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Task co-use and product improvement: An organization design perspective

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Abstract

Research Summary: Co-using tasks—using the same task to produce more than one product—promises economies of scope. However, task co-use also ties products together, changing a firm's task network by introducing cross-product interdependencies. In light of these interdependencies, we identify an unrecognized downside of task co-use for product reliability: Cross-product interdependencies complicate task design and increase the risk of malfunctions. Hence, task co-use may carry a reliability penalty. Second, we propose that the reliability penalty of task co-use may shrink with experience as cross-product interdependencies allow for cross-improvements and therefore potentially higher improvement rates of task co-using products. We study the US automotive industry and find our predictions supported, indicating that task co-use is a critical design parameter with important consequences for reliability and product improvement.

Managerial Summary: Using the same tasks to produce multiple products can help firms lower costs and achieve economies of scope. However, this practice also links products more tightly together, creating interdependencies across product lines. These interdependencies can make tasks harder to design and manage, increasing the likelihood of errors or malfunctions. As a result, task co-use may reduce product reliability—an important but often overlooked drawback. At the same time, co-used tasks can enable portfolio-wide improvements— improvements across products. As firms gain experience, problems identified in one product can lead to improvements that benefit others using the same tasks. Over time, these cross-improvements accelerate product improvement for task co-using products and can reduce the initial reliability disadvantage. Evidence from the U.S. automotive industry supports these arguments. The findings show that task co-use is a key design decision that involves meaningful trade-offs between cost savings, reliability, and improvement. For managers, this highlights the importance of carefully evaluating when and how tasks should be co-used across products, as these choices have lasting implications for product quality and improvement.

KEYWORDS

automotive industry, failure, multiproduct firms, organization design, task co-use

1 | INTRODUCTION

A key role of firms is to organize complex tasks—such as the production of an airplane—into subtasks and manage the resulting task network (Puranam, 2018; Puranam et al., 2012; Thompson, 1967). Tasks are activities that transform inputs into outputs (Baldwin, 2024; Puranam et al., 2012). Configuring tasks takes time and money (Amit & Schoemaker, 1993; Dierickx & Cool, 1989), making it attractive to leverage tasks—once configured—as much as possible. Multi-product firms can do so by co-using a task, that is, using the same task in two or more products. Firms can co-use operationally simple tasks like making the same sauce for different restaurant dishes, but also highly complex ones like using the same extreme ultraviolet lithography technology for different microchips. The benefits from task co-use are intuitive: Task co-use lets firms use fewer resources to design and produce an output and creates scope economies (Montgomery, 1994; Panzar & Willig, 1981) that are generally considered a key motivation for corporate diversification (Folta et al., 2016; Helfat & Eisenhardt, 2004).

However, for organization designers, task co-use is interesting because it changes a firm's task network, introducing cross-product interdependencies. Due to these interdependencies, task co-use may come with unrecognized costs: cross-product interdependencies make designing a reliable task configuration more difficult. Co-used tasks must be functional across all products, which complicates the interdependencies to be considered and reduces the degrees of freedom in configuring tasks (Fisher et al., 1999; Krishnan and Gupta, 2001, Ramdas, 2003). Co-use foregoes the opportunity to tailor tasks to a single product, which may result in less internally consistent outputs—that is, products that are more susceptible to malfunctions and defects. In short, task co-use may come with a reliability penalty. In this paper, we examine this potential consequence for reliability by first asking: *Does task co-use (on average) come at the expense of product reliability?* Second, we take into account that the reliability penalty of task co-use can shrink with experience. Reliability can improve as reliability issues—that is, defects—surface and firms discover remedies to problematic task configurations. While all products improve with defect experience, task co-using products are exposed to their own and co-using products' remedies due to their cross-product interdependencies. Because of the interdependencies introduced by task co-use, improvements in one product may "travel" from one product to another and cross-improve products. Hence, we further ask: *Do task co-using products benefit from cross-improving reliability?*

We address these questions in the US automotive industry from 2006 to 2015. Cars are a complex product, and the co-use of interdependent tasks is common (MacDuffie, 2013). While tasks—that is, actions—are hard to observe, completed tasks produce an output that allows us to empirically infer task co-use from its outputs: when two or more vehicles employ the same component, we assume the underlying task of designing and producing the component is co-used. We indeed find that products co-using tasks are initially less reliable than those that do not task co-use, but task co-using products recover reliability through cross-improvement; co-using products become more reliable as a result of defects that did not affect their own functioning but the functioning of other, co-using products.

We make three main contributions: First, we add to the organization design literature (Baldwin & Clark, 2000; Puranam et al., 2012; Raveendran et al., 2020) by identifying task co-use as a relevant design parameter and developing a theoretical framework on how task co-use can affect the reliability and adaptation patterns of end products. Including task co-use in theories on the performance of task structures is a step toward integrating the scope of firms in task design. Second, by linking research on organization design with research on scope in corporate strategy (Folta et al., 2016; Helfat & Eisenhardt, 2004; Levinthal & Wu, 2010), we expand prior work by shifting to a (more) micro perspective on scope. Although it is known that scope-related gains of diversification can fall short due to coordination costs (Brahm et al., 2017; Hashai, 2015; Rawley, 2010; Zhou, 2011), prior work on scope considers interdependencies and the resulting coordination costs as exogenous, built-in features of industries, firms, or products. We highlight that interdependencies can be designed by co-using interdependent tasks and managed as firms recover—at least parts of—the initial reliability penalty with experience. Hence, an important implication is that the time horizon under consideration matters: In the short run, reliability is likely to be negatively affected by task co-use, while (some of) this disadvantage may subside with experience and cross-improvements. Finally, we complement prior research on organizational adaptation, particularly on how interdependencies influence adaptation and search (Ethiraj & Levinthal, 2004; Siggelkow & Levinthal, 2003; Sorenson, 2003). By introducing task co-use, we highlight the fact that adaptation patterns of single-product or -business firms may differ from those of multi-product and -business firms.

2 | THEORETICAL BACKGROUND

2.1 | Task co-use

Task co-use refers to using a task in two or more products. A task is the basic unit of any design or production process: an action, choice, or technology that transforms inputs into outputs

(Puranam et al., 2012, p. 421), such as the task of making a product component. Many tasks are time-consuming and costly to configure (Karim et al., 2023) such as figuring out the necessary actions and technology to make a product component: it takes around 18 months to develop an advanced computer chip, several years for medical and automobile components, and up to 30 years for a new type of aircraft engine such as the turbofan with costs summing up to hundreds of millions US dollars (Bailey, 2023; Coy, 2015; Van Norman, 2016). With the initial task configuration being costly, it is attractive to use a once-configured task more than once. Especially, multi-product firms can use the same task for different products (or areas) and realize economies of scope (Panzar & Willig, 1981).

Co-use refers to using a task in two or more products that are marketed—that is, designed and produced—*contemporaneously*, that is, leveraging intra-temporal economies of scope (Helfat & Eisenhardt, 2004) as opposed to re-using or redeploying a task and inter-temporal economies of scope that refer to moving a task from one product to another *over time*. Because tasks transform inputs into outputs, products that co-use the same task also share the task output: for example, they contain the same product component.[1]

Co-use is a common practice across industries: restaurants co-use the same sauce for several dishes—co-using the "sauce-making task,"[2] video game developers increasingly co-use the same middleware components across games, such as game engines—co-using the respective "coding tasks" (Miric et al., 2023); and task co-use is common in manufacturing: car, airplane, and white goods manufacturers co-use the same vehicle, airplane, or microwave components across different products—co-using the "component-development task" (Ramdas et al., 2003; Reuters, 2015). Tasks are "fractal": larger tasks typically consist of a set of smaller tasks (Baldwin & Clark, 2000), that is, making a component is a subtask to the larger task of making a product. For our purposes, the tasks we study must affect product reliability, be sufficiently costly to design and set up to make task co-use economically attractive, while being flexible enough to make task co-use a managerial choice.

Tasks and their structure are critical to the functioning of the overall solution—both its baseline reliability (Brusoni et al., 2007; Englmaier et al., 2018; Raveendran et al., 2016) and the adaptive improvement of that reliability with experience (Brusoni et al., 2007; Ethiraj & Levinthal, 2004; Siggelkow & Levinthal, 2003).

2.2 | Reliability and (cross-)improvement

Product reliability is the lower bound of product quality: whether a product functions as intended without unplanned malfunctions or product failures (Gao et al., 2021; Guajardo et al., 2012). It mirrors the minimum product qualities expected of firms to participate in the market—for example, if a medicine lowers symptoms or a microwave heats food without unacceptable side effects—linking it closely to product performance (Chen & Nguyen, 2013). Besides the time and cost needed to remedy malfunctions, sales typically stall once consumers learn

[1]We use this property for the empirical identification of tasks. A completed task includes inputs, action, and outputs. While the action—that is, task—itself is hard to observe, task outputs (and most inputs) are observable. Hence, empirically we make the necessary assumption that tasks with the same task output also use the same action and inputs in the making of the outcome. Firms concerned with efficiency will follow this logic to avoid unnecessary duplication of effort.

[2]Indeed, several chain restaurants use dipping sauces to accompany different dishes to increase the variety of flavors (and therefore dishes) at low cost (Brandau, 2012).

that a product fails to deliver its intended use. If a malfunction endangers customer health or safety, firms also face legal liability and the prospect of highly publicized scandals that can tarnish their reputation, risking long-term performance consequences (Freedman et al., 2012; Liu et al., 2017; Rhee & Haunschild, 2006). For example, the airplane manufacturer Boeing struggled with faulty flight-control components for their 737 MAX plane in 2019, leading to accidents and grounded flights. Even now, Boeing faces persistent customer wariness and sizable financial losses (Leggett, 2024).

