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Out Of Focus: Competitive Dynamics Of Partial Substitutability

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Abstract

An extensive literature on competition between substitute technologies assumes that any buyer will only adopt a single technology. I propose that this assumption biases predicted outcomes, with implications for strategic decisions on technology trajectories, competition, the adoption and diffusion of new technologies, and long-term industry evolution. Buyers may choose the single option that best meets their range of needs but, given a range of needs, many will buy multiple technologies, to use each where most appropriate. You might predict that laptops will disrupt desktops, or that tablets will disrupt laptops. As partial substitutes, however, many buyers will adopt more than one of these technologies. In this paper I develop a formal model to better explore substitute competition, arguing that optimal technology trajectories in a "single purchase world" may be sub-optimal in a "multiple purchase world." I further develop the model to show how adoption history affects technology adoption and diffusion, which can create roadblocks or bridges not explained by existing models. Based on the model, I develop hypotheses arguing that the introduction of a new substitute not only directly affects existing competitors through substitutability, but also indirectly affects the relative opportunities between competitors through indirect complementarity, where the introduction of a technology may induce switching between related substitutes. I test my predictions in the digital camera industry, using a novel dataset that allows me to use metadata from photos uploaded to a popular photo sharing site to track individual adoption and use over time. In line with predictions, user adoption of smartphones is associated with changes in adoption behavior for interchangeable lens cameras, as more distant substitutes, and the co-use of multiple partial substitutes.

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OUT OF FOCUS: COMPETITIVE DYNAMICS OF PARTIAL SUBSTITUTABILITY

Dedicated to Jennie and Ada.

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ABSTRACT

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Andrew P. Boysen

Daniel A. Levinthal

An extensive literature on competition between substitute technologies assumes that any buyer will only adopt a single technology. I propose that this assumption biases predicted outcomes, with implications for strategic decisions on technology trajectories, competition, the adoption and diffusion of new technologies, and long-term industry evolution. Buyers may choose the single option that best meets their range of needs but, given a range of needs, many will buy multiple technologies, to use each where most appropriate. You might predict that laptops will disrupt desktops, or that tablets will disrupt laptops. As partial substitutes, however, many buyers will adopt more than one of these technologies. In this paper I develop a formal model to better explore substitute competition, arguing that optimal technology trajectories in a "single purchase world" may be sub-optimal in a "multiple purchase world." I further develop the model to show how adoption history affects technology adoption and diffusion, which can create roadblocks or bridges not explained by existing models. Based on the model, I develop hypotheses arguing that the introduction of a new substitute not only directly affects existing competitors through substitutability, but also indirectly affects the relative opportunities between competitors through indirect complementarity, where the introduction of a technology may induce switching between related substitutes. I test my predictions in the digital camera industry, using a novel dataset that allows me to use metadata from photos uploaded to a popular photo sharing site to track individual adoption *and use* over time. In line with predictions, user adoption of smartphones is associated with changes in adoption behavior for interchangeable lens cameras, as more distant substitutes, and the co-use of multiple partial substitutes.

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CHAPTER 1 : INTRODUCTION

The threat of substitutes is critical in the strategy literature (e.g., Porter, 1979, 1985), and these dynamics are often explored in the rich body of research on the displacement of one technology by another, considering demand-side factors. However, a complete understanding of substitute competition has been limited by a common simplifying assumption, that competing substitutes are mutually exclusive. The classic question asks why existing technologies fail in the face of innovative substitute technologies (Henderson and Clark, 1990; Christensen and Bower, 1996; Adner, 2002) or, symmetrically, what is necessary for an incumbent to succeed (Henderson, 1995; Tripsas, 1997). This stream of literature typically assumes the emergence or sustainability of a single dominant technology or, perhaps, market segmentation through competitive isolation or retreat to a defensible niche (e.g., Adner, 2002; Adner and Snow, 2010). Where the success of multiple survivors is considered, it tends to be in the context of winning eco-systems of *complementors* working together (Kapoor, 2013).

This research has yielded considerable insight into "zero-sum" competition between close substitutes, where only a single technology may be viable, as frequently illustrated in the winner-take-all examinations of the empirical contexts used in this stream of literature. While competition with close substitutes is absolutely critical for competitive success, mangers are also encouraged to consider the question of substitutes more broadly, to the point of considering means for using less of an offering, use of a used version of an offering, or even the choice to not use anything (Porter, 1985, p. 276). Within this range, it is important to recognize that many competing technologies are in fact only partial substitutes, with lower performance on one or more dimensions important to some buyers (e.g., more hard drive capacity or a smaller physical size). The belief that innovation success requires the failure of a competing substitute can lead to a myopic focus on dyadic competition that may actually be counterproductive. Even within a traditional framework, being a disruptor can lower profits through increased price competition in attempting to steal share (Adner and Zemsky, 2005). The challenge in predicting outcomes with the dyadic competitive framework has even led some to question the value of disruption theory (King and Baatartogtokh, 2015). However, choice is not restricted to head-to-head winner-take-all competition, or retreating to defensible niches. When technologies are only partial substitutes they may each be best for a subset of possible situations, and for buyers who place sufficient value on those unique situations the choice is not simply between either one or the other, but perhaps both.

The dyadic-comparison single-purchase assumption is a very strong assumption that hides viable paths for competing technologies. Whether comparing desktops to laptops, or digital cameras and smartphones, the persistence of the legacy technology is not necessarily due to offering greater utility than any alternative for a sufficiently large number of buyers (though some buyers may buy only one), but rather that many buyers will buy both technologies, using each when a particular offering provides the greatest utility.

This research opens up a new avenue for understanding substitute technology competition by modeling how the ability to create value in the presence of substitutes depends on the interaction between the preference structure *within* a given buyer[1] and the range of technologies available to that buyer. I develop a utility function where an individual's preferences are decomposed into a range of situations where the importance of each technical attribute is allowed to vary. Existing models of differentiated technology competition can predict which single offering will create the most value, based on an aggregated utility function (a single weight on each performance dimension), but cannot predict which combination or combinations of partial-substitutes might create even greater value. A model which decomposes the needs of that buyer might predict a supplemental purchase in addition to the single best offering, but may also predict a combination of products that does not include that single most valuable offering.

[1] Preference structure within the individual stands in contrast to the preference structure of aggregated individuals, as in Adner (2002).

This model of partial substitute competition is broadly applicable to a wide range of industries. For example, over-the-air broadcast television using an antenna can be seen as competing against streaming services such as Netflix. However, because the competition offers a compelling alternative to cable, antenna sales and usage are increasingly common with the rise of streaming services (Dixon, 2017). As focus shifts to value of an offering conditional on the prior adoption, this model can also be applied. For example, while range has long been seen as a barrier to adoption of electric vehicles, many families own multiple vehicles. Conditional on owning one vehicle capable long trips, an electric vehicle may be a viable supplement, to be used for daily commuting. In contrast, prior adoption may limit the co-use of a new technology. Mobile payments, for example, may be particularly valuable for those without traditional financial accounts, but the lower incremental value conditional on prior adoption of credit cards may slow adoption for users of incumbent offerings. The model can even be applied to relatively mundane purchases, such as when buying shoes. Many people have multiple pairs, to cover their range of needs (e.g., work, casual, hiking), and the purchase of an additional pair may depend in part on the incremental value of the new pair, conditional on ownership of many other pairs, relative to the cost of the incremental purchase.

In Chapter 2 I propose that improvements to increase standalone value creation (when considering head-to-head competition against all potential substitutes) may actually decrease value creation when considering situations where the offering might actually be used as part of a buyer's technology portfolio. In situations where an offering would be used as part of portfolio regardless of improvement (areas of strength), the full utility of any improvement is realized. In situations where improvement would cause the buyer to *switch* to using the offering as part of their portfolio (areas of relative parity), only a portion of incremental utility is realized (the difference between new utility and the utility of the alternative offering). In situations where even the improved offering would not be used as part of the portfolio (areas of weakness), none of the incremental utility is realized. This is sufficient for realized incremental value to be lower than what is predicted by a dyadic model of value creation, and may even cause incremental value to become negative. The differences in the relative preference for each performance dimension across these situations can also mean that improving performance along one dimension may maximize incremental value under constrained choice, but improvement on another may maximize incremental value when recognizing that buyers may purchase multiple technologies.

I also argue that adoption of a technology critically depends on the adoption history of buyers, which constrains adoption in several ways. If prior technologies are on a similar technology trajectory (same dimensions of relative strength), the new technology faces a replacement challenge - incremental utility, given the prior technology for which the cost has already been incurred, must be sufficiently high to justify the cost. This is a difficult challenge to overcome, and can be seen in current markets with slowing replacement sales for smartphones and cameras. If prior technologies are on a different technology trajectory (different dimensions of relative strength), the new technology faces a supplement challenge - incremental utility in areas of strength, given that it will be used only in a subset of situations, must be sufficiently high to to justify the cost. This can be seen in the purchase of a new camera, given the buyer already owns a smartphone with a camera. While incremental value is reduced by the presence of a competing technology, this can be a lower hurdle relative to what is predicted by single-choice models of technology competition, in that the technology does not need to be good enough to *replace* an incumbent in order to gain a foothold, but can instead provide sufficient value for a narrower subset of situations to justify addition to a buyer's technology portfolio.

In Chapter 3, predictions based on the model are developed. This is done through the formalization of conditional value, numerically illustrated, to show how the preference structure of an individual determines adoption choices, conditional on the prior adoption of a substitute. More specifically, adoption behavior is predicted for buyers of fixed-lens and interchangeable-lens cameras, conditional on observed indicators of preferences, and whether or not they have previously adopted the camera functionality of a smartphone. In the sections that follow, I argue that the adoption of a technology that is a more distant substitute for some offerings than others will be associated with an increased rate of adoption for the former relative to the latter. Further, I argue that greater individual-level variance in situational preferences will be associated with the adoption of more flexible technologies and multiple technologies, to best meet their range of needs.

In Chapter 4, the predictions from Chapter 3 are tested in the context of the digital camera industry, where many users use multiple devices, such as a standalone camera alongside a smartphone. These predictions describe how demand might shape this opportunity landscape through the rise of partial substitutes. First, the adoption of a new technology (smartphone) that is a closer substitute for some technologies (compact cameras) than others may shape future adoption decisions, inducing buyers to switch to the more distant technology (SLR and mirrorless cameras). Next, measures of within-individual preference variance are created, based on the range of subjects photographed, and the range of technical dimensions for those photos. Greater variance is predicted to be associated with more technically flexible technologies (interchangeable lens cameras), and the co-use use of multiple devices.

These predictions are tested using a novel dataset of metadata from 100 million images uploaded to Flickr, a popular photo sharing site. This rich data allows individuals to be followed over time, observing not only their adoption decisions, seen in the initial use of a new device, but continued usage over time, including the co-use of partially substituting devices. In addition, this data incorporates detailed data on the subject matter of each photo, measured through the application of machine learning by Yahoo Labs, and detailed technical details for each photo, such as shutter speed, aperture, and focal length. These data allow for multiple measures of within-individual time-varying situational variance. Results are consistent with model predictions.

1.1. Background

The threat of substitutes has long been a fixture in the field of strategic management (e.g., Porter, 1979, 1985). Nowhere has this been more prominent than in the field of technology strategy. While new technologies are important to the general process of creative destruction (e.g., Schumpeter, 1942, 1947), the nature of each technology comes into focus when theories are developed to explain why some technologies (or their associated firms) fail despite apparent advantage, or succeed despite apparent disadvantage. Supply-side theories have explored the architecture of technologies (Henderson and Clark, 1990), the presence of complementary assets (Tripsas, 1997), and technical interdependence in the ecosystem (Adner and Kapoor, 2010, 2014), but demand-side theories have also featured prominently in the literature on the success or failure of competing technologies. These theories have considered how product variety can deter entry in markets with heterogeneous preferences (Eaton and Kierzkowski, 1984), how over-supply of performance for less demanding segments can create opportunities for disruption (Christensen and Bower, 1996), how the application of technologies to niches with different preferences can trigger technological "speciation" and creative destruction (Levinthal, 1998), how customer (and supplier) learning can lead to the emergence (or not) of a dominant design (Windrum and Birchenhall, 1998), how the structure of demand can drive industry life cycles or disruption (e.g., Adner and Levinthal, 2001; Adner, 2002; Tripsas, 2008), as well as addressing other related concerns. While providing great insight into the processes of disruption, predicted outcomes often fail to materialize, leading some to question the value of disruption theory (King and Baatartogtokh, 2015).

My exploration of technological competition most closely aligns with the demand-side theories mentioned above, but differs with a focus on the potential for co-existence of partially substituting technologies even within a single buyer. Some of these theories describe a transitory co-existence (e.g., Christensen and Bower, 1996), until a technology targeted to one segment disrupts the other. Others allow for retreat into a defensible niche (Adner and Snow, 2010), or competitive isolation where each technology survives to service a different portion of the market with different preferences (Adner, 2002). These place a ceiling on the market, with each technology taking a share of potential buyers, through the assumption that each buyer will choose the offering best meeting their particular needs or preferences.

The assumption that a buyer will choose the technology best suited to their needs has a basis in reality, and many historical examples to illustrate this. A newspaper, for example, might rely on a single piece of equipment (or several of the same type) for all their printing needs (see Tripsas, 1997, 2008). Other industries, however, do not necessarily require buyers to purchase a single technology for all their needs, but allow for the purchase of multiple partially-substituting technologies for their varying needs. An example of this can be seen in computing, where the popular press frequently predicted laptops disrupting desktops, or tablets disrupting laptops. Existing models might predict a particular winning technology, or segmentation based on the needs of different buyers. Even marketing from within the industry often treats the purchase decision as a single best choice for the offering best meeting the needs of a particular buyer (see Appendix A.1 for an example). Many buyers, however, will choose a desktop, laptop, *and* tablet, to use each when it best suits their needs.

The intuition that buyers might buy multiple technologies that can also be seen as competing or substituting technologies is the basis for the model I will develop in the following sections, where buyers are defined by multiple sub-utility functions based on their varying needs. This allows the identification of criteria sufficient for the co-existence of substitute technologies "within" a particular buyer. Subsequent sections will focus on different aspects of the base model to identify trade-offs in the choice of technological trajectories that are missed by existing models, and explore how the adoption history of buyers shapes the subsequent adoption and diffusion of new technologies.

1.2. Value creation and technology trajectory

When considering how substitute technologies compete against each other, it is helpful to revisit a core idea from the strategy literature - the idea of competitive advantage through value creation. Value is created when the utility of an offering to buyers exceeds the cost (or opportunity costs) of creating that offering, with added value or competitive advantage when the difference between the two exceeds the value created by competing offerings (Brandenburger and Stuart, 1996; Porter, 1998; Macdonald and Ryall, 2004). Most value-based theory on competition between competing technologies focuses on buyer preferences and, by extension, willingness to pay (e.g., Adner, 2002; Tripsas, 2008). Formalization of the value-based perspective have addressed questions about the sustainability of advantage from a technology, the persistence of substitution, order of niche entry, and effects on prices and innovation incentives (Adner and Zemsky, 2006, 2005).

These tools generally assume the choice of a single offering/technology at the buyer level. This is typically also constrained to the purchase of a single unit for purposes of tractability (e.g., Macdonald and Ryall, 2004; Brandenburger and Stuart, 2007; Chatain and Zemsky, 2011), even where "coalitions" of buyers are necessary to produce an offering (as in Stuart, 1997, where a focal firm has a choice of upstream buyers and downstream sellers). Greater insight for *how* technologies compete often arises through some degree of multidimensionality with a vector of individual preferences across dimensions of technical performance (Adner and Levinthal, 2001; Adner, 2002).

To explore the implications of a sub-utility maximizing utility function, first consider a typical utility function for individual i, for offering k from firm F_k, with performance dimensions X_1 and X_2, with relative utility weights β_1 and β_2, respectively, and a diminishing marginal utility rate of α.

$$V_i(k) = WTP_{ik} - c_k \tag{1.1}$$

$$V_i(k) = \beta_{1i} X_{1k}^{\alpha} + \beta_{2i} X_{2k}^{\alpha} - c_k \tag{1.2}$$

While these models provide an intuition for how preferences might drive investment choices in horizontal differentiation, and how those choices might affect performance, they are constrained by a preference structure that does not allow multiple choice, based on the varying situations an individual is exposed to. A computer buyer who values a balance of technical performance and portability is not the same as a buyer who sometimes values technical performance, and other times values portability. An individual vector capturing total preference for each attribute cannot say whether the buyer will buy a laptop (balanced preference for both), or a tablet and a desktop (sometimes valuing one, and sometimes the other). It cannot identify the utility from each combination of offerings. By extension, an individual preference vector, with a single measure of preference for each attribute, provides limited guidance for how firms should invest in environments where choice between partial substitutes is not constrained to a single offering. This intuition is formalized in the next chapter.

CHAPTER 2 : MODEL

The central premise of this research is that some buyers may adopt *multiple competing technologies*. In the business-to-consumer space, this can be seen in the case of one buyer purchasing a laptop, while another buyer purchases a desktop and tablet. In the business-to-business case, consider a hospital considering diagnostic imaging technologies. While some might be close substitutes, a full service hospital might purchase equipment for X-ray, CT, MRI, and PET diagnostic imaging, to use each as most appropriate. Neither of these can be captured by the utility function in Equation 1.2, where choice is optimized according to the aggregate weight on each possible performance dimension. To address this problem, I propose a base model of buyer utility that is defined by varying preference for each performance dimension across multiple situations, showing how this allows for multiple technologies to co-exist in a buyer's "technology portfolio."

2.1. Joint value

In contrast to the utility function in Equation 1.2, disaggregating "situations" to create a summation of situation-specific utility functions, as seen in Equation 2.2, significantly alters the choice process.

$$V_i(k) = WTP_{ik} - c_k \tag{2.1}$$

$$V_i(k) = \sum_{s=1}^{S} (\beta_{s1i} X_{1k}^{\alpha} + \beta_{s2i} X_{2k}^{\alpha}) - c_k \tag{2.2}$$

Absent any information about joint utility, complementarity, or substitutability, a typical assumption in value-based modeling is that creating the most value, relative to other players, is a path to superior performance, with "added value" placing a ceiling on potential value capture (Brandenburger and Stuart, 1996).[1]. This is often a reasonable and useful heuristic

[1]With heterogeneous buyer preferences, in the absence of price discrimination, market-price effects also

when comparing substitutes in a single-choice environment. A computer buyer might be interested in the single device that best meets their range of needs. In this environment, substitute threat comes only in increasing value, or $WTP - cost$, of competing offerings, with increased WTP coming from any performance dimension. A tablet competing against a laptop may increase willingness-to-pay for a buyer by increasing power *or* reducing weight to improve portability.

With this alternative specification, however, buyers are not constrained to a single purchase within a particular technology space. Pairwise comparison to identify the offering with the greatest value creation is no longer be sufficient. Using Equation 2.2, the buyer who consistently values performance and portability (β_1 and β_2) across all situations can maximize utility from a single offering, but the buyer who sometimes values performance ($\beta_1 > \beta_2$), and other times values portability ($\beta_2 > \beta_1$) is maximizing the summation of sub-utility functions, and may do that with a single offering (Equation 2.2), or with multiple, as seen in Equation 2.4.

Joint utility function for S situations, with combined purchase of k and k''.

$$V_i(k, k'') = WTP_{ik} + WTP_{ik''|k} - c_k - c_{k''} \tag{2.3}$$

$$V_i(k, k'') = \sum_{s=1}^{S} max((\beta_{s1i} X_{1k}^{\alpha} + \beta_{s2i} X_{2k}^{\alpha}), (\beta_{s1i} X_{1k''}^{\alpha} + \beta_{s2i} X_{2k''}^{\alpha})) - c_k - c_{k''} \tag{2.4}$$

One option might dominate when considering which offering best meets a whole range of needs, in a dyadic comparison with each other offering. That decision can change when the buyer considers what multiple technologies might meet their range of needs, and the "single best" option may not even make the final cut. A buyer having a "technology portfolio," a term I will use to describe the collective possessions of an individual available for meeting particular needs, whether considered/acquired simultaneously, or previously acquired but

become important (Stuart Jr, 2015), as some buyers may be priced out of their most value-creating choice. In pilot simulations using pricing choice along with my proposed model structure the two were highly correlated. To focus attention on what is new, I rely entirely on value-based modeling in this paper.

relevant to a current purchase decision, changes that decision outcome. With multiple technologies in a portfolio, the incremental (added) value of an offering depends on the utility only from those situations where the technology will be used (where it is "situationally best" - e.g., the tablet for situations when portability dominates derived utility).

Table 1: Parameter definitions

Parameter	Definition
V_i	Value function, defined as individual-specific (i) willingness to pay minus cost
k	An offering, where a distant substitute to k is signified by k'', and an intermediate substitute is signified by k'
s	A situation, as distinguished by varying preference weights (relative to all situations, S) for one or more performance dimensions
X	Performance along subscripted dimension 1... n (two dimensions used throughout paper) for the subscripted offering
β	Preference in situation s for dimension X_1... X_n, for individual i
α	Diminishing marginal utility of an offering ($0 < \alpha < 1$)
c	Cost of the subscripted offering
WTP	Willingness to pay for, or utility of, an offering, captured in the non-cost portion of value (V)
Δ_k	Change in a performance dimension, for an improved offering ($\Delta > 0$)
δ	Change in cost, for an improved offering (unconstrained)

2.2. Incremental utility and added value

The implications of this function are key to correctly evaluating incremental utility and added value. An individual considering the purchase of two technologies, rather than one, will evaluate the *total utility* using the *best offering for each situation*, against the cost of acquiring both technologies. If a buyer already has a technology in their portfolio, it has no marginal cost. The implications of this are discussed in the following extension of the base model. The value of a combined purchase for a buyer's portfolio (e.g., offerings k and k'') exceeds the value of a single greatest offering (e.g., k'), which is to say $V_i(k, k'') > V_i(k') > V_i(k)$, when the following is true.

$$\sum_{s=1}^{S} max((\beta_{s1i}X_{1k}^{\alpha} + \beta_{s2i}X_{2k}^{\alpha}), (\beta_{s1i}X_{1k''}^{\alpha} + \beta_{s2i}X_{2k''}^{\alpha})) - c_k - c_{k''}$$
$$> \sum_{s=1}^{S}(\beta_{s1i}X_{1k'}^{\alpha} + \beta_{s2i}X_{2k'}^{\alpha}) - c_{k'} > \sum_{s=1}^{S}(\beta_{s1i}X_{1k}^{\alpha} + \beta_{s2i}X_{2k}^{\alpha}) - c_k \quad (2.5)$$

Subtracting $V_i(k)$ to create necessary conditions for the purchase of a combination or a single offering yields the following, where value must be positive for the possibility for any purchase.

$$\sum_{s=1}^{S} max((\beta_{s1i}X_{1k}^{\alpha}+\beta_{s2i}X_{2k}^{\alpha}),(\beta_{s1i}X_{1k''}^{\alpha}+\beta_{s2i}X_{2k''}^{\alpha}))-\sum_{s=1}^{S}(\beta_{s1i}X_{1k}^{\alpha}+\beta_{s2i}X_{2k}^{\alpha})-(c_k-c_k)-c_{k''}$$
$$> \sum_{s=1}^{S}(\beta_{s1i}X_{1k'}^{\alpha}+\beta_{s2i}X_{2k'}^{\alpha}) - \sum_{s=1}^{S}(\beta_{s1i}X_{1k}^{\alpha}+\beta_{s2i}X_{2k}^{\alpha}) - (c_{k'}-c_k) > 0 \quad (2.6)$$

For a particular offering (e.g, k'') to add sufficient value, given the other (k), to be chosen over the single best technology (k'), this simplifies to:

$$\sum_{s=1|WTP_{sik''}>WTP_{sik}}^{S} ((\beta_{s1i}X_{1k''}^{\alpha}+\beta_{s2i}X_{2k''}^{\alpha})-(\beta_{s1i}X_{1k}^{\alpha}+\beta_{s2i}X_{2k}^{\alpha}))-c_{k''}$$
$$> \sum_{s=1}^{S}(\beta_{s1i}X_{1k'}^{\alpha}+\beta_{s2i}X_{2k'}^{\alpha}) - \sum_{s=1}^{S}(\beta_{s1i}X_{1k}^{\alpha}+\beta_{s2i}X_{2k}^{\alpha}) - (c_{k'}-c_k) > 0 \quad (2.7)$$

$$V(k''|k) > V(k') - V(k) > 0 \quad (2.8)$$

Alternatively stated, $V_i(k, k'') > V_i(k') > V_i(k)$ when the added utility of k'', given k, in situations where $WTP_{sik''} > WTP_{sik}$, minus the incremental cost of k'', exceeds the difference in value between offerings k' and k. This is to say that the added value of k'', given k, must exceed the value difference between k' and k, for the combination to be superior to the single best offering.[2] Offerings k and k'' together may be more valuable than either alone, as in this example, even though the combined value is less than the sum of their standalone value creation. As partial substitutes, they are sub-additive. This also holds if the most valuable combination also includes the single most valuable offering, where the added value of the supplement (e.g., k), given the single greatest value creator (k') must be greater than 0 (i.e., $V(k|k') > V(k') - V(k') = 0$), for the combination of k and k' to be

[2] At this point, this is symmetric. The value of k, given k'', must also exceed the difference in value between k' and k'', or else the combination would not be superior. For whichever of k or k'' offers more (less) standalone value, the gap between k' and the other will be larger (smaller).

more valuable than k' alone.

This is equivalent to the following transformation of Equation 2.7, which makes the importance of relative performance on each dimension more explicit.

$$\sum_{s=1|WTP_{sik''}>WTP_{sik}}^{S} (\beta_{s1i}(X_{1k''}^{\alpha} - X_{1k}^{\alpha}) + \beta_{s2i}(X_{2k''}^{\alpha} - X_{2k}^{\alpha})) - c_{k''}$$
$$> \sum_{s=1}^{S}(\beta_{s1i}(X_{1k'}^{\alpha} - X_{1k}^{\alpha}) + \beta_{s2i}(X_{2k'}^{\alpha} - X_{2k}^{\alpha})) - (c_{k'} - c_k) > 0 \quad (2.9)$$

For Inequality 2.9 to be true, at least one of $X_{1k''}^{\alpha} - X_{1k}^{\alpha}$ or $X_{2k''}^{\alpha} - X_{2k}^{\alpha}$ must be positive. Because at least one of $X_{1k}^{\alpha} - X_{1k''}^{\alpha}$ or $X_{2k}^{\alpha} - X_{2k''}^{\alpha}$ must also be positive (based on the symmetric equivalent of Inequality 2.9, where k and k'' are reversed), the other must be negative. If not, regardless of the β weights, $V_i(k, k'')$ could not be more than the greater of $V_i(k)$ or $V_i(k'')$. This means that $X_{1k} > X_{1k''}$ and $X_{2k''} > X_{2k}$, or vice versa, for a combination to be superior. This implies that horizontal differentiation is critical to supplementation by partial-substitutes. With vertical differentiation, the buyer would simply choose the offering creating the most value for them, based on their preferences for absolute performance weighted against cost.

Without loss of generality, going forward I will treat the identities k and k'' such that $X_{1k} > X_{1k''}$ and $X_{2k''} > X_{2k}$. Thus, for $WTP_{sik''} > WTP_{sik}$ (situations where k'' is more useful than k), $\beta_{s1i}(X_{1k''}^{\alpha} - X_{1k}^{\alpha}) + \beta_{s2i}(X_{2k}^{\alpha} - X_{2k''}^{\alpha}) > 0$ (the utility difference is positive), $0 > \beta_{s1i}(X_{1k''}^{\alpha} - X_{1k}^{\alpha})$ (k'' is disadvantaged on X_1), and $\beta_{s2i}(X_{2k}^{\alpha} - X_{2k''}^{\alpha}) > 0$ (k'' is advantaged on X_2).

In a dyadic comparison, perhaps a desktop dominates a tablet, and the tablet offers no incremental utility or added value (ignoring cost). When considering a tablet as a supplement to a desktop (it is not a compliment, because of negative cross-price elasticity - the utility of a desktop and tablet is less than the sum of the utility of the desktop and the utility of the tablet), attention shifts entirely to situations where the tablet is superior, and is ignored for situations where the desktop is superior, and added value depends on the incremental utility in the former.

2.3. Innovation incentives

In technology industries, innovation is generally seen as necessary for ongoing survival, whether incremental or radical in terms of performance (or performance dimensions), or process. Improvements take place along a performance trajectory, defined by the relative level of each dimension of performance, perhaps including cost, (Adner and Levinthal, 2001; Adner, 2002), with position on the trajectory defined by the performance along each dimension in a given period. Value-based strategy provides a map for how to remain competitive, through targeted efforts to maximize the gap between willingness to pay and cost (Brandenburger and Stuart, 1996; Macdonald and Ryall, 2004). To the extent that gap exceeds the value created from any other offering under consideration, value has been added, and may be captured. As shown in the base model, however, the firm that creates the most standalone value through their offering may not create the most value (or add any value) when combinations of offerings are considered.

In this section I extend the base model to propose that investments that increase the standalone competitiveness of an offering may *decrease* competitive advantage when the offering is considered as one of multiple technologies a buyer might adopt in building their technology portfolio. This could happen where investments primarily improve performance across situations where another part of a buyer's portfolio provides greater performance, and increased willingness to pay in the remaining situations where the offering will be used can't justify the investment. While this idea holds generally, the specifics can depend on whether the investment is focused on a dimension of relative strength, or relative weakness, as the firm decides whether to increase depth in current area of focus, expand into adjacent use-cases, or attempt to target all uses as a market leader.

2.3.1. Product improvement

When the ability to capture value depends on the possibility of being purchased into a technology portfolio, this has important implications for investment behavior. Consider F_k's various investment alternatives for improving k. First, consider an investment in improving X_{1k} by Δ_k, with an increase in cost of δ_k.[3]

$$V_i(k_{\Delta X_1}) = \sum_{s=1}^{S}(\beta_{s1i}(X_{1k} + \Delta_k)^{\alpha} + \beta_{s2i}X_{2k}^{\alpha}) - (c_k + \delta_k) \tag{2.10}$$

This increases standalone value by the following.

$$V_i(k_{\Delta X_1}) - V_i(k) = \sum_{s=1}^{S}(\beta_{s1i}((X_{1k} + \Delta_k)^{\alpha} - X_{1k}^{\alpha})) - \delta_k \tag{2.11}$$

Because $X_{1k} > X_{1k''}$ and diminishing marginal utility for improved performance, this increases standalone utility less than improving $X_{1k''}$ by Δ_k would increase utility. This implies a marginal advantage to investing in areas of relative weakness (relative to competitors, holding supply-side factors constant), with any improvement at a lower point along the curve of diminishing marginal utility. As shown in the next subsection, however, the relative effect of investing in each area (compared against substitute technologies) can differ when the offering is only one possible option in a technology portfolio.

$$\sum_{s=1}^{S}(\beta_{s1i}((X_{1k''} + \Delta_k)^{\alpha} - X_{1k''}^{\alpha})) - \delta_k > \sum_{s=1}^{S}(\beta_{s1i}((X_{1k} + \Delta_k)^{\alpha} - X_{1k}^{\alpha})) - \delta_k \tag{2.12}$$

In the subsections that follow, improvements in X_1 and X_2 will be modeled and discussed as a discrete choice, with one improving an area of strength and the other an area of weakness. In reality, this is a continuous choice, where firms decide on their trajectory with more or less (but not necessarily zero) improvement on each performance dimension. If a firm

[3] Increments are considered to be constant across examples. Supply side factors that might make these different between performance dimensions are outside the scope of this paper.

continues on a constant trajectory, improvement in their area of strength will dominate. As that trajectory shifts towards that of other buyer segments/competitors, investment proportionately shifts to improvement in an area of relative weakness. The discrete treatment makes this distinction more clear, for the purposes of easing the development of intuition.

2.3.2. Product improvement in an area of relative strength

As shown in the base model, the effect on value creation for a combination being purchased for a portfolio is not the same as the effect on standalone value creation. As opposed to the value creation seen in Equation 2.2, the value creation of a combination with an improved offering k is as shown in Equation 2.13.

$$\begin{aligned} & V_i(k_{\Delta X_1}, k'') \\ & = \sum_{s=1}^{S} max((\beta_{s1i}(X_{1k}+\Delta_k)^\alpha + \beta_{s2i}X_{2k}^\alpha), (\beta_{s1i}X_{1k''}^\alpha + \beta_{s2i}X_{2k''}^\alpha)) - (c_k+\delta_k) - c_{k''} \end{aligned} \tag{2.13}$$

This increases the added value of k, to that shown in Equation 2.14. This added value increases in two ways. The first part reflects increased utility to the buyer in situations where k would be used in the portfolio regardless of any improvement, while the second part reflects increased utility in situations where k'' would be preferable to k, but inferior to $k_{\Delta X_1}$.

$$\begin{aligned} V_i(k_{\Delta X_1}, k'') - V_i(k'') = & \sum_{s=1|WTP_{sik}>WTP_{sik''}}^{S} (\beta_{s1i}((X_{1k}+\Delta_k)^\alpha - X_{1k''}^\alpha) + \beta_{s2i}(X_{2k}^\alpha - X_{2k''}^\alpha)) \\ + & \sum_{s=1|WTP_{sik\Delta}>WTP_{sik''}>WTP_{sik}}^{S} (\beta_{s1i}((X_{1k}+\Delta_k)^\alpha - X_{1k''}^\alpha) + \beta_{s2i}(X_{2k}^\alpha - X_{2k''}^\alpha)) - (c_k+\delta_k) \end{aligned} \tag{2.14}$$

For situations where a buyer would already use offering k (regardless of any improvement), the full value of any improvement is realized. In those situations, an approximation using an increase in standalone value introduces no bias in an investment choice decision. Where preferences reverse (a buyer would use the offering for a situation only because of the improvement, equivalent to $WTP_{sik\Delta} > WTP_{sik''} > WTP_{sik}$, because $X_{1k} > X_{1k''}$ and $X_{2k''} > X_{2k}$, it follows that $((X_{1k} + \Delta_k)^\alpha - X_{1k''}^\alpha) > ((X_{1k} + \Delta_k)^\alpha - X_{1k}^\alpha)$, and $0 > (X_{2k}^\alpha - X_{2k''}^\alpha)$. This says that while k is growing its advantage on X_1 by Δ_k, for situations where k was marginally dominated, but now dominates with the improvement, the buyer experiences even greater benefit from the switch along X_1 (experiencing an improvement along X_1 that is greater than Δ_k, equal to $\Delta_k + X_{1k} - X_{1k''}$), but also loses performance on X_2 (losing $X_{2k} - X_{2k''}$). On net, the buyer does receive extra utility from this switch to the improved version of k, but this improvement is *less* than what would be approximated using a calculation of the improvement in standalone utility for those situations. This begins to introduce bias when using standalone value to make investment decisions when in fact the offering will be considered as part of a technology portfolio. This is because $WTP_{sik''} > WTP_{sik}$, so $\beta_{s1i}((X_{1k} + \Delta_k)^\alpha - X_{1k}^\alpha) > \beta_{s1i}((X_{1k} + \Delta_k)^\alpha - X_{1k''}^\alpha) + \beta_{s2i}(X_{2k}^\alpha - X_{2k''}^\alpha))$, which is to say that the added WTP for situations where the optimal choice for which offering to use reverses is less than the added WTP of the standalone offering in those same contexts. This is because the portion of the increased WTP below the WTP created by k'' in those situations adds no value for the individual. Rather than realizing the full increase in utility in these situations, the buyer only realizes the incremental utility that exceeds the utility already available from other parts of their technology portfolio.

For situations where $WTP_{sik''} > WTP_{sik\Delta}$, which is to say situations where k will not be used when part of the portfolio, despite any increase in performance, the added utility of k and the incremental WTP from the investment remain 0, regardless of any improvement in standalone value. This introduces substantial bias when using standalone value to make investment decisions when in fact the offering will be considered as part of a technology portfolio. When considered on a standalone basis, utility for this situations is increased, while there is no increase when the offering is part of a portfolio.

Note that nothing in Equation 2.14 requires that the incremental value from the investment be positive when k and k'' are purchased together, even if the value of the standalone offering has increased. The added WTP from the investment for the standalone offering exceeds the added WTP from the investment for the offering as part of a portfolio (Inequality 2.15), which means the latter improvement may lower value creation.

$$\begin{aligned}
&\sum_{s=1}^{S} \beta_{s1i}(((X_{1k} + \Delta_k)^{\alpha} - X_{1k}^{\alpha})) - \delta_k \\
&\qquad > \sum_{s=1|WTP_{sik}>WTP_{sik''}}^{S} (\beta_{s1i}((X_{1k} + \Delta_k)^{\alpha} - X_{1k}^{\alpha})) \\
&+ \sum_{s=1|WTP_{sik\Delta}>WTP_{sik''}>WTP_{sik}}^{S} (\beta_{s1i}((X_{1k} + \Delta_k)^{\alpha} - X_{1k''}^{\alpha}) + \beta_{s2i}(X_{2k}^{\alpha} - X_{2k''}^{\alpha})) - \delta_k
\end{aligned} \tag{2.15}$$

For the investment to be additive to the combination, the incremental value derived from improved performance X_1 where $WTP_{sik} > WTP_{sik''}$ and $WTP_{sik\Delta} > WTP_{sik''} > WTP_{sik}$ must exceed not only the incremental cost (δ_k), but also the utility lost on dimension X_2 where $WTP_{sik\Delta} > WTP_{sik''} > WTP_{sik}$ (Equation 2.16 - note the reversal of X_{2k} and $X_{2k''}$, as the negative value was subtracted from both sides). More concisely, any increase in utility for situations where the offering otherwise would not be used, in an area of relative strength, is offset by the previous advantage of the other offering in the portfolio, in the area of relative weakness.

$$\begin{aligned}
&\sum_{s=1|WTP_{sik}>WTP_{sik''}}^{S} (\beta_{s1i}((X_{1k} + \Delta_k)^{\alpha} - X_{1k}^{\alpha})) \\
&\qquad + \sum_{s=1|WTP_{sik\Delta}>WTP_{sik''}>WTP_{sik}}^{S} (\beta_{s1i}((X_{1k} + \Delta_k)^{\alpha} - X_{1k''}^{\alpha})) \\
&\qquad\qquad > \delta_k + \sum_{s=1|WTP_{sik\Delta}>WTP_{sik''}>WTP_{sik}}^{S} (\beta_{s2i}(X_{2k''}^{\alpha} - X_{2k}^{\alpha}))
\end{aligned} \tag{2.16}$$

Taken together, buyers will realize the full utility gain from performance improvements for situations where they would use a given offering even in the absence of improvement, will realize partial utility gain from performance improvements for situations where they would switch to the offering due to the improvement, and will realize no utility gain from performance improvements for situations where they would not use the offering regardless of the improvement. Any incremental value creation calculated on the assumption of a standalone purchase is reduced based on the range of situations where use is contingent on the improvement, or where usage will not occur regardless of the improvement. The standalone approximation of value creation is increasingly useful as the number of situations where an offering is most useful (within a comparison set of technologies in or being considered for a technology portfolio) increases.

2.3.3. Product improvement in an area of relative weakness

At the highest levels, there are some symmetries in investing in an area of weakness to investing in an area of strength. Equation 2.17 mirrors Equation 2.10, showing the standalone value of an improved offering. This represents an investment improving performance along dimension X_2. This subsection will assume that $X_{2k''} > X_{2k} + \Delta_k$, such that the substitute offerings have absolute but different strengths. Absent this assumption, k would dominate on both dimensions, and k'' would have a lower WTP across all situations. There is nothing about this model which precludes that, which would essentially transform the question into one of vertical differentiation, but that would be moving beyond the scope of this research. In contrast to Equation 2.12 above, increasing X_{2k} for k by Δ_k will increase utility of the standalone offering more than increasing $X_{2k''}$ for k'' by the same amount.

$$V_i(k_{\Delta X_2}) = \sum_{s=1}^{S} (\beta_{s1i} X_{1k}^{\alpha} + \beta_{s2i}(X_{2k} + \Delta_k)^{\alpha}) - (c_k + \delta_k) \tag{2.17}$$

The value of the improved version of k, as part of a technology portfolio with k'', can be seen in Equation 2.17, with the incremental value of the improved k, given k'' in a technology portfolio, in Equation 2.18.

$$V_i(k_{\Delta X_2}, k'') = \sum_{s=1}^{S} max((\beta_{s1i}X_{1k}^{\alpha} + \beta_{s2i}(X_{2k} + \Delta_k)^{\alpha}), (\beta_{s1i}X_{1k''}^{\alpha} + \beta_{s2i}X_{2k''}^{\alpha})) - (c_k + \delta_k) - c_{k''} \tag{2.18}$$

$$V_i(k_{\Delta X_2}, k'') - V_i(k'') = \sum_{s=1|WTP_{sik}>WTP_{sik''}}^{S} (\beta_{s1i}(X_{1k}^{\alpha} - X_{1k''}^{\alpha}) + \beta_{s2i}((X_{2k} + \Delta_k)^{\alpha} - X_{2k''}^{\alpha})) + \sum_{s=1|WTP_{sik\Delta}>WTP_{sik''}>WTP_{sik}}^{S} (\beta_{s1i}(X_{1k}^{\alpha} - X_{1k''}^{\alpha}) + \beta_{s2i}((X_{2k} + \Delta_k)^{\alpha} - X_{2k''}^{\alpha})) - (c_k + \delta_k) \tag{2.19}$$

As with Equation 2.14, Equation 2.18 is composed of two parts, with the first from increased utility to the buyer in situations where k would be used in a situation, *regardless* of improvement, and the second part from increased utility where k would be used in a situation *because* of the improvement. Note that while the improvement increases the performance difference applied to β_2, this value is *still negative*. Rather than growing an advantage on X_1 as in the subsection above, the disadvantage on X_2 has been reduced. As before, even if standalone value of an offering has increased, the incremental utility from the improvement may not exceed the incremental cost.

2.4. Investment choice

Investments in areas of strength or weakness must take into account where utility will actually be realized, or decisions may be sub-optimal. This impacts the trajectory of a technology, which may differ from what would be ideal under an assumption of standalone value creation as the determinate of value capture.

The sections above describe how to measure incremental utility from product improvement, for products considered in isolation or purchased in combination with another. If the firm is maximizing standalone value creation, it would invest in X_1 if the following is true, otherwise X_2.

$$\sum_{s=1}^{S}(\beta_{s1i}((X_{1k}+\Delta_k)^{\alpha}-X_{1k}^{\alpha}))-\delta_k>\sum_{s=1}^{S}(\beta_{s2i}((X_{2k}+\Delta_k)^{\alpha}-X_{2k}^{\alpha}))-\delta_k \tag{2.20}$$

If the firm is maximizing value creation when purchased in combination with k'', it would invest in X_1 if the following is true, otherwise X_2.

$$\begin{aligned}
&\sum_{s=1|WTP_{sik}>WTP_{sik''}}^{S}(\beta_{s1i}(X_{1k}+\Delta_k)^{\alpha}-X_{1k}^{\alpha})\\
&+\sum_{s=1|WTP_{sik\Delta X1}>WTP_{sik''}>WTP_{sik}}^{S}(\beta_{s1i}((X_{1k}+\Delta_k)^{\alpha}-X_{1k''}^{\alpha})+\beta_{s2i}(X_{2k}^{\alpha}-X_{2k''}^{\alpha}))-\delta_k\\
&\qquad>\sum_{s=1|WTP_{sik}>WTP_{sik''}}^{S}(\beta_{s2i}(X_{2k}+\Delta_k)^{\alpha}-X_{2k}^{\alpha})\\
&+\sum_{s=1|WTP_{sik\Delta X2}>WTP_{sik''}>WTP_{sik}}^{S}(\beta_{s1i}(X_{1k}^{\alpha}-X_{1k''}^{\alpha})+\beta_{s2i}((X_{2k}+\Delta_k)^{\alpha}-X_{2k''}^{\alpha}))-\delta_k
\end{aligned} \tag{2.21}$$

These simply state that when the incremental value from investing X_1 exceeds the incremental value of investing in X_2, the firm will invest in X_1, otherwise X_2, whether the firm is looking at standalone or combined incremental value. However, either of these being true does not imply that the other is also true.

Across situations, the total individual standalone utility may be optimized by improving X_1, while total utility as part of a portfolio may be optimized by improving X_2. This is because of a difference in the situations relevant to a purchase decision. If a buyer will make a single purchase choice, buying the product that maximizes their realized value across all situations. Improvement for any situation (even if a very poor performer in some situations) will increase willingness to pay for the buyer, which may make addressing weakness critical for success. By contrast, buyers building a portfolio of technologies may be interested a more specialized offering to supplement something already in their portfolio, in which case advantage might come from adding more value in a subset of situations.

Reversal, where improvement in one dimension is optimal for standalone value and another for combined value, can driven by individuals who would reverse their technology choice for a situation based on the improvement (with a reduced portion of incremental value realized), or would continue to use another option despite the improvement (no realized incremental value). As noted in the sections above, realized gains in utility from improvement are the same for situations where a focal offering would be already be used. This does not mean it represents the best avenue for increasing market power. "Transforming" Equation 2.20 so that it becomes Equation 2.21 requires subtracting the "lost utility" that is not realized when the offering is part of a combination. This can be seen in Inequality 2.22, *which only holds when Inequality 2.23 is true.* This requires that, for consistency between optimal investment when assuming standalone purchase versus the possibility of portfolio purchase, the "lost" utility from investing in an area of weakness exceeds the "lost" utility from investing in the area of strength plus the difference in value between alternatives when considering standalone value alone. Inconsistency is increasingly likely as more value is "lost" from the "best" option (more of the gain comes from situations where the offering is less preferred), less value is "lost" from the alternative (most of the value coming from situations where the alternative is or will be preferred), and the gap between standalone approximations of incremental value is greatest.

$$
\begin{aligned}
&\sum_{s=1}^{S}(\beta_{s1i}((X_{1k}+\Delta_k)^{\alpha}-X_{1k}^{\alpha})) - \sum_{s=1|WTP_{sik\Delta X1}>WTP_{sik''}>WTP_{sik}}^{S}(\beta_{s1i}(X_{1k}^{\alpha}-X_{1k''}^{\alpha})) \\
&\qquad - \sum_{s=1|>WTP_{sik''}>WTP_{sik\Delta X1}}^{S}(\beta_{s1i}((X_{1k}+\Delta_k)^{\alpha}-X_{1k}^{\alpha})) - \delta_k \\
&> \sum_{s=1}^{S}(\beta_{s2i}((X_{2k}+\Delta_k)^{\alpha}-X_{2k}^{\alpha})) - \sum_{s=1|WTP_{sik\Delta X2}>WTP_{sik''}>WTP_{sik}}^{S}(\beta_{s2i}(X_{2k}^{\alpha}-X_{2k''}^{\alpha})) \\
&\qquad - \sum_{s=1|>WTP_{sik''}>WTP_{sik\Delta X2}}^{S}(\beta_{s2i}((X_{2k}+\Delta_k)^{\alpha}-X_{2k}^{\alpha})) - \delta_k
\end{aligned} \tag{2.22}
$$

$$
\begin{aligned}
&\sum_{s=1|WTP_{sik\Delta X2}>WTP_{sik''}>WTP_{sik}}^{S}(\beta_{s2i}(X_{2k}^{\alpha}-X_{2k''}^{\alpha})) + \sum_{s=1|>WTP_{sik''}>WTP_{sik\Delta X2}}^{S}(\beta_{s2i}((X_{2k}+\Delta_k)^{\alpha}-X_{2k}^{\alpha})) \\
&> \sum_{s=1|WTP_{sik\Delta X1}>WTP_{sik''}>WTP_{sik}}^{S}(\beta_{s1i}(X_{1k}^{\alpha}-X_{1k''}^{\alpha})) + \sum_{s=1|>WTP_{sik''}>WTP_{sik\Delta X1}}^{S}(\beta_{s1i}((X_{1k}+\Delta_k)^{\alpha}-X_{1k}^{\alpha})) \\
&\qquad + \sum_{s=1}^{S}(\beta_{s1i}((X_{1k}+\Delta_k)^{\alpha}-X_{1k}^{\alpha})) - \sum_{s=1}^{S}(\beta_{s2i}((X_{2k}+\Delta_k)^{\alpha}-X_{2k}^{\alpha}))
\end{aligned} \tag{2.23}
$$

If an offering dominates in a narrow set of situations, but is only marginally dominated in many more, improvement for the many situations may add more value than improvement for the few. This would shift situations from the third part of either side of Inequality 2.22 to the second part. Rather than losing all of the incremental value for those situations, only a subset is lost. This also shifts those situations into the "use regardless" category (holding competitors' positioning constant), for future increases in utility to be fully realized. It could also be, however, that the many situations are not "adjacent," with ability to increase value limited to the narrower niche. In this case, those additional situations all remain in the third part of either side of Inequality 2.22.

2.4.1. Illustration of investment incentives

To give an example, a DSLR camera might provide the most utility in situations where absolute technical performance is valued over convenience. Increasing the portability of that camera might improve performance in situations where convenience is valued over technical performance. Considered in isolation, willingness to pay has increased. Comparing this against any other other individual offering, this offering has become more competitive. But perhaps a buyer already has a smartphone with a high quality camera and, despite owning a DSLR, would use their smartphone in those situations where portability is valued over technical performance. While the DSLR has become more valuable in isolation, none of that incremental utility is realized in those situations where the smartphone is still preferred. If improved portability increases costs, or if competing manufacturers have focused on technical performance, this firm may have actually decreased their ability to capture value in this competitive environment.

When considered in isolation, increasing value for any situation can increase willingness to pay. When considered in a competitive environment where buyers may purchase multiple technologies, competitors have two levers for increasing willingness to pay. They can focus any increase in utility on situations where they already dominate, or they can focus any increase in value on situations where they are marginally inferior, with the incremental value coming from the addition of new situations where the technology now dominates. According to the model developed above, an improvement that most increases that standalone willingness to pay for an offering may not be optimal for increasing willingness to pay for the offering in combination with other technologies. The effect of an investment will depend on the relative importance for each dimension for increasing willingness to pay in isolation, willingness to pay in situations where the technology dominates, willingness to pay in situations where the technology is marginally dominated, and the relative importance of standalone and combination modes of competition.

2.5. Path dependence

The section above considered individual decisions in isolation. Based on a given state of demand and competition, what are the implications of alternative investment paths. Taken together, though, several periods of prior purchases that are now part of a buyer's "portfolio" create critical path dependencies that will determine whether a new offering is viable, independent of the standalone utility of the offering relative to the cost. That path dependence may favor some new offerings over others. While any partial substitute will reduce how much a buyer might pay for an offering, there may be a net advantage if competing offerings are disadvantaged even more. If a buyer already owns a smartphone, this will reduce the potential incremental value of a compact camera more than it will reduce the potential incremental value of a DSLR camera. While the smartphone may reduce the incremental utility of each, even if a compact camera might be preferred on a standalone basis, the existence of a smartphone in the portfolio can lead to preference reversal between options.

Path dependence also becomes important when considering replacement purchases. Over the years, many buyers have purchased multiple cameras and/or multiple smartphones. Because of diminishing marginal utility, ever greater performance improvements on existing dimensions can be required to drive replacement sales. This creates the challenges seen for many manufacturers currently, where it is becoming increasingly difficult to justify an upgrade at a given cost, with each buyer reaching this point at different times, depending on their overall willingness to pay for performance. At some point, the only opportunities for maintaining sales will require attempts to capture share from rivals, or finding ways to improve performance on new dimensions. In this sense, the broad interpretation of substitutes as including prior versions of an offering also become relevant, though typically ignored in most models of competition between substitute technologies. These intuitions are formalized in the subsections below.

2.6. Portfolio addition

The models above consider value created through the purchase of one or more items at a given time, to illustrate how the purchase of a given technology may need to create incremental value, given another technology. This logic can hold whether that other technology has been purchased previously or is being considered concurrently. However, given the frequency of multiple technology purchases over time, it is important to think about the implications of earlier purchases on later purchases. This serial purchase behavior introduces an important element of path dependence to any purchase consideration. As noted above, in Equation 2.9 (whether k or k'' is the focal technology), for an offering k to be additive to k'' such that the combination exceeds the value created by k', the incremental willingness to pay, from the subset of situations where the buyer would use k over k'' if both were in their portfolio, minus the cost, $c_{k''}$, must exceed the difference in total value between k and k'. Taking ownership of k'' as a given alters this calculation. In the consideration of k', the cost $c_{k''}$ has already been incurred, so the relevant consideration moves to the full cost c_k' rather than just the difference in cost. In addition, rather than taking the absolute difference in willingness to pay, willingness to pay is defined by those situations where the buyer would use k' instead of k'', were it also part of their portfolio. The realization of the full cost (rather than the cost difference) of the market leading option is now relevant, creating a form of disadvantage. The relevance of performance differences in situations only where k' performs better than k'' creates a form of absolute advantage, in that every advantage of k' is summed, with no reduction from disadvantage to k''. This absolute disadvantage is reduced, however, if k' has greater overlap with k'' than k. This means that knowing whether k or k' would create more incremental utility if also purchased by the buyer (Equation 2.24) cannot be inferred from simply knowing $V(k') > V(k)$.

$$\sum_{s=1|WTP_{sik}>WTP_{sik''}}^{S} (\beta_{s1i}(X_{1k}^{\alpha} - X_{1k''}^{\alpha}) + \beta_{s2i}(X_{2k}^{\alpha} - X_{2k''}^{\alpha})) - c_k$$
$$\geq\leq \sum_{s=1|WTP_{sik'}>WTP_{sik''}}^{S} (\beta_{s1i}(X_{1k'}^{\alpha} - X_{1k''}^{\alpha}) + \beta_{s2i}(X_{2k'}^{\alpha} - X_{2k''}^{\alpha})) - c_{k'} \quad (2.24)$$

In essence, this path dependent competition between k and k' requires a comparison between $V(k|k'') - V(k'')$ and $V(k'|k'') - V(k'')$, or the added value of each, given k''. Ignoring the constant, $V(k'')$, this essentially compares $V(k|k'')$ and $V(k'|k'')$. While the value of the latter possible combination has been assumed away previously, for simplicity, it is not necessarily a given that it will be less than the former.[4] The relative preference between these bundles depends on the individual's preferences across situations. As described earlier, for convenience and without loss of generality, offering k specializes in X_1 while offering k'' specializes in X_2, with offering k' treated as a generalist with a balance of each, at a lower level (rather than a vertically differentiated specialist or generalist, better than one or both across all possible situations). Conceptually, this makes k a better supplement for k'' than k' (k and k'' each have less overlap with the other than with k'), though it still depends on the demand structure. For an individual that places little value on X_1 under any circumstances (in which case k has little appeal, regardless of prior adoption history), but sufficiently high value both X_1 and X_2 in some circumstances, the adoption of k' may make sense even with high overlap with k''. As a numerical example, consider a buyer with β_1 and β_2 values of (0,1) and (1,0), for two situations. This buyer already owning k'' (strength on X_2) would have no effect on the relative valuation of k (strength on X_1), but would lower the relative valuation of k' (balance of X_1 and X_2). The buyer may buy either or neither, depending on cost, but k would likely have the advantage. If the buyer's preferences were (0,1) and (0.5,0.5), they may buy either or neither, depending on cost and absolute performance

[4]If this were not the case for some users, the latter bundle would become the relevant bundle for comparison in a simultaneous purchase decision, with the purchase of k' a given.

along each dimension.[5] If the preferences were (0,1) and (1,1), k', they may buy either or neither, depending on cost and absolute performance along each dimension, but the odds of an incremental purchase making sense have increased. Shifting the balanced preference towards X_2 would benefit k' over k, but would also reduce the added value of k' over k'' for that situation.

The consideration of k or k', given k'', may seem trivial, given the arguments above, but it highlights an important dynamic. Namely, even in a dyadic comparison between two offerings where one creates more standalone value than other (in this case, $V(k') > V(k)$, as given above), the weaker option may dominate, depending on the current portfolio of a buyer. By way of contrast, consider if the buyer had previously acquired k'. As standalone offerings, k and k'' specialized for different situations are both disadvantaged, with the purchase of either not dependent on their relative value.[6] Instead, the only criteria for the purchase of either is their added value given k'. While this describes the contrast of a second adoption decision from the first (whether an individual or joint purchase), and highlights the critical importance of a first purchase for the evolution of other offerings, this pattern continues for as long as further adoptions of any type continue, with implications for any subsequent introduction of new offerings.

2.7. Replacement purchases

Prior purchases from the same firm act as substitutes that also affect the consideration of new offerings. Many technologies go through cycles of replacement purchases, but replacement purchases depend on incremental value (whether from investments in areas of strength or weakness) exceeding cost. Replacement purchases may also depend on what other technologies are in a buyer's "portfolio." If an offering is running out of replacement purchase runway, it can seek to disrupt others, or move in new directions (particularly if being converged upon).

[5] With no interaction term for X_1 and X_2, trade-offs are compensatory.

[6] This assumes there are no situations where *both* k and k'' would perform better than the balanced offering k'. As long as $V(k') > V(k)$ and/or $V(k') > V(k'')$, this will hold.

As is taught in any MBA classroom, it is important to consider the question of substitutes broadly. “Substitutes” can be defined to include purchasing a used version of a product or choosing not to purchase at all (Porter, 1985, p. 276). Non-purchase based on current ownership of a prior version can be thought of either of these, or somewhere in between, but is certainly consistent with a broad conceptualization of substitutes. Replacement purchases, or the purchase of something new to replace something similar, are critically important in many industries, particularly once the market has been saturated. With the increasingly saturated smartphone market, for example, many believe that most buyers in the United States with an interest in having a smartphone already have one, meaning that the only way for firms to keep selling phones is to convince buyers to replace their current device with a new device (whether of the same brand, or a different brand). In contrast to the idea of portfolio supplementation, where a buyer might consider using a new technology in place of another only in a subset of situations, replacement purchases can be thought of as replacing that existing possession across most or all situations. However, with diminishing returns to any particular dimensions, development may shift in ways that encroach on other offerings, as smartphones have increasingly encroached on standalone navigation, camera, camcorder, and content consumption devices.

The mechanics of value increases through technical improvement to drive initial sales, generally, are described in Equations 2.11 and 2.14. With replacement purchases, the minimum thresholds for *any* purchase increase to the willingness to pay (utility) of whatever the buyer already owns. Modifying Equation 2.10, a replacement purchase could happen when one of the following, depending on the trajectory of improvement, is true.

$$\sum_{s=1}^{S}(\beta_{s1i}(X_{1k}+\Delta_k)^{\alpha}+\beta_{s2i}X_{2k}^{\alpha})-(c_k+\delta_k)>\sum_{s=1}^{S}(\beta_{s1i}X_{1k}^{\alpha}+\beta_{s2i}X_{2k}^{\alpha}) \tag{2.25}$$

$$\sum_{s=1}^{S}(\beta_{s1i}X_{1k}^{\alpha}+\beta_{s2i}(X_{2k}+\Delta_k)^{\alpha})-(c_k+\delta_k)>\sum_{s=1}^{S}(\beta_{s1i}X_{1k}^{\alpha}+\beta_{s2i}X_{2k}^{\alpha}) \tag{2.26}$$

Similar to situations where a purchase is considered given the buyer already owns something else, this comparison is against willingness to pay without regard to sunk costs. In contrast, however, this value is considered for all situations where the legacy offering is used, as long as performance is equal to or greater than the prior offering for all situations. This representation considers replacement specifically, but the range of situations defining incremental value could be narrowed by other technologies in the portfolio. In this case, incremental value would be defined by the best performer for each situation, on the right side of Inequalities 2.25 and 2.26. Reaching this hurdle is only a minimum threshold, with replacement purchase decisions also taking into account other offerings. With use of a specialized offering limited to a subset of situations, encroachment by offerings applied to a broader range of situations is possible, if not likely. For example, compact cameras generally improve on only a few dimensions, for use in a few types of situations. As smartphones continue to improve, they may increasingly be more valuable in some of those situations, particularly in comparison to a compact technology that may be several generations old. This further raises the hurdle for any replacement purchase of a compact camera, either by reducing the number of applicable situations, or further raising the bar in some of those situations, beyond the performance of the technology (compact camera) being replaced.[7]

The challenge of driving repeated replacement sales is as apparent in the model above as in the real world. A given increase in performance on an existing dimension is less and less valuable to buyers as the "base" performance for comparison increases with each prior replacement purchase. Maintaining sales primarily through replacement purchases (outside of products that depreciate) based on the same performance dimensions becomes an ultimate Red Queen's race, as any improvement to drive current sales just makes future sales even harder to generate. This challenge increases if competitors can achieve footholds in particular situations based on a different mix of performance dimensions. An offering

[7] There may also be cognitive effects. If the smartphone is now used for birthday parties, and the compact camera is only used for trips to the zoo, the new camera may be evaluated only for trips to the zoo, even if it may also be superior to the smartphone for birthday parties. Such effects are outside the scope of this proposal.

k'' may not create sufficient value to be added to a portfolio along with k, at the time k is purchased (Inequality 2.27).

$$0 > \sum_{s=1|WTP_{sik''}>WTP_{sik}}^{S} (\beta_{s1i}(X^{\alpha}_{1k''} - X^{\alpha}_{1k}) + \beta_{s2i}(X^{\alpha}_{2k''} - X^{\alpha}_{2k})) - c_{k''} \tag{2.27}$$

However, the development hurdle for supplementation by k'' may be lower than it is for replacement by an improved k. At the moment of first purchase, the value of buying a replacement k, with no improvement yet, is $-c_k$. $F_{k''}$ has a head start to capturing a foothold as long as $V(k,k'') - V(k) > -c_k$.[8] As soon as Inequality 2.27 reverses, with utility of k'' for the subset of situations where it will be used sufficient to justify the cost, k'' becomes viable as a portfolio addition. This narrows the application of k to a smaller set of situations, raising the hurdle for a replacement purchase. Given the cost of supplementation by a partial substitute, there may be strategic value in designing a product to preclude the purchase of others, though supplementation in areas of substantial weakness may only have modest effect on the hurdle for replacement, particularly in early stages of an industry. For a replacement purchase to take place, with a portfolio that also includes a partial substitute, one of the following must be true, depending on the focal performance dimension.

$$\begin{aligned}
&\sum_{s=1|WTP_{\Delta sik}>WTP_{sik}>WTP_{sik''}}^{S} (\beta_{s1i}((X_{1k} + \Delta_k)^{\alpha} - X^{\alpha}_{1k})) \\
&+ \sum_{s=1|WTP_{\Delta sik}>WTP_{sik''}>WTP_{sik}}^{S} (\beta_{s1i}((X_{1k} + \Delta_k)^{\alpha} - X^{\alpha}_{1k''}) + \beta_{s2i}(X^{\alpha}_{2k} - X^{\alpha}_{2k''})) \\
&> (c_k + \delta_k)
\end{aligned} \tag{2.28}$$

[8]As with everything, this depends on the defined utility function, where a single discrete unit is used in each situation. This has been consistent throughout, but bears repeating here. The same logic would not apply if considering a second scoop of ice cream.

$$\sum_{s=1|WTP_{\Delta sik}>WTP_{sik}>WTP_{sik''}}^{S} (\beta_{s2i}((X_{2k}+\Delta_k)^\alpha - X_{2k}^\alpha))$$
$$+ \sum_{s=1|WTP_{\Delta sik}>WTP_{sik''}>WTP_{sik}}^{S} (\beta_{s1i}(X_{1k}^\alpha - X_{1k''}^\alpha) + \beta_{s2i}((X_{2k}+\Delta_k)^\alpha - X_{2k''}^\alpha))$$
$$> (c_k + \delta_k) \quad (2.29)$$

As with the analysis of baseline portfolio supplementation, the decision is based on situations where the buyer would use the technology, regardless of any improvement (now situations where they use the prior version), and situations where the buyer would go from using a competing technology in their portfolio to using the improved version of the focal technology. Continued improvement of k on X_1 may continue to increase willingness to pay in situations where that dimension matters most, but over the long term performance on that dimension may reach where further improvement can have little effect on willingness to pay. This would indicate pressure towards competitive convergence (with a shift in trajectory towards X_2), *unless* a new performance dimension can be identified. This may not occur symmetrically. For example, if situations where X_2 is relatively more important also place significant weight on X_1, but situations where X_1 dominate would benefit little from improved performance on X_2, it may not be possible to create incremental value in currently dominated situations. This is dynamic described by Adner (2002), except that a specialist in X_1 may not be able to survive without replacement sales, independent of k'' being sufficient for situations where X_1 is most important. Though the discussion thus far as focused on two performance dimensions, the firm could also seek to improve k along a new performance dimension, which might allow it to break into additional situations or continue to add value in situations where it already dominates. While camera manufacturers have little hope of disrupting the smartphone industry, for example, new niches are being found for using cameras in sporting activities (GoPro) or in attaching them to drones.

2.8. New markets

Situations where a seller is targeting buyers who already possess a technology that is a partial substitute are pretty common. In developed economies, most buyers will have at least something useful for meeting their range of needs, even if a recent innovation offers an order of magnitude improvement in performance. However, buyers can also enter with no prior technology adoption within a technology space. This could be based on cohort entry into a market (e.g., new buyers who have turned 18, and have no legacy financial services products), economic dynamism (e.g., the church of new venture formation in developed economies), or economic development (e.g., the growing middle class in "bottom of the pyramid" economies, where whole classes of offerings/services may be offered for the first time).

While perhaps a special case, this can be very important for the adoption or diffusion of new technologies. Financial services like Venmo may have limited appeal for older buyers who already have a range of financial products, but when compared head-to-head against those offerings by new college students entering the market for financial services for the first time, the threshold for adoption is much lower. Similarly, in economies where land-line telecommunications never experienced widespread adoption, the threshold for adopting wireless communication is lower, and rapid adoption of later generation technologies might happen without the market conditions typically required for disruption.

As a standalone consideration, the fact that a more innovative offering might have trouble gaining market share with legacy buyers, independent of any traditional "switching cost," but do better with new buyers is not entirely novel (see many discussions of cell phone adoption in the developing world for the most frequent example). But, if early adoption is driven by these dynamics as opposed to typical assumptions about the unique preferences of "early adopters," it could have important implications for ultimate diffusion and evolution of technology. Crossing the chasm is not *necessarily* a question of meeting different preferences that drive early/late adoption, but could instead be a matter of facing the same preferences in the face of legacy technologies in buyer portfolios after more rapid adoption by those without such considerations. Given the frequent early adoption of new technologies by younger demographics (e.g., Facebook, Venmo, Uber, AirBnB), it is critically important for decision makers to be aware of how much of that is driven by unique preferences as opposed to similar preferences but different adoption histories. This matters for new ventures deciding on an expansion plan, and incumbents evaluating the threat from potentially disruptive entrants.

The implications of path dependence on adoption are also important when considering the requirements for achieving critical mass. Holding target adoption constant, if early adoption is driven by the entry of new buyers, the rate of buyer entry becomes a critical factor. If entry is based on cohorts (e.g., age cohorts), demographics become important in determining viability. If viability requires 5 million customers in the first year, but only 3 million young adults will enter the market over that time frame, a successful strategy requires appealing not only to new buyers, but to buyers with legacy technologies in their portfolio. This might require development focused on adoption based on standalone value for new buyers, and adoption/replacement for a subset of situations for legacy buyers. If viability requires only 1 million customers, narrower focus (for first adoption, as opposed to supplementation) becomes possible.[9]

While most models of "early adopters" are based on unique preferences, my model does not require that the preferences of early adopters differ in *any* way.[10] Adoption can be driven by the prior adoption, or not, of substitute technologies. Early adopters might be new to the market (no prior adoption), or might have a history of adoption that favors the entrant (i.e., having adoption a more specialized offering like k'', instead of a more broadly useful offering like k'). If adoption is driven by different preferences, early adopters may be drawn to niche

[9]Cognition can also play a role here, depending on the adoption rules of new buyers. Initial adoption could be based on which situation(s) become salient first, what information has been received at the moment of adoption, or whether the new adopter considers combinations of offerings, or follows a sequential adoption rule.

[10]This model also, of course, includes demand heterogeneity, but assuming that is the only difference explaining early adoption may also introduce substantial bias.

applications that are irrelevant to the larger market, with additional diffusion requiring a trajectory appealing to a broader range of situations. By contrast, if adoption is driven by path dependence, and preferences are actually the same, early adoption might be driven by value across a range of situations by new buyers, but diffusion to legacy buyers may require greater focus on niche applications to create sufficient value in a subset of situations that the value in those niches can justify the cost of supplementing their technology portfolio.

CHAPTER 3 : HYPOTHESIS DEVELOPMENT

The assumption of mutual exclusivity tends to focus attention on the adoption decision. Even when recognizing that substitutes might provide a subset or superset of the focal functionality, prior research has focused on whether one product or service supplants another (e.g., Porter, 1985, pp. 273-276). However, even if an offering is adopted, the ability to add and capture value depends in part on the possibility of co-adoption, as discussed in the previous chapter. When technologies are horizontally differentiated partial substitutes, each may be best for a subset of *buyer situations* and for buyers who value incremental performance in these varying situations the choice is not simply between one or the other, but perhaps both.

This chapter extends the model developed in the previous chapter developing predictions for observable behavior. This is done through the formalization of conditional value, numerically illustrated, to show how the preference structure of an individual determines adoption choices, conditional on the prior adoption of a substitute. More specifically, adoption behavior is predicted for buyers of fixed-lens and interchangeable-lens cameras, conditional on observed indicators of preferences, and whether or not they have previously adopted the camera functionality of a smartphone. In the sections that follow, I argue that the adoption of a technology that is a more distant substitute for some offerings than others will be associated with an increased rate of adoption for the former relative to the latter. Further, I argue that greater individual-level variance in situational preferences will be associated with the adoption of more flexible technologies and multiple technologies, to best meet their range of needs.

3.1. Substitute proximity and indirect complementarity

The technologies which are the focus of this research are traditionally defined as substitutes. The incremental utility realized by purchasing a camera is reduced by the prior adoption of another camera or smartphone. The incremental value of an offering k, *conditional on* a partial substitute k'' is shown in Equation 3.1.[1] Figure 1 plots a numeral illustration, with the value of fixed offerings k and k' conditional on a hypothetical offering k'', $V(k|k'')$ and $V(k'|k'')$, as the performance of k'' increases, using Equation 3.1.[2] For the purposes of this example, offering k can be thought of as an SLR camera, with relatively high performance for photo quality, and relatively low performance for convenience and portability. Offering k'' can be thought of as the camera feature of a smartphone, with relatively low performance for photo quality, and relatively high performance for convenience. Offering k', a substitute with a technological trajectory between that of k and k'', which can be thought of as a compact camera, balancing photo quality against convenience. In this illustration, the buyer is defined by two situations, each aligned with the technological trajectory of either k (the SLR or mirrorless camera) or k'' (the smartphone camera).[3] As the performance of k'' increases, the conditional values of k and k' fall.

$$V_i(k|k'') = \sum_{s=1|WTP_{sik}>WTP_{sik''}}^{S} (\beta_{s1i}(X_{1k}^{\alpha} - X_{1k''}^{\alpha}) + \beta_{s2i}(X_{2k}^{\alpha} - X_{2k''}^{\alpha})) - c_k \tag{3.1}$$

This figure holds the performance of offerings k and k' constant, so that the performance of k'' indicates performance relative to k and k'. The increasing performance of k'' in this static model is not time, strictly speaking, but can be thought of as time to the extent that smartphone camera performance improves at a constant rate relative to SLR and compact camera performance.

[1] The conditional value assumes the presence of the partial substitute at no incremental cost, in contrast to joint valuation, where the cost of each offering is incurred.

[2] In this plot, $X_{1k} = 90$, $X_{2k} = 10$, and α takes a value of 0.5. The performance of k'' is defined as $X_{1k''} + X_{2k''}$, with the ratio $X_{1k''} : X_{2k''}$ equal to $\beta_{21i} : \beta_{22i}$, or $1 : 9$ (proportional to Situation 2). Where the performance of k'' is 100, on the x axis, $X_{1k''} = 10$ and $X_{2k''} = 90$. Offering k' represents a fixed substitute with a technological trajectory between that of k and k'', with $X_{1k'} = 50$, $X_{2k'} = 50$. The individual is defined by two symmetrical situations, with the preferences for one defined by $\beta_{11i} = \beta_{22i} = 0.9$ and $\beta_{12i} = \beta_{21i} = 0.1$. For cost, $c_k = 3$, $c_{k'} = 2$, and the cost of k'' is sunk. The independent effect of each parameter will be clarified by subsequent analyses.

[3] Here, k'' is used to reference the previously adopted technology because the analyses focus on the relative effect on two offerings, k and k', with k'' being closer to the latter than the former. This naming convention seemed to be the best way to keep that clear in the mind of the reader.

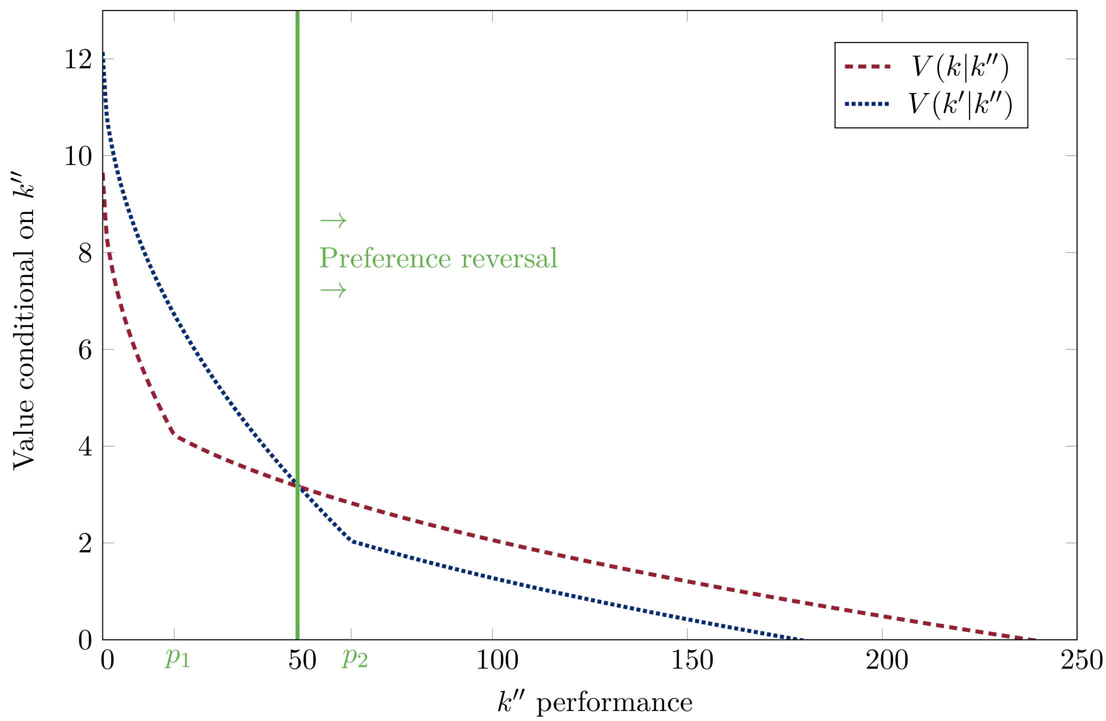

Figure 1: Preference reversal. Conditional and added value of fixed distant (k) and proximate (k') substitutes to k'', as k'' performance improves. $\beta_{11i} = \beta_{22i} = 0.9$, $\beta_{12i} = \beta_{21i} = 0.1$, $X_{k1} = 90$, $X_{k2} = 10$, $c_k = 3$, $X_{k'1} = 50$, $X_{k'2} = 50$, $c_{k'} = 2$, $X_{k''1} : X_{k''2} = 1 : 9$, $\alpha = 0.5$.

Compared dyadically, the unconditional value of offering k' exceeds the value of offering k in this example. This can be observed in the conditional value plots where the performance of k'' equals zero. This gap is captured in the added value of each offering, which is also plotted. As the performance of k'' increases from zero, it reduces the conditional value of both offerings, k and k'. It does this by offering increased utility across all situations, with the majority of that utility realized in the situation for which it is best suited - situations where utility is driven more by convenience than photo quality.

Until performance threshold $p1$ in Figure 1, the conditional value of each is falling at an equal rate. The quality of the smartphone is improving, reducing the incremental utility of a dedicated camera. Until threshold $p1$, a dedicated camera remains superior across all situations, regardless of type - this is why the conditional value of each type is equally affected. At performance threshold $p1$ the utility of offerings k and k'' is equal *in those* *situations where convenience matters most* - the domain of weakness for k, and strength for k''. While the photo quality performance of k'' remains much lower, that disadvantage is matched by superior performance in terms of convenience. Beyond threshold p_1, the conditional value of k continues to be affected by an improving k'', but only in the area where k is at a relative advantage. This introduces the conditional summation shown in Equation 3.1, where $WTP_{sik} > WTP_{sik''}$ (situations where the utility of offering k exceeds the utility of offering k''). Prior to threshold $p1$ that condition is true for all situations.[4]

Once a smartphone is superior to an SLR for situations where convenience matters most, continued improvement in performance for those situations no longer affects the conditional value of SLRs. Improved performance for situations where photo quality matters most will continue to affect the conditional value of SLRs. The overall rate of conditional value decline will slow relative to k', which continues to be affected by utility improvements for smartphones across all situations.

The difference in relative rate of conditional value decline continues until performance threshold p_2. Prior to reaching