge resources and where its knowledge resources are related in unexploited ways, structural recombination has a positive effect on innovation. Where no such untapped synergies exist, structural recombination has an insignificant impact on subsequent innovation. Further, the positive effect of structural recombination on innovation is stronger for firms with strong performance, supporting the idea that structural recombination enables the realization of internal knowledge synergies. Structural recombination is thus seen to play an important role in driving firm innovation, albeit one that is contingent upon the existence of untapped knowledge synergies within the firm.

In highlighting the role of structural recombination in unlocking internal knowledge synergies, our paper contributes to the literature on firm innovation and the KBV (Kogut and Zander, 1992; Grant, 1996a). The KBV sees the integration and recombination of knowledge as a central reason for the existence of firms (Kogut and Zander, 1992; Grant, 1996b), and internal knowledge recombination has been identified as a key source of organizational innovation and competitive advantage (Hargadon and Sutton, 1997; Galunic and Rodan, 1998; Rosenkopf and Nerkar, 2001). While existing work on internal knowledge recombination has focused on the transfer of knowledge across divisional boundaries (Tsai, 2002; Hansen and Lovas, 2004; Miller et al., 2007), the epistemic nature of internal boundaries (Kogut and Zander, 1996; Brown and Duguid, 2001) and the stickiness of firm knowledge (Von Hippel, 1994;
Szulanski, 1996) suggest that inter-unit transfer alone may be insufficient to realize the full potential of knowledge synergies within the firm. In particular, where innovation requires reciprocal interaction across pragmatic and semantic boundaries then knowledge transfer may prove inadequate, and knowledge transformation may be required (Van de Ven et al., 1976; Carlile and Rebentisch, 2003; Carlile, 2004). Our paper suggests that in such cases structural recombination is an important alternate means of enabling knowledge recombination within the firm, redrawing internal boundaries to exploit unrealized relatedness between high quality knowledge resources. The recognition that structural recombination may help unlock internal knowledge synergies has important managerial implications moreover, suggesting that managers may use structural recombination as a means to driving firm innovation, but only where they have high quality knowledge resources that are related in unexploited ways.

In highlighting this alternate means of enabling internal knowledge recombination, the paper also connects to work on structural integration in the post-merger context (Puranam and Srikanth, 2007; Puranam, Singh and Chaudhuri, 2009). In line with this work, our study shows that structural integration plays an important role in enabling the coordination and recombination of knowledge (Puranam, Singh and Chaudhuri, 2009), with such integration being beneficial despite the disruption associated with structural change where the units being recombined have strong existing knowledge (Puranam, Singh and Zollo, 2005) and there is substantial potential for knowledge recombination (Puranam and Srikanth, 2007). Our study complements this work in two ways: first, it develops a detailed theoretical account of the difficulties of inter-unit knowledge transfer that is grounded in the knowledge based view, thus highlighting the need for structural recombination to capture previously unrealized synergies, such as those associated with acquisitions. Second, it empirically demonstrates that structural integration enables knowledge recombination not only in post-merger contexts, but in organizations more generally.

This is not to suggest, of course, that dissolving any and all internal boundaries will be beneficial to firm innovation. Knowledge resources with little or no connection should be housed in separate units, since separating these resources will create sub-communities of embedded knowledge and practice (Brown and Duguid, 1991, 2001; Kogut and Zander, 1992; Karim, 2012) and maximize the depth of
innovation (Argyres and Silverman, 2004). Our arguments suggest, and our results show, that structural recombination is only beneficial where potential but unexploited knowledge synergies exist within the firm. Nor is it our contention that structural recombination should replace inter-unit transfer as a means of realizing internal knowledge synergies. Rather, in line with models of punctuated equilibrium (Romanelli and Tushman, 1994) and organizational balance (Cardinal, Sitkin and Long, 2004), we see structural recombination as a complement to inter-unit knowledge sharing, with regular transfers across intra-organizational boundaries being supplemented by occasional redrawning of boundaries to enable more radical internal knowledge recombinations in the face of changing environmental conditions.

In addition to contributing to the literature on innovation and the knowledge based view, the paper also contributes to the literature on dynamic capabilities in general, and structural change in particular. In line with work in the dynamic capabilities tradition, our paper argues and finds evidence for the role of internal reconfiguration in enabling organizations to develop new capabilities and adapt to changing conditions (Garud and Nayyar, 1994; Capron et al., 1997; Brown and Eisenhardt, 1999; Galunic and Eisenhardt, 2001; Karim and Mitchell, 2004). More specifically, the paper sheds new light on the consequences of changes in organizational structure. While prior work on organizational restructuring has generally emphasized the negative and disruptive effects of structural change (Bowman et al., 1999; McKinley and Scherer, 2000), our study offers a more positive view, arguing that under the right circumstances disruption may have a beneficial effect (Amburgey, Kelley and Barnett, 1993; Zellmer-Bruhn, 2003). In particular, our study joins Karim (2009) in being among the first to examine the effect of structural recombination on innovation. Our work differs from Karim’s (2009) study, however, both because she focuses on the disruptive effects of recombination while we emphasize its potential to unlock knowledge synergies, and because, in contrast to her paper, we take a contingent perspective on structural recombination, moving beyond the average effect of structural recombination to consider the conditions under which such recombination is more or less beneficial. As such, our study provides a more nuanced

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13 Karim (2009) measures innovation as entry into new product lines, a measure that is both less granular and conceptually distinct from the patent based measures used in our study.
perspective on the effects of structural recombination on innovation.

Our study could be improved in several ways. Though our two-stage empirical approach partially controls for the endogeneity of the structural recombination decision, we cannot entirely account for the intent behind the recombination. Controlling for the intent behind different recombinations would certainly be useful, though it’s difficult to know how intent could be measured in this context. In addition, though we are interested in the recombination of specific business units, our analysis is at the firm level, due to the difficulty of assigning both patent and financial data to individual units. Our study is also limited in that we have no information on the structure of R&D within the firm, and therefore cannot control for the role of a centralized R&D unit in realizing internal knowledge synergies (Cardinal and Opler, 1995). While this is certainly an important alternative, it is worth noting that such centralization is not without its difficulties – separating R&D from downstream activities may compromise the firm’s ability to translate new technologies into marketable products (Cardinal and Hatfield, 2000), and may also reduce knowledge sharing between units (Tsai, 2002). Even if it were the case that firms had fully centralized their R&D, moreover, this would only bias against our results, since firms where all knowledge was centralized would see little or no gains from the recombination of business units. A final limitation of the study is that our sample is restricted to 71 firms due to the intricate mapping required to trace the evolution of firms’ business units; a larger sample would serve as a good robustness check of our results.

In summary, our study highlights the role of structural recombination in unlocking the potential for knowledge recombination within the firm. We show that firms with high quality knowledge resources that are related in unexploited ways see an improvement in firm innovation following structural recombination. Structural recombination is thus seen as a means of realizing knowledge synergies within the firm, one that complements the more traditional sharing of knowledge across internal boundaries. The study thus contributes to the literature on firm innovation and the knowledge based view, highlighting an alternate means of recombining knowledge within the firm, as well as to work on organizational and structural change, taking a contingent view of the effects of structural recombination on innovation.
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### Table 1
**Summary Statistics & Correlation Matrix**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Patent Stock (citation-weighted)</td>
<td>186.44</td>
<td>451.48</td>
<td>0.05</td>
<td>2099.68</td>
<td>1.00</td>
<td></td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>2 Recombination (t-1)</td>
<td>1.26</td>
<td>3.43</td>
<td>0.00</td>
<td>26.00</td>
<td>0.37</td>
<td>1.00</td>
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<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>3 Unexploited relatedness</td>
<td>0.12</td>
<td>0.24</td>
<td>-0.43</td>
<td>0.70</td>
<td>-0.55</td>
<td>-0.29</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>4 Knowledge generality</td>
<td>0.47</td>
<td>0.16</td>
<td>0.00</td>
<td>0.81</td>
<td>0.04</td>
<td>-0.01</td>
<td>-0.21</td>
<td>1.00</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>5 Knowledge quality</td>
<td>1.09</td>
<td>0.55</td>
<td>0.11</td>
<td>3.17</td>
<td>-0.11</td>
<td>-0.07</td>
<td>-0.06</td>
<td>0.36</td>
<td>1.00</td>
<td></td>
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<td></td>
<td></td>
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<tr>
<td>6 Medical sales</td>
<td>10.48</td>
<td>2.60</td>
<td>6.21</td>
<td>16.02</td>
<td>0.48</td>
<td>0.44</td>
<td>-0.49</td>
<td>0.00</td>
<td>-0.11</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7 % Medical</td>
<td>0.70</td>
<td>0.37</td>
<td>0.00</td>
<td>1.00</td>
<td>-0.45</td>
<td>-0.25</td>
<td>0.46</td>
<td>0.03</td>
<td>0.18</td>
<td>-0.23</td>
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Random-effects probit model. Dependent variable is dummy variable that takes the value 1 if the firm undertook any structural recombination between t and t+1, 0 otherwise. Independent variables are measured at t, except recombination lag, which is measured between t-1 and t. Model includes constant term. Figures in parentheses are robust standard errors. Significance level (two-sided): † <10%, *<5%, **<1%, ***<0.1%
Table 3
Main Results

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Dependent variable is patent stock at t+1. All models include firm and period fixed effects, as well as a constant term. Figures in parentheses are robust standard errors. All models have Prob>F less than 0.1%.
Significance level (two-sided): † <10%, *<5%, **<1%, ***<0.1%
### Table 4
Robustness and Supplementary analyses

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Dependent variable is patent stock at t+1, except in model 8, where it is (citation-weighted) patents between t and t+1. All models show fixed effect panel regressions, except for model 9, which is a system dynamic panel model (xtkdpsys in STATA). ‘High’ and ‘Low’ refer to values above and below the sample median respectively. All models include a constant term. Figures in parentheses are robust standard errors. Significance level (two-sided): † <10%, *<5%, **<1%, ***<0.1%
Figures are based on model 7 in Table 2. Figures show change in patent stock based on predicted values when all other variables are held at their sample means. High and low values refer to upper quartile and lower quartile values respectively.