Task structure can be an important driver of product reliability. Task structures can lock firms into suboptimal solutions for end products (Brusoni et al., 2007) and slow down the development of a reliable solution (Raveendran et al., 2016). Multi-product firms can importantly differ in their task structure with respect to their task co-use across products, which in turn can result in differences in reliability and its improvement.

Product reliability is rarely stable throughout a product's lifecycle. Notably, reliability problems—that is, defects—are typically more frequent in new products (Levitt et al., 2013) and in R&D-intensive firms (Thirumalai & Sinha, 2011). Over time, as defects surface, firms identify potential reliability issues, develop remedies, and improve reliability. In multi-product firms, a defect can force improvement of the products affected by it, but it can also cross-improve other products. *Cross-improvement* occurs if a defect in one product leads to improvements in another product in a firm's portfolio that has not been hit by the initial defect. Both reliability as such and improvement patterns may be affected by a firm's task structure and, in particular, task co-use.

2.3 | Reliability penalty for task co-using products

Task co-use creates new interdependencies between contemporaneous products because co-used tasks often interact with other tasks necessary to complete a product unless a firm manages to perfectly decouple or modularize a co-used task from other tasks—a worthy goal that is difficult to achieve in practice (MacDuffie, 2013). By way of an illustration, consider a *task y*, a subtask in the making of Product A, where it interacts with a set of surrounding *tasks x*. If this *task y* is now co-used in Product B—where it interacts with a different set of *tasks z*—the co-use of *y* connects Product A and B's task structures and indirectly links *tasks x* and *z* that surround the co-used *task y* (see Figure 1). The more a co-used task interacts with others in the task structure, that is, the less decoupled it is, the stronger the newly created interdependency.

Task interdependencies can take different forms and can, for instance, be sequential, reciprocal, or pooled (Puranam et al., 2012; Thompson, 1967). Interdependencies may arise from joint dependence on the same constrained inputs (Obel & Burton, 1984) as well as from task outputs (Milgrom & Roberts, 1995). For instance, a task may only be completed while another task is not using the input; outputs of some tasks may be inputs of other tasks; or outputs may need properties that align with properties of another task's outputs—such as the design of two product components that need to align in size and performance properties. For our purposes, what matters is that co-used tasks have some sort of interdependence with other tasks, but we remain agnostic about the specific type of interdependence.

Co-using imperfectly decoupled tasks introduces additional, cross-product interdependencies. These interdependencies can lower product reliability across the set of co-using products. Because the task must perform reliably in every product, designers must account for product-specific as well as cross-product interdependencies: specifications working for one

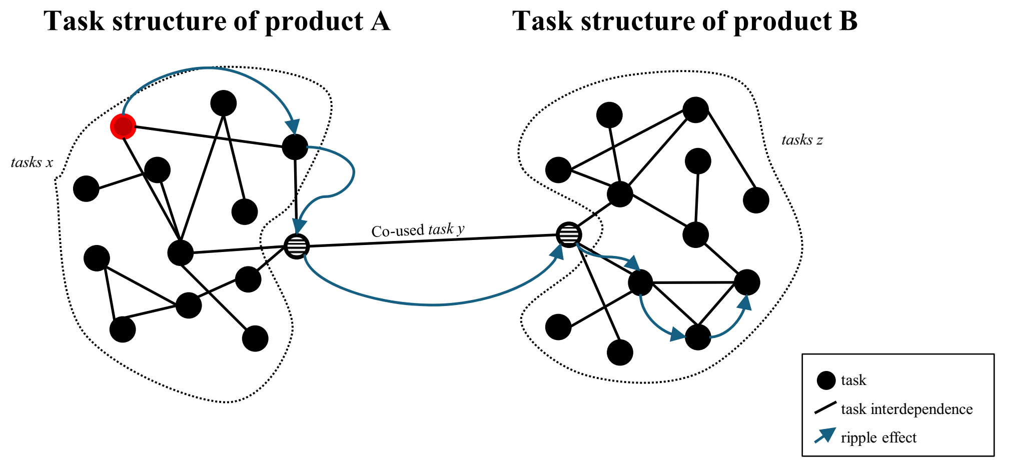


FIGURE 1 Illustration of two products A and B co-using task *y* and the resulting task structure with potential cross-improvement effects.

product may not work for another co-using product. This complicates the web of interdependencies to consider and reduces the degrees of freedom in task configuration. While for a single-used task *y*1, the only interdependencies to consider are those with Product A's other tasks *x*, for a co-used task *y*2, any configuration needs to consider interdependencies both with Product A's other tasks *x* and Product B's other tasks *z*. Complexity increases with the number of interdependent product-specific tasks *x* and *z* and each additional co-using product (e.g., an additional Product C and its tasks *w*), while complexity decreases when firms can successfully standardize the interfaces of co-used tasks across products, creating "thin" crossing points (Baldwin, 2008) that minimize interdependencies with other tasks. Although such perfect modularity is theoretically desirable, firms across many industries often struggle to fully decouple tasks (Schilling, 2000; Simon, 1981). For instance, despite extensive efforts, automobile manufacturers have not achieved full modularization in vehicle design (MacDuffie, 2013), and similar attempts in airplane manufacturing have also met with limited success (Allworth, 2013; Kotha & Srikanth, 2013). At least temporarily, most industries likely face significant task interdependencies, as modularization typically involves a lengthy learning process (MacDuffie, 2013). Early on, industries often have high levels of unstandardized task interdependencies, as has been the case in the computer industry, which only gradually settled on effective modular designs (MacDuffie, 2013; Sanchez & Mahoney, 1996).

As long as a co-used task is not perfectly decoupled from other tasks via standardized interfaces, task co-use makes finding the right task configuration more difficult. A more complicated web of interdependencies and fewer degrees of freedom in task configuration both increase the time and cost associated with configuring co-used tasks: each solution needs to be tested across a wider web of interdependencies, while the set of possible solutions is smaller. Time and cost can increase exponentially as interdependencies are hard to detect and substantial experimentation and product understanding is needed to understand task interdependencies (Baldwin & Clark, 2000), especially for complex products built with a portfolio of inputs with different properties and cross-dimensional task output interactions that can be geographical, time, functional, thermal, organizational and more. In complex products, it may even be impossible to identify certain design interdependencies ex-ante (Ziegler, 2005); some interdependencies only become apparent in the finished product, as observed in the noise and vibration characteristics of mechanical systems (MacDuffie, 2013; Whitney, 2004). The higher time and cost requirements associated with configuring co-used tasks increase the probability of compromises and overlooked interdependencies. Both can interfere with the functioning of the co-used or other interdependent tasks and thereby lower product reliability. While not all interference affects overall product quality in a significant way, noise in the functioning of the co-used and surrounding tasks increases the likelihood of reliability issues of task co-using products. Beyond the frequency of issues, co-use additionally risks joint malfunctions of co-using products increasing the costs of malfunctions.

Compromises with potential effects on reliability may be necessary for co-used tasks even if firms spend the additional time and costs to uncover and consider all dependencies under task co-use. With all interdependencies being considered, co-use continues to constrain the degrees of freedom in design: a task cannot be tailored to the unique needs of any specific product, but is to be optimized for functioning in all products. Research in engineering indicates that tasks tailored to one specific product may result in higher quality because components can be optimized to the unique needs of a product (Fisher et al., 1999), a level of "product integrity" and optimization that cannot be reached for co-used tasks (Clark & Fujimoto, 1990). Taken together, task co-use may hence be associated with a lower reliability of the resulting product and we formalize the hypothesis as:

Hypothesis H1. *Task co-use is associated with lower product reliability.*

2.4 | Cross-improvement for task co-use products

So far, we outlined that task co-use may be associated with lower product reliability because co-use complicates the web of task interdependencies, increasing the likelihood of compromises and overlooked interdependencies. Part of this reliability penalty may be driven by time constraints that limit the possibility of building knowledge about all interdependencies at the point of task configuration. Over time, however, firms may become aware of overlooked issues so that reliability improves with this experience. As firms experience defects in past versions of a product and understand the fuller spectrum of interdependencies, they can use this understanding to develop remedies and avoid defects in future versions of the product. Remedies are improved task configurations that are robust to the interdependencies involved.[3]

A product's reliability can improve with the remedy of its own prior defects: a product is affected by a reliability issue that is solved, resulting in an improved product afterwards. This dynamic holds equally for task co-using and non-task-co-using products. In multi-product firms, however, a defect can also trigger the cross-improvement of other products—products that were not affected by the initial defect. Prior defects in other products may contain general information that can help improve reliability irrespective of task co-use—after a defect in one product, firms may, for instance, implement better test procedures for the respective task for their entire portfolio. Cross-improvement, however, may occur more often for task co-using products than for non-task-co-using products.

[3]Firms can also reduce interdependencies at task interfaces, that is, modularize tasks (Baldwin & Clark, 2000). This, however, involves a full task re-configuration or -shuffling, so that firms restart at a—hopefully improved—experience curve.

Cross-improvement can be fueled by the interdependencies created by task co-use. Consider again the two Products A and B that co-use *task y*. In Product A, the co-used *task y* interacts with *tasks x*; hence any defect resolution of Product A's *tasks x* requires firms to re-evaluate how those adjustments interact with *y*. Any insights about *task y* and its interdependencies help improve Product A, and—because *y* is co-used—also improve *task y* and knowledge about its potential interdependencies in B. A defect resolution in Product A's surrounding *tasks x* can even trigger cross-improvement beyond the co-used task and improve surrounding *tasks z* in a co-using Product B: for any potential adaptation in the co-used *task y* after a defect in Product A's *tasks x*, firms must re-evaluate how adjustments of *y* interact with Product B's surrounding *tasks z*, potentially leading to improvements in *tasks z* as well.

The effect is triggered by *prior* defects and their correction in other products. Although this implies that the dynamic unfolds over time—prior defects can only exist if there is a past—our argument is not that the dynamic benefit of task co-use is driven by time or the accumulation of design and production experience in and of themselves. Rather, it is that task co-using products are more likely to cross-improve: an improvement in one product (after a defect) is more likely to trigger an adaptation in task co-using products than non-task-co-using products. In line with prior work showing that task structures can affect adaptation (Brusoni et al., 2007; Chen et al., 2019; Siggelkow & Levinthal, 2003), cross-improvement occurs because task co-use links products' task structure. A "one-product problem" can become a "whole-portfolio upgrade" especially for task co-using products, increasing the rate of improvement for co-using products. We summarize these arguments in two connected hypotheses.

Hypothesis H2a. *Prior defects of other products improve the focal product.*

Hypothesis H2b. *The improvement due to defects of other products is stronger if the products co-use tasks.*

3 | EMPIRICAL CONTEXT

We test our arguments in the automobile industry, in which most firms are multi-product firms, selling more than one car model. This creates potential for task co-use across products with attractive cost savings. In 2015, Toyota, for instance, estimated that increasing co-use with its new TNGA vehicle platform would cut development costs by 20% and reduce parts costs by $1000 per vehicle (Inagaki, 2015). However, cars are complex technical products and task interdependencies in their making are the norm (Pillai et al., 2020). Task interdependencies remained tenaciously relevant in the automotive industry despite substantial efforts to modularize vehicle design: inspired by the success of modular structures—with reduced or standardized interfaces—in the computer industry (Baldwin & Clark, 2000), the automobile industry worked for years to achieve such structures until eventually abandoning the intention—and hope—to achieve truly modular products in the early 2000s (Jacobides et al., 2016; MacDuffie, 2013). Major manufacturers such as Ford admitted that they struggled to understand the interdependencies between major components well enough to achieve a modular design: "I'm not sure we have the systems engineering capabilities to design a module. When you're designing a whole set of components brought together in a module, you need to understand every interface deeply." (MacDuffie, 2013, p. 23). Full modularization was impossible—at least based on manufacturers' current design capabilities, and task interdependencies persist in vehicle design and production (MacDuffie, 2013).

Task interdependencies also persisted amidst increased outsourcing in the automotive industry. Large, interdependent tasks were only outsourced to suppliers with whom manufacturers maintained close ties—often spin-outs of the original manufacturer, maintaining a large number of former employees or suppliers situated close to a manufacturer in the manufacturer's "supplier park" (Sako, 2009). Hence, "far from a reduced amount of coordination between OEM and supplier, collaboration [...] has intensified over time. Module designs remain closed, proprietary, and customized by model" in the automotive industry (MacDuffie, 2013, p. 29). Even the definitions-in-use of modularity in the automotive sector differ in some points from the academic literature and its usage in other sectors (Jacobides et al., 2016) as the industry's definition allows for interdependencies between modules (MacDuffie, 2013).[4] Interdependencies persist, even for components that appear fully modular to the layperson, such as engine oil: engine oil often is specific to engines in terms of its viscosity, temperature behavior and compatibility with sealing materials (Nehrkorn, 2025).

Empirically, tasks and therefore task co-use and interdependencies are notoriously hard to measure. However, while the action—that is, task—itself is difficult to observe, task outputs (and most inputs) are observable. Products that use the same component—a task output—are likely to co-use the task of making the component as well, a property that we use empirically: we approximate the co-use of a component-making task by the co-use of the resulting component. Although an approximation, firms concerned about efficiency will strive to comply with this assumption and avoid unnecessary duplication of efforts.

We proxy task co-use with the co-use of a rather large component: cars' co-use of their vehicle platform. A vehicle platform broadly refers to a car's platform chassis: historically a body-on-frame assembly and roughly the sheet-metal plate—and therefore originally termed platform—that carries the rest of a car's components (Setright, 1977). In modern cars, the concept of a sheet-metal plate carrying major car parts has been extended, and a vehicle platform refers to the "large base component" of a car that now already comprises several smaller components—such as the underbody (front floor, underfloor, engine compartment, frame) as well as the suspensions with axles (Muffatto, 1999). The platform is a core component that determines large parts of a car's architecture—the arrangement of functional elements, mapping of functional elements to physical components, and the specification of the interfaces between interacting physical components (Ulrich, 1995). However, although the vehicle platform is used as the stable core component of cars with to some extent variable peripheral components—analogous to platforms in truly modular architectures (Baldwin & Woodard, 2009)—unlike those ideal platforms, vehicle platforms remained proprietary with only some of their numerous interdependencies standardized and selectively shared with suppliers (Gawer, 2014; Sako, 2009). Vehicle platforms are not an open industry standard as the term "platform" might suggest, and not fully modularized: Engineers at Hyundai and its main supplier, for instance, explain that "We (Hyundai/Mobis) can't address NVH [noise-vibration-harshness] issues within chassis alone: it is tied to many other aspects of product design. When we have NVH issues, Hyundai and Mobis engineers meet frequently to resolve them" (MacDuffie, 2013, p. 28). The task of making a vehicle platform is interdependent with other vehicle-making tasks—aligning the empirical context with our theoretical argument.

[4]The industry's definition of a module is "a large chunk of physically adjacent components produced as a subassembly" (MacDuffie, 2013, p. 14).

TABLE 1 Descriptive statistics.

	Mean	SD	p50	Min	Max
Reliability complaints	205.3	374.9	69.0	0.0	4501.0
Task co-use	1.0	1.2	1.0	0.0	5.0
Prior defects of other, task co-using products	2.8	4.1	1.0	0.0	38.0
Prior defects of other, non-co-using products	23.3	22.6	15.0	0.0	117.0
Product age	3.5	3.2	3.0	0.0	25.0
Production experience (in 1000)	938.6	1442.7	402.3	0.0	12,266.1
Prior product-specific defects	1.4	3.1	1.0	0.0	73.0
Prior co-shared defects	1.0	1.5	0.0	0.0	11.0
Previous product generations	1.8	2.2	1.0	0.0	12.0
Sales volume (in 1000)	67.1	87.9	36.1	0.1	764.5
Price (in 1000US$)	33.9	21.5	27.8	10.0	376.5
Luxury segment	0.4	0.5	0.0	0.0	1.0
Share of voluntary recalls	0.6	0.4	0.9	0.0	1.0
Share of supplier involvement	0.3	0.4	0.3	0.0	1.0
Age of the co-used task	4.7	3.0	4.0	0.0	13.0
Tailored task	0.7	0.5	1.0	0.0	1.0
Production task co-use	2.8	3.9	1.0	0.0	30.0
No. of products	9.9	5.0	9.0	1.0	20.0
Newly launched products	1.2	1.1	1.0	0.0	6.0
No. of plants	15.1	11.4	13.0	1.0	42.0
No. of platforms	6.4	3.2	6.0	1.0	14.0
Total production volume (in 100,000)	14.6	13.0	11.0	0.1	48.9

Note: $N = 1676$.

Vehicle platform co-use varies over cars of the same manufacturer: while some products co-use their platform, others do not. In our sample, 54% of products co-use while 46% do not (see Table 1 for details). A side property of platform co-use, and task co-use in general, is that task co-use makes products more similar—that is, it correlates with product standardization.[5] The higher the number of distinct tasks co-used between two products, the more standardized those two products generally become. An important conceptual difference between task co-use and product standardization, however, is that the proposed effects on reliability build on how much co-used tasks are interdependent with other tasks as opposed to being fueled by the degree of standardization (how many distinct tasks are co-used) per se.[6] Standardization also differs from the scope of task co-use, that is how many distinct products co-use a task.

[5]We think of product standardization as offering the same product across different markets and customers and as the opposite of customization.

[6]In theory, we could imagine two highly standardized Products A and B that co-use a high number of tasks, but the tasks are perfectly decoupled from the rest of the products' tasks. Products A and B would be free of the effects on reliability we propose, even though they are highly standardized.

In line with our arguments, anecdotal evidence from the industry suggests that vehicle platform co-use and hence the co-use of the associated task of making the platform indeed holds a trade-off for firms: while cost savings amount to attractive 20% (Dalroad, 2023; Inagaki, 2015), platform co-use is also associated with reduced reliability because of interdependencies that raise complexity and require compromises. For instance, by co-using its MQB platform for combustion engine and electric vehicles for several years, Volkswagen could only fit a T-shaped battery pack between the axles (Belingardi & Scattina, 2023). This raised complexity and reliability concerns about extra cooling: the traction inverter, DC-DC unit and charger had to be bolted where there was space—often in the nose where heat and vibration are higher. Over time, that placement was associated with coolant leakages and electronic failures (myVW, 2018). Co-used platforms often work reliably in some vehicles with interdependency-related issues surfacing in other co-using vehicles, such as Ford's D4 platform that worked well with the Ford Flex but experienced suspension problems in Explorer cars: the cross-axis ball joint connecting platform and suspension system suffered from fractures in combination with other Explorer specifications (NHTSA, 2019; Shepardson, 2021). Over the history of the industry, firms have been especially prone to missing interdependencies and face reliability issues when introducing platform co-using products under time pressure: GM, for instance, experienced numerous reliability issues related to their first front-wheel-drive platform in 1980—from early rust problems due to different water entry points in different vehicles, to loosening interior trims, and unreliable transmissions (Hunting, 2019). More recently, in 2020, Ford had to fix several reliability issues related to a new, co-used vehicle platform for the Explorer and Aviator models: the Explorer experienced transmission-related issues that prevented the vehicle from going into park or braking in the park position, that is, vehicles were rolling away unsupervised, while the Aviator experienced suspension-related issues. Faced with growing investor scrutiny, Ford acknowledged the complexity of designing a new co-used platform and admitted: "simply put, we took on too much. We signed up for too much at launch" (Roeder, 2020). More generally, the industry considers lower component co-use as one potential explanation of why Japanese manufacturers outperformed US manufacturers on reliability for many years (Fisher et al., 1999). Hence, we now systematically test the relationship between co-use and reliability.

4 | DATA AND METHODS

We collected data on products' (car models') technical specifications, location of production, and US sales from Ward's Automotive (www.wardsauto.com). We focus on cars sold in the United States and have information on all car models sold between January 2006 and December 2015.[7] We complement this information with data from the National Highway Traffic Safety Administration (NHTSA) on products' reliability. The NHTSA collects customer complaints about safety-related reliability issues in cars sold in the United States to investigate possible defects that affect more than one driver and may require a safety recall. Hence, the recorded complaints are malfunctions that impaired the core functionality of the product (i.e., the possibility of safe driving), often reporting accidents associated with the malfunctions. The NHTSA is not interested in smaller performance glitches: "An example of a safety-related defect is a steering component that breaks, causing a driver to lose control. However, an air conditioner

[7]We drop products from manufacturers that only produce electric cars or that sold only one car model in our study period.

that does not work properly isn't considered a safety-related defect, because it does not pose a risk to motor vehicle safety" (NHTSA, 2025). Complaints at the NHTSA proxy to what extent a car model fulfills its core functionality of safe driving—a car's core reliability.

A car model represents a specific product in our context that is updated for each car *model-year*.[8] Car manufacturers produce different car models (e.g., Volkswagen produces the VW Golf and VW Passat). Car models (e.g., the VW Golf) can be produced in different generations (VW Golf IV, V, VI, etc.), which will each be produced over several model-years (2006 VW Golf V). Design and task changes during the model-year are rare in the automobile industry, and improvements tend to occur yearly. Hence, a car model-year (e.g., the 2006 VW Golf V) represents a specific configuration of a car—that is, the yearly version of a product.

We then study how the reliability of products' yearly version (car models over their model years) is affected by task co-use and past defects in other products. Our regression model can be summarized as:

$$\begin{aligned} \mathit{Product\ reliability}_{p,t} = \beta_0 + \beta_1 \mathit{Task\ co-use}_{p,t} + \beta_2 \mathit{Prior\ defects\ of\ task\ co} \\ - \mathit{using\ products}_{-p,t-1,t-2,t-3} + \beta_3 \mathit{Prior\ defects\ of\ non} \\ - \mathit{co-using\ products}_{-p,t-1,t-2,t-3} + \beta_4 \mathit{Controls} + \beta_5 \mathit{Firm}_p \\ + \beta_6 \mathit{Year}_t + \epsilon_{p,t} \end{aligned}$$

Our dependent variable measures the built-in reliability of the yearly t version of product p—that is, the reliability of a car model of a specific model year. The reliability is set at time t when a product is marketed and cannot be re-designed anymore. However, an important property of this variable is that while reliability is built into the product before it is marketed, reliability issues may show up over time, that is, years after a product has been marketed. To take this into account, for each specific yearly product version (car model of a specific model year), our reliability variable considers reported defects that surface up until 6 years after a specific yearly product version has been brought to market (see Figure 2 for an illustration of the timeline by means of the VW Golf 2010 as an exemplary observation).[9] We use the logarithm rather than the count of our dependent variable to capture its right-skewed distribution. Yet, our results are robust when using its count and negative binomial regression models (Appendix 1).

Task co-use is the scope of task co-use for the respective yearly t version of product p. As explained before, we proxy task co-use by measuring whether a car model co-uses its vehicle platform with other cars. Task co-use equals the number of car models based on the same vehicle platform as the focal product p, t—the focal car model-year.

To measure potential cross-improvement from solved defects in other products, we use data on product recalls. Product recalls imply that a firm's products have safety-relevant defects that require a solution if a firm does not want to have its products banned from sale and risk hefty fines (NHTSA, 2015). Hence, recalls go hand in hand with understanding and solving a reliability issue. Focusing on recalls has two key advantages for identifying cross-improvement: first, recalls are costly to firms and firms strive to avoid them—that is, firms have little incentive to

[8]Car model-years are a full year and run from September to August.

[9]Prior research indicates that it usually takes up to 6 years after the launch of a car model-year until the majority of issues surface (Shah et al., 2017).

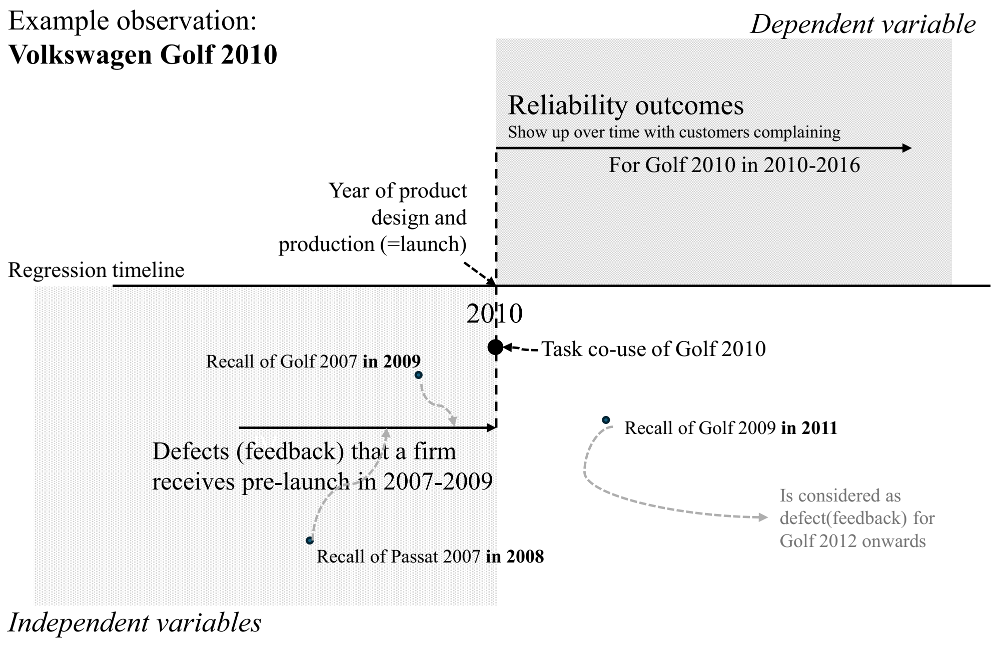
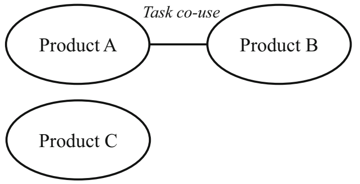


FIGURE 2 Schematic illustration of the measured timeline of variables. A snapshot for the Volkswagen Golf 2010 as example observation.

intentionally build in safety-relevant reliability issues that they are aware of or leave them unsolved. Hence, recalls are an indication that a firm became aware of a reliability issue that it was not previously aware of. Second, while complaints may already bring defects to a firm's awareness, a recall indicates the point in time when a firm solved the issue and implemented an improvement that can ripple through to other products. The improvement in case of recall is unplanned, and recall-relevant defects legally oblige firms to update products, making it less susceptible to strategic consideration. Prior defects of other products measure the number of recalls of an automaker's car models net of the focal car model that occurred before the focal product was made (see Figure 2). Recalls have to occur before the production of the focal product p,t—that is, before time t—so that firms can consider the experience in the making of the focal product. We only include defects (recalls) that occurred before the production of the focal car model-year. Following prior research indicating that recent experience is more relevant to firms and experience dating back many years may be obsolete or forgotten (Haunschild & Rhee, 2004), we consider recalls occurring in the 3 years prior to the making of the focal product.[10] For example, if the focal product is the Volkswagen Golf 2010 as illustrated in Figure 2, recalls of other products are recalls in Volkswagen cars that occurred in 2009, 2008, and 2007. We then split recalls into Prior defects of task co-using products—the number of recent recalls of other task co-using—and Prior defects of non-co-using products. All variables measuring defects in other products only include defects that *do not* directly involve the co-used task. For example, if a firm has two Products A and B, and A is the focal product, defects in other products measure defects that exclusively affected Product B and not the focal product A—A alone

[10]As it is an empirical question how fast experience turns irrelevant, we test different time windows in Appendix 1 and find our findings qualitatively robust for windows of 1–5 years (see Appendix 1).



Types of defects for the focal product A

Variable name	Description	Products that are knocked out by the defect
Product-specific defects	Defects that only knock out the focal product	A
Defects of co-used tasks	Defects in the co-used task that knock out all co-using products including the focal product	A and B
Defects of other co-using products	Defects that only knock out other co-using products but not the focal product	B
Defects of other non-co-using products	Defects that only knock out other non-co-using products but not the focal product	C

FIGURE 3 Illustration and description of types of defects.

or A jointly with B, as illustrated in Figure 3. With defects in other products, we test whether a defect in, for example, Product B improves future reliability of the non-defective product A (i.-e., leads to cross-improvement of A), conditional on whether Product A and B task co-use or not. As a control variable, we also measure defects that directly affected a co-used task and therefore knock out both the focal Product A and the co-using Product B. Remedy of those defects directly improves both Products A and B without the cross-improvement effects we study and therefore are not the central variable of interest. We also control for a focal product's independent defects that affect the focal Product A but no other product.

To obtain data on firms' product recalls, we used the NHTSA database and collected further information from firms' Safety Defect and Noncompliance Report that needs to be submitted to the NHTSA in case of recalls.[11] Our final data includes 297 car models manufactured by 36 automakers from 2006 to 2015.[12] We include firm and year fixed effects in all estimations and cluster standard errors at the decision-making entity, the automaker. Our results are robust to estimations with firm-year fixed effects. We do not include product-level fixed effects in our main analysis because our theoretical argument is about differences between products. Task co-use barely varies within products—at least in our context—and its direct effect is not identifiable with product fixed effects. However, the results for the interaction effect hypothesized in H2a/H2b remain consistent with product fixed effects (see Table 5). Further, recent work showed that including failure and success experience in the same estimation may bias results (Bennett & Snyder, 2017), so we align our regression specifications with Bennett and Snyder's (2017) recommendations. Since one of our controls—a firm's production experience for a product—may still reflect success experience we exclude it in an additional test. Our results are robust (see Appendix 1).

[11]We collected 2837 recall reports. Four trained coders read all reports and manually coded if a defect was caused by a design or a manufacturing mistake, if the report mentions the involvement of a supplier and how firms first discovered a defect. The inter-rater reliability has been checked using Cohen's alpha. Cohen's alpha indicated substantial agreement (>0.7) for all variables and coders. The coders and one of the authors met weekly during the coding. During these meetings, all cases that were unclear were discussed. If raters agreed the recall was classified as manufacturing or design recall, respectively. If the differences could not be resolved because the description was not sufficiently clear the recall was coded as recall with an “unclear cause” and we neither count it as manufacturing nor as design recall.

[12]The automakers are: Acura, Audi, BMW, Buick, Cadillac, Chevrolet, Chrysler, Dodge, Ford, GMC, Honda, Hummer, Hyundai, Infiniti, Isuzu, Jaguar, Jeep, Kia, Land Rover, Lexus, Lincoln, Mazda, Mercedes-Benz, Mercury, Mini, Mitsubishi, Nissan, Pontiac, Porsche, Saab, Saturn, Scion, Subaru, Suzuki, Toyota, Volkswagen.

4.1 | Control variables

We control for variables at the model-, task- and firm-level that may affect product quality. *Product Age*: Product reliability may be lower in the first years after the launch of a new product line or after significant changeovers, and improve with time. Therefore, we include the number of years passed since the launch of a product line (car model). *Production experience*: The number of units produced of a product may affect its reliability (Levitt et al., 2013), and we include the number of units produced of the focal car model to control for a firm's model-specific production experience. *Prior product-specific defects* is the count of all recalls that affected the focal car model in the 3 years prior to its making. *Prior co-shared defects* is the count of all recalls that jointly affected the focal car model and other car models, that is, defects of a co-used task, consistently for a three-year window. *Previous generations*: As firms may transfer knowledge across product generations, car models may be more reliable if they have been produced for several generations, and we control for the number of previous generations. *Sales volume*: Defects and malfunctions may be discovered faster the more products are sold and used, and we account for the number of sold vehicles of the focal car model-year. *Price*: As firms' motivation to avoid defects as well as customers' expectations may vary with the price of a car, we control for the focal car model-year's price in '000 US$. To further account for a car's product positioning, the binary variable *luxury segment* includes whether a vehicle is sold in the luxury segment of the industry or not. *Share of voluntary recalls*: Prior research suggests that volition can impact a firm's response to product recalls (Haunschild & Rhee, 2004). Hence, we control for the share of voluntary recalls among the recalls affecting a focal car model in the past 3 years.[13] *Share of supplier involvement*: To avoid an automaker's reliance on external suppliers driving our results, we include the share of recalls with supplier involvement among the recalls affecting a focal car model in the past 3 years.[14] We further control for the age of the co-used task, as co-used tasks may improve with time as well. *Age of the co-used task* is the number of years passed since the first use-year of a vehicle platform. The binary variable *Tailored task takes* into account that a task—in our case the task of making the vehicle platform—has been originally configured for the focal car model or configured for other car models. *Production task co-use*: We proxy the co-use of production tasks of products by observing whether products are produced in the same facility. Production task co-use equals the number of car models built in the same factory as the focal car model-year. For products produced in more than one facility, we count the number of different car models built with the focal car model across factories. *No. of products*: We control for the size of a firm's product portfolio by including the number of car models produced in a given year. *No. of platforms* is the number of vehicle platforms of an automaker in a given model-year. *No. of plants* is the number of active plants of an automaker in a given model-year. *Total production volume*: Prior work observed that high utilization can result in decreased reliability in a hospital setting (Kc & Terwiesch, 2011) and in automotive plants (Shah et al., 2017) as high utilization decreases time for quality checks. Hence, we include the total global production volume of a firm in the year of production of the focal car model-year as a control.

[13]Our results are robust to including the share of voluntary recalls among all recalls of a firm or among recalls affecting other models. As the variance inflation factors for these models indicate a substantial correlation among the independent variables, we preferred the above specification.

[14]Results are robust if we include the share of recalls with supplier involvement among all recalls of a firm or among recalls affecting other models as a control.

TABLE 2 Correlations.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.
1. Ln(Reliability complaints+1)																					
2. Task co-use	0.161																				
3. Prior defects of other, task co-using products	0.218	0.395																			
4. Prior defects of other, non-co-using products	0.335	−0.024	0.046																		
5. Product age	−0.297	−0.115	−0.241	0.071																	
6. Production experience (in 1000)	0.407	0.150	0.232	0.238	−0.058																
7. Prior product-specific defects	0.087	−0.107	−0.063	0.096	0.341	0.090															
8. Prior co-shared defects	0.093	0.260	0.087	0.177	0.290	0.147	0.227														
9. Previous product generations	0.239	0.148	0.300	0.132	−0.152	0.563	0.042	0.067													
10. Sales volume (in 1000)	0.617	0.174	0.349	0.315	−0.144	0.699	0.180	0.179	0.470												
11. Price (in 1000US$)	−0.541	−0.115	−0.124	−0.206	0.117	−0.249	−0.090	−0.077	−0.030	−0.327											
12. Luxury segment	−0.512	−0.151	−0.196	−0.364	0.008	−0.248	−0.146	−0.185	−0.095	−0.384	0.653										
13. Share of voluntary recalls	0.123	0.063	0.002	0.086	0.169	0.061	0.189	0.354	0.050	0.112	−0.040	−0.121									
	0.107	0.121	0.080	0.117	0.190	0.120	0.150	0.386	0.076	0.144	−0.047	−0.125	0.520								

TABLE 2 (Continued)

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.
14. Share of supplier involvement																					
15. Age of the co-used task	−0.104	0.209	0.031	0.011	0.423	0.214	0.151	0.186	0.060	0.067	0.044	−0.002	0.163	0.201							
16. Tailored task	0.025	−0.379	−0.163	0.047	0.099	0.114	0.081	−0.053	0.115	0.074	0.039	0.003	−0.027	−0.036	−0.248						
17. Production task co-use	0.105	0.274	0.087	−0.072	−0.073	0.379	−0.079	0.033	0.218	0.189	0.017	0.120	−0.017	0.058	0.078	−0.066					
18. No. of products	0.124	0.290	0.119	0.564	0.130	0.251	0.039	0.187	0.182	0.260	−0.006	−0.164	0.041	0.102	0.090	−0.098	0.270				
19. Newly launched products	0.118	0.161	0.124	0.279	−0.081	0.082	−0.033	0.054	0.092	0.153	−0.028	−0.067	−0.052	0.014	−0.066	−0.073	0.224	0.517			
20. No. of plants	0.271	0.216	0.166	0.651	0.099	0.399	0.095	0.214	0.262	0.419	−0.171	−0.349	0.048	0.053	0.134	−0.046	0.155	0.809	0.413		
21. No. of platforms	0.144	−0.023	0.033	0.667	0.141	0.207	0.086	0.119	0.138	0.244	0.005	−0.130	−0.009	0.055	−0.100	0.084	0.102	0.833	0.402	0.725	
22. Total production volume (in 100,000)	0.319	0.204	0.144	0.631	0.089	0.457	0.092	0.210	0.262	0.436	−0.196	−0.346	0.034	0.059	0.163	−0.050	0.174	0.719	0.358	0.928	0.652

Note: $N = 1678$.

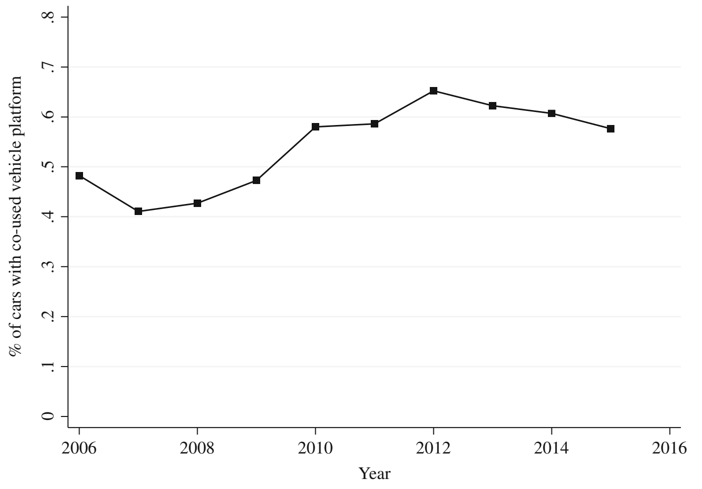


FIGURE 4 Share of cars with co-used vehicle platform over time.

TABLE 3 ANOVA comparing variance in task co-use within and between firms.

	Sum of squares	df	Mean square	F	p
Between firms	96.082	35	2.745	14.07	0.000
Within firms	319.91	1640	0.195		
Total	415.992				
R^2 (adj.)	0.215				

Note: $N = 1676$.

5 | RESULTS

Table 1 shows descriptive statistics, and pairwise correlations are in Table 2. On average, a car model year experiences around 200 reliability complaints within the first 6 years after its launch, and most firms produce more than nine different car models in the same year.

Task co-use varies across car models: roughly half of all cars co-use a vehicle platform, with prevalence peaking around 2012 in our sample (Figure 4). On average, platform design tasks are co-used across two car models, although some models share a platform with up to five other models (see Table 1). In Table 3, we explore variation in task co-use across products within and across firms. While we find that firms differ in their use of task co-use (ANOVA, $p < 0.001$), only a fraction of the variation is explained by differences across firms: we find an R^2 below 0.22 and 77% of the total variance in task co-use occurs within firms across different products, speaking for an analysis at the product level.

In Table 4, we test Hypothesis H1, whether task co-use is associated with a reliability penalty. Column (1) includes all control variables, and we add the task co-use variable in column (2), finding support for our prediction: task co-use significantly increases a product's reliability complaints ($p = 0.007$). A car model that co-uses the platform-making task with one other car model is predicted to receive 16.7% more reliability complaints. We take the scope of co-use—that is, the number of products that co-use with the focal product as the primary specification.

TABLE 4 Results on Hypothesis H1.

ln(complaints+1)	(1)	(2)	(3)	(4)	(5)	(6) Co-use = 1
Task co-use		0.167			0.170	0.159
		(0.059)			(0.063)	(0.058)
Task co-use (binary)			0.254			
			(0.107)			
Ln(Task co-use+1)				0.355		
				(0.119)		
Product age	−0.099	−0.091	−0.097	−0.092	−0.093	−0.133
	(0.041)	(0.040)	(0.037)	(0.039)	(0.049)	(0.031)
Production experience	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prior product-specific defects	−0.001	0.004	0.001	0.005	−0.004	0.036
	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.035)
Prior co-shared defects	−0.038	−0.068	−0.046	−0.066	−0.044	−0.001
	(0.028)	(0.029)	(0.026)	(0.027)	(0.037)	(0.017)
Previous product generations	0.004	−0.001	0.002	−0.001	−0.003	0.017
	(0.048)	(0.049)	(0.049)	(0.049)	(0.056)	(0.043)
Sales volume	0.009	0.008	0.008	0.008	0.008	0.006
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Price	−0.022	−0.022	−0.023	−0.023	−0.022	−0.033
	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.003)
Luxury segment	−0.651	−0.579	−0.642	−0.590	−0.573	−0.225
	(0.190)	(0.181)	(0.172)	(0.170)	(0.206)	(0.261)
Share of voluntary recalls	0.289	0.317	0.299	0.309	0.313	0.179
	(0.103)	(0.103)	(0.102)	(0.101)	(0.116)	(0.133)
Share of supplier involvement	−0.128	−0.150	−0.118	−0.131	−0.134	0.021
	(0.102)	(0.104)	(0.092)	(0.097)	(0.124)	(0.127)
Age of the co-used task	−0.035	−0.039	−0.040	−0.040	−0.029	−0.024
	(0.022)	(0.023)	(0.023)	(0.023)	(0.029)	(0.027)
Tailored task	−0.000	0.088	0.082	0.116	0.140	0.085
	(0.135)	(0.132)	(0.151)	(0.142)	(0.152)	(0.132)
Production task co-use	0.055	0.050	−0.069	0.134	0.063	0.051
	(0.012)	(0.011)	(0.125)	(0.075)	(0.015)	(0.016)
No. of products	−0.078	−0.110	−0.070	−0.100		−0.147
	(0.039)	(0.042)	(0.031)	(0.037)		(0.034)
Newly launched products	0.020	0.031	0.033	0.039		−0.001
	(0.026)	(0.027)	(0.026)	(0.027)		(0.034)

TABLE 4 (Continued)

ln(complaints+1)	(1)	(2)	(3)	(4)	(5)	(6) Co-use = 1
No. of plants	−0.015	−0.010	−0.020	−0.014		0.006
	(0.020)	(0.020)	(0.015)	(0.017)		(0.021)
No. of platforms	−0.016	0.015	−0.004	0.017		−0.004
	(0.039)	(0.043)	(0.036)	(0.039)		(0.059)
Total production volume	0.003	0.004	0.011	0.008		0.004
	(0.015)	(0.015)	(0.016)	(0.015)		(0.019)
Constant	5.631	5.379	5.507	5.315	4.492	5.470
	(0.323)	(0.307)	(0.323)	(0.303)	(0.271)	(0.460)
Firm FE	Yes	Yes	Yes	Yes		Yes
Year FE	Yes	Yes	Yes	Yes		Yes
Firm-year FE					Yes	
R^2	0.683	0.690	0.680	0.685	0.730	0.693
Observations	1676	1676	1676	1676	1676	909

Note: Standard errors clustered on the firm level in parentheses.

The effect is robust to a binary operationalization, column (3) and its log, column (4). Results are robust to the inclusion of firm-year fixed-effects, column (5). In column (6), we restrict our analysis to co-using products and find that the scope of task co-use continues to be associated with more reliability complaints. Together, this suggests that both task co-use as a binary characteristic and its scope—the number of co-using products—are associated with lower reliability, supporting Hypothesis H1.

We test the predictions for Hypotheses H2a and H2b in Table 5. We do not find support that prior defects in other products in general are associated with a lower number of reliability complaints in the focal product (column (1)), as proposed in H2a. However, when we split prior defects of other products in defects that occurred in products co-using with the focal product versus defects in non-co-using products in column (2), we find that, in line with H2b, prior defects in other, task co-using products are associated with fewer reliability complaints on the focal product ($p = 0.067$), while we observe no statistically meaningful effect for prior defects of other products that do not co-use. We find support that cross-improvement due to defects of other products is stronger if the products co-use tasks; the difference in coefficient sizes is statistically meaningful with $p < 0.05$. Because products can only experience prior defects in co-using products if they co-use in the first place, we restrict the sample to co-using products in column (3) and as expected, find even more pronounced support for our initial patterns.[15] Columns (5) and (6) repeat the analysis including

[15]In line with our theoretical argument, our analysis focuses on how prior *defects of other* products relate to reliability, that is, defects that *do not directly occur in the co-used tasks*. Defects in the co-used task directly affect both other products *and* the focal co-using product. We control for those defects, and one noteworthy finding is that defects in co-used tasks relate to more pronounced reliability improvements than defects that only affect the focal product itself. This is in line with research that finds that complicated defects—in our case, defects in co-used tasks with additional cross-product interdependencies—need more thorough investigation, making them more informative (Haunschild & Sullivan, 2002).

TABLE 5 Results on Hypotheses H2a and H2b.

ln(complaints+1)	(1)	(2)	(3) Co-use = 1	(4)	(5) Co-use = 1
Task co-use	0.167	0.194	0.184	0.045	0.037
	(0.058)	(0.053)	(0.046)	(0.041)	(0.063)
Prior defects of other products	−0.001				
	(0.005)				
Prior defects of other, task co-using products		−0.024	−0.028	−0.018	−0.021
		(0.013)	(0.012)	(0.010)	(0.009)
Prior defects of other, non-co-using products		0.001	−0.011	0.003	−0.004
		(0.005)	(0.005)	(0.003)	(0.005)
Product age	−0.091	−0.095	−0.144	−0.098	−0.163
	(0.041)	(0.042)	(0.033)	(0.040)	(0.071)
Production experience	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prior product-specific defects	0.004	0.004	0.028	−0.001	0.056
	(0.012)	(0.012)	(0.036)	(0.011)	(0.034)
Prior co-shared defects	−0.069	−0.072	−0.003	−0.073	−0.022
	(0.028)	(0.029)	(0.016)	(0.020)	(0.021)
Previous product generations	−0.001	0.006	0.021	−0.084	−0.034
	(0.049)	(0.050)	(0.045)	(0.179)	(0.357)
Sales volume	0.008	0.009	0.007	0.008	0.005
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Price	−0.022	−0.021	−0.032	−0.014	−0.019
	(0.004)	(0.004)	(0.003)	(0.016)	(0.023)
Luxury segment	−0.579	−0.596	−0.257	−0.147	−0.397
	(0.181)	(0.179)	(0.271)	(0.154)	(0.083)
Share of voluntary recalls	0.317	0.304	0.169	0.077	0.057
	(0.103)	(0.100)	(0.131)	(0.089)	(0.093)
Share of supplier involvement	−0.150	−0.141	0.033	−0.090	0.015
	(0.104)	(0.107)	(0.129)	(0.067)	(0.104)
Age of the co-used task	−0.039	−0.038	−0.026	−0.017	0.058
	(0.023)	(0.023)	(0.027)	(0.017)	(0.028)
Tailored task	0.088	0.070	0.079	−0.222	−0.577
	(0.132)	(0.123)	(0.129)	(0.154)	(0.223)
Production task co-use	0.050	0.049	0.051	0.006	0.023
	(0.011)	(0.012)	(0.016)	(0.015)	(0.010)
No. of products	−0.109	−0.114	−0.145	−0.026	−0.054
	(0.042)	(0.039)	(0.030)	(0.042)	(0.037)

TABLE 5 (Continued)

ln(complaints+1)	(1)	(2)	(3) Co-use = 1	(4)	(5) Co-use = 1
Newly launched products	0.031	0.034	0.002	0.014	−0.005
	(0.027)	(0.026)	(0.034)	(0.025)	(0.034)
No. of plants	−0.010	−0.009	0.010	−0.004	0.018
	(0.020)	(0.019)	(0.018)	(0.016)	(0.011)
No. of platforms	0.015	0.030	0.034	−0.017	−0.017
	(0.043)	(0.040)	(0.053)	(0.039)	(0.057)
Total production volume	0.004	0.004	0.006	−0.000	0.008
	(0.015)	(0.014)	(0.016)	(0.013)	(0.015)
Constant	5.385	5.371	5.588	5.162	5.283
	(0.307)	(0.314)	(0.469)	(0.726)	(1.987)
Firm FE	Yes	Yes	Yes		
Year FE	Yes	Yes	Yes	Yes	Yes
Product FE				Yes	Yes
R^2	0.690	0.692	0.697	0.234	0.274
Observations	1676	1676	909	1676	909

Note: Standard errors clustered on the firm level in parentheses.

product fixed-effects with comparable results. Since the decision of co-using a task rarely varies within products, we run our main analysis with firm and year fixed effects: co-use indeed varies so little within a product that statistically we cannot test H1 with product fixed effects. In addition, co-use is likely to correlate across models within the same firm, providing more grounds for firm-level fixed effects.[16] However, testing H2 also with product fixed-effects combined with the fact that task co-use barely varies within products gives us an advantage with respect to the results' interpretation: with task co-use largely being constant within products, the reliability improvements from defects in co-using products can be attributed to differences in product defects rather than changes in task co-use. That is, the fact that within-product task co-use is essentially constant lets us pinpoint the mechanism to be the other, that is, product defects and therefore updates in other products.

The result remains qualitatively unchanged in a number of different specifications, such as a count specification of the dependent variable and negative binomial regression models, and shorter and longer estimation windows (see Appendix 1). Our measure of reliability is based on customer complaints; we also find similar patterns if we use industry expert ratings on reliability to measure our dependent variable. Consistent with the idea that reliability captures the lower bound dimension of product quality—whether a product functions as intended, we find our results supported for different operationalizations of this lower bound but do not find support that task co-use lowers products' upper bound quality, such as cars'

[16]Co-use is likely to correlate across models within the same firm: partly mechanically (co-use will affect at least two car models from the same manufacturer) and partly managerially (a firm whose management sees value in co-using tasks for one model is likely to arrive at a similar conclusion for other models).

TABLE 6 Heterogenous effects.

ln(complaints+1)	(1)	(2)	(3)	(4)
Task co-use	0.260	0.090	0.196	0.043
	(0.072)	(0.118)	(0.055)	(0.041)
Tailored task	0.222	0.068	0.066	−0.229
	(0.160)	(0.124)	(0.125)	(0.161)
Share of supplier involvement		−0.189	−0.160	−0.045
		(0.261)	(0.247)	(0.216)
Co-use × Tailored task	−0.110			
	(0.059)			
Co-use × Supplier involvement		0.191		
		(0.211)		
Prior defects of other, task co-using products	−0.023	−0.024	−0.062	−0.006
	(0.013)	(0.013)	(0.047)	(0.031)
Defects of co-using products × Supplier involvement			0.068	−0.023
			(0.080)	(0.054)
Prior defects of other, non-co-using products	0.001	0.001	0.001	0.003
	(0.005)	(0.005)	(0.005)	(0.003)
Controls	Yes	Yes	Yes	Yes
Constant	5.244	5.473	5.455	5.445
	(0.307)	(0.350)	(0.345)	(1.045)
Firm FE	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	Yes
Product FE				Yes
R^2	0.693	0.692	0.692	0.234
Observations	1676	1676	1676	1676

Note: Standard errors clustered on the firm level in parentheses.

speed or other performance parameters that can increase value for more demanding customers.[17]

We run a further test on the boundaries of our argument: we observe the co-use of a "design" task that involves substantial product design steps, that is, a task of making a product component. Our theoretical argument, however, may be more general and may also hold in case of co-use of a production-related task that satisfies the boundary condition of having interdependencies with other tasks. To proxy whether products co-use production-related tasks, we measure the extent to which a product co-uses its production plant with other products and find the patterns of our results supported with the production-related measure of co-use (see Appendix 2).

[17]We obtained industry expert ratings from the car comparison website U.S. News, a media and consumer advice company (https://cars.usnews.com/cars-trucks). U.S. News aggregates quality ratings on different dimensions and from different providers on reliability, but also upper-bound quality dimensions such as cars' look and feel. Re-running our analysis with these alternative measures yields similar patterns to our original results for the alternative ratings of safety and dependability (i.e., reliability) but not for the "upper bound" quality ratings such as performance and critics' tone.

TABLE 7 Product culling.

	(1) DV: Culled (0/1) reg	(2) probit	(3) Excl. products that are culled in the next year	(4) Excl. products that are culled in the next 2 years
Task co-use	−0.004	−0.073	0.160	0.158
	(0.004)	(0.111)	(0.042)	(0.044)
Prior defects of other, task co-using products	0.001	0.004	−0.022	−0.021
	(0.001)	(0.023)	(0.010)	(0.011)
Prior defects of other, non-co-using products	0.000	0.001	0.003	0.007
	(0.000)	(0.011)	(0.006)	(0.005)
Constant	1.028	−0.592	5.139	4.728
	(0.052)	(0.686)	(0.235)	(0.378)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.707	N/A	0.702	0.707
Observations	1676	1356	1422	1192

Note: Standard errors clustered on the firm level in parentheses.

6 | SUPPLEMENTARY ANALYSIS

6.1 | Heterogenous effects

An important element of our theoretical argument is interdependencies between the co-used and other tasks. The reliability of co-using products is expected to be lower because the additional cross-product dependencies make product design more complicated and constrained. If this is the case, conditions that soften the challenge and give firms more flexibility to manage the interdependencies should alleviate the reliability consequences of co-use. Firms, for instance, may have more flexibility to consider interdependencies and incorporate constraints if a task is newly configured for a product rather than using pre-configurations from another product. The flexibility may be especially relevant if a task is co-used and additional cross-product interdependencies need to be considered. In line with this prediction, we indeed find that the negative association between co-use and reliability is less pronounced if the co-used task has been originally configured for the respective product (Table 6 column (1), $p = 0.071$).

Moreover, firms' boundaries may influence the observed dynamics: Firms are more likely to outsource tasks with little interdependencies because coordination is harder across firm boundaries (Baldwin, 2024). A high degree of outsourcing may be an indication of fewer interdependencies, mitigating the reliability penalty but also lowering cross-improvement. However, if outsourcing occurs despite interdependencies, outsourcing can also worsen the reliability penalty from co-use because coordination of the persisting interdependencies becomes harder. To proxy the (net) effects of a firm's outsourcing, we measure the share of prior defects involving a supplier. In Table 6 columns (2) and (3), we interact the measure with our main effect. We do

TABLE 8 Product age.

	(1)	(2)	(3)	(4)
Task co-use	0.202	0.076	0.235	0.087
	(0.090)	(0.077)	(0.078)	(0.063)
Product age	−0.085	−0.085	−0.089	−0.088
	(0.044)	(0.039)	(0.045)	(0.039)
Co-use × Product age	−0.012	−0.015	−0.014	−0.017
	(0.017)	(0.018)	(0.015)	(0.017)
Prior defects of other, task co-using products			−0.025	−0.020
			(0.013)	(0.010)
Prior defects of other, non-co-using products			0.001	0.003
			(0.005)	(0.003)
Constant	5.367	5.582	5.361	5.545
	(0.300)	(1.082)	(0.311)	(1.086)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes		Yes	
Year FE	Yes	Yes	Yes	Yes
Product FE		Yes		Yes
R^2	0.690	0.231	0.692	0.236
Observations	1676	1676	1676	1676

Note: Standard errors clustered on the firm level in parentheses.

not find support that outsourcing changes the reliability consequences of co-use or weakens cross-improvement. This finding may be context-specific: as discussed before, although car manufacturers outsource tasks with fewer interdependencies (Argyres & Bigelow, 2010), interdependencies persist for a significant part of outsourced tasks and close relationships with suppliers are common (MacDuffie, 2013).

6.2 | Alternative explanations

Firms may accept lower reliability if they have plans to cull a product. A concern then may be that products with co-used tasks have a higher probability of being culled than other products, and firms intentionally invest less in the reliability of co-used tasks and the associated products. This alternative explanation for our findings on H1 is not supported by our additional analysis in Table 7, where we test whether task co-use predicts a product's likelihood of being discontinued (column (1) for results from OLS estimations, and column (2) for probit). Because the intention to cull a product may also influence adaptation, we test if our results remain robust if we exclude products that will be terminated in the following year (columns (3)–(4)) or the following 2 years (columns (5) and (6)). Our findings remain unchanged.

Another concern may be that time-related processes other than pre-experienced defects explain the observed improvement rates. In particular, co-using products may have a slower 'baseline' improvement rate that allows for more defects in other products to accumulate before the focal product gets adapted, and we risk wrongly attributing "secular" time-trends to improvement effects from pre-experienced defects. To address this concern, we control for a product's age and thus its baseline improvement rate in all estimations, as well as a firm's product-specific production experience. Further, in Table 8, we find no support that baseline improvement rates differ in co-using and non-co-using products (columns (1) and (2)). The improvement due to co-using products' defects remains robust even after controlling for different baseline improvement rates of co-using products (columns (3) and (4)). Moreover, improvement rates may increase with attention, as the remedy of defects requires deliberate effort. However, we do not find evidence that firms' attention notably differs between co-using and non-co-using products.[18]

Co-use may be an especially attractive choice for cost leadership firms compared to differentiators: foremost, it helps reduce costs and correlates with product standardization. While this holds interesting practical implications discussed later, it would be an empirical concern if firms' or products' positioning (rather than their co-use) explains our results. Cost leaders may be less reliable to begin with—the most concerning source of endogeneity in empirically studying task co-use outside the lab, without random assignment of task co-use across products and firms. Firm, firm-year and product fixed effects control for this concern to the extent that firms' positioning does not vary substantially over time, within a year, or for a particular product, respectively. As a further way to control for firms' product positioning over time, we include product (list) price and whether products are considered to compete in a premium segment in our estimations. The most powerful indication, however, that our results persist beyond potential endogeneity from positioning is that our results remain robust for the subsample of products that were selected into task co-use in the first place (see Tables 4 and 5). Even if conditioning on those 'treated' products—removing potential variation in the initial co-use decision—we observe a negative association between the scope of task co-use and reliability.

7 | DISCUSSION AND CONCLUSION

We study the consequences of task co-use from an organization design angle to connect the organization design literature with research on firm scope. Taking an organization design perspective shifts the focus to the interdependencies created by task co-use and their implications for product reliability and adaptation: specifically, we develop why task co-use—because of the resulting interdependencies—can increase the likelihood of reliability problems. The reliability penalty of co-use, however, is temporary. Higher improvement rates help co-using products catch up on reliability because the very interdependencies that initially undermine the reliability of co-using products allow co-using products to improve not only after their own reliability issues but also cross-improve with other products' prior reliability issues. We find empirical support for these predictions in the US automotive industry and the co-use of tasks across cars made between 2006 and 2015.

[18]Attention would be a relevant force in our set-up if co-using products not only improve more because they get more directly exposed to defects via their cross-product interdependencies network, but if firms pay more attention to defects in task co-using products. Proxying attention by the size of defects, we find that attention intensifies improvement from defects, but we do not find differences in how attention shifts improvement for co-using and non-co-using products.

We make three main contributions. First, we add to the literature on organization design (Baldwin, 2024; Englmaier et al., 2018; Puranam et al., 2012) by identifying task co-use as a relevant design parameter. Although task co-use is a widespread feature in multi-product or -business firms, its performance implications have largely gone unnoticed in the organization design literature. We build on prior work establishing the importance of interdependencies for the performance of task structures (Baldwin & Clark, 2000; Raveendran et al., 2020) to develop a theoretical framework on how task co-use can affect the reliability and adaptation patterns of the end products. Explicitly including task co-use in theorizing the performance implications of task structures is a step toward integrating the scope of firms in task design.

Second, by linking the literature on scope in corporate strategy (Folta et al., 2016; Helfat & Eisenhardt, 2004; Levinthal & Wu, 2010) with the organization design literature, we expand prior research on firm scope by shifting to a (more) micro perspective focused on how scope is organizationally designed with varying levels of task co-use. This perspective lets us theorize the implications of interdependencies introduced by co-used tasks. A new insight of our study is that feared coordination costs linked to intra-temporal economies of scope (Rawley, 2010; Zhou, 2011) may be more manageable with experience than expected. This moves the conversation from interpreting complexity as a mere stumbling block for scope expansions to considering the time horizon of planned co-use. Using a task-based perspective to predict the implications of resource co-use lets us infer that co-using resources may come with a reliability penalty if resources are inputs to a co-used task with interdependencies; even the co-use of fungible resources—resources with a small drop in value if they are applied in their second-best use (Montgomery & Wernerfelt, 1988) and scale-free resources without opportunity costs (Levinthal & Wu, 2010) may suffer a reliability penalty. For instance, data can be viewed as a fungible and scale-free resource (Giustiziero et al., 2023) and based on these properties, predestined for co-use with little to no interdependencies (Giarratana et al., 2021). However, once data is used as input to a co-used task, interdependencies can arise from the task rather than the resource itself. For instance, data itself may be co-used without particular interdependencies to consider: Using data in business area A does not affect data use in business B. However, co-using the task of predicting demand in business areas A and B with the data as input may create interdependencies: for instance, consider a situation in which the task of predicting demand ideally aggregates segments in a small area A, but should separate demand across consumer segments for the large area B characterized by strong consumer heterogeneity. Co-using the very same task with the data as input across the two businesses may result in suboptimal outcomes for at least one business area. Hence, the co-use of resources may come with frictions that are caused by frictions in the also co-used actions performed with them. More closely linking research on resources and tasks joins an emerging stream of research (Karim et al., 2023) and is a promising avenue for future work.

Third, our work complements prior research on organizational adaptation, in particular work on how interdependencies influence adaptation and search (Ethiraj & Levinthal, 2004; Siggelkow & Levinthal, 2003; Sorenson, 2003). By introducing task co-use, we highlight the fact that adaptation patterns of single-product or -business firms may differ from those of multi-product and -business firms. Prior work has also predominantly interpreted interdependencies as impediments for adaptation because they make adaptation and system-wide changes more complicated (Aggarwal & Wu, 2015; Clement, 2023; Henderson & Clark, 1990). In theorizing interdependencies from task co-use, we highlight that once set up, cross-product interdependencies can also benefit adaptation rates, and we contribute empirical evidence to a literature stream dominated by computational methods.

A practical implication of our results is that managers need to weigh in early reliability shortfalls when deciding whether to co-use a task. Because this 'set-up penalty' diminishes as experience accumulates, the attractiveness of co-use is affected by the intended time horizon of co-use. Our finding that reliability increases with cross-product experience further highlights the value of portfolio-wide knowledge-sharing mechanisms—such as integrated defect databases and information-sharing platforms—that may strengthen cross-improvement effects.

Our study has some limitations. We test our predictions with data from one industry. An important property of the automotive industry is that despite efforts to design ideal-typical modules that are decoupled from the rest of the product (Ulrich, 1995), true decoupling proved difficult and co-used tasks interact with other tasks (MacDuffie, 2013). Interdependencies of co-used tasks are a necessary boundary condition for the dynamics we outlined and the generalizability of our results—a condition met by many industries. Many products (systems) are not decomposable into modules (Schilling, 2000; Simon, 1981), and even if decomposable, modularization is typically a process, and decoupled structures require advanced product understanding. Hence, decoupled structures are rare in young industries and most industries may find themselves in a situation of co-using tasks with interdependencies, at least temporarily. Further, we study co-use of a major task: the vehicle platform. Its co-use may trigger co-use of other tasks and thus lead to a larger effect. Conversely, co-use of less influential tasks is likely to have a less pronounced effect. Because tasks and task interdependencies are notoriously hard to measure empirically, we are bound to using proxies. Exploring the theorized dynamics for an artificial (lab) task with controlled interdependencies or in a simulation model could generate insights into how the type of interdependencies affects the implications of task co-use as well as long-term adaptive consequences beyond our 10-year observation period. An "ideal" field study of identifying and measuring the effects of task co-use would feature products that have been randomly assigned to or barred from task co-use, for example, through regulatory requirements or M&A activity, and draw on more detailed data on a product's and a firm's task structure, especially the degree of task interdependencies. Moreover, information on the efforts to remedy defects and the corresponding cross-improvements would help to further confirm our proposed micro-mechanisms, and we hope to inspire this future work on the topic. It would be particularly interesting, for instance, to understand how task co-use influences other outcomes related to interdependencies, such as imitation (Balachandran & Clement, 2025; Ethiraj et al., 2008).

Taking an organization design and task perspective on co-use, we develop why leveraging a task contemporaneously across products—that is, intra-temporal economies of scope—may suffer a reliability penalty. This penalty wears out with experience as the cross-product interdependencies brought by co-use allow for cross-improvements. A broader take-away from our study is that examining scope from a task perspective, bridging research on organization design and corporate strategy (Karim et al., 2023; Raveendran et al., 2020) may help us further understand new aspects of performance differences across firms of varying scope.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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APPENDIX 1: Robustness

ln(complaints+1)	(1) One-year window	(2) Five-year window	(3) Count variable as DV (nbreg)	(4) Count variable as DV (nbreg)	(5) Excl. Controls measuring success experience
Task co-use	0.177	0.203	0.137	0.043	0.186
	(0.057)	(0.055)	(0.049)	(0.025)	(0.044)
Prior defects of other, task co-using products	−0.029	−0.017	−0.012	−0.014	−0.027
	(0.022)	(0.009)	(0.011)	(0.005)	(0.012)
Prior defects of other, non-co-using products	−0.002	0.003	0.004	0.000	−0.000
	(0.004)	(0.007)	(0.006)	(0.002)	(0.006)
Constant	5.403	5.344	5.847	1.265	5.077
	(0.299)	(0.330)	(0.324)	(0.168)	(0.263)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Product FE				Yes	
R^2	0.690	0.693			0.687
Observations	1676	1676	1676	1608	1676

Note: Standard errors clustered on the firm level in parentheses.

APPENDIX 2: Production task co-use

ln(complaints + 1)	(1)	(2) Excluding extreme values
Production task co-use	0.049	0.046
	(0.012)	(0.018)
Prior defects of other, production task co-using products	−0.032	−0.032
	(0.018)	(0.018)
Prior defects of other, non-co-using products	0.001	0.000
	(0.005)	(0.005)
Constant	5.356	5.371
	(0.325)	(0.333)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
R^2	0.691	0.693
Observations	1676	1604

Note: Standard errors clustered on the firm level in parentheses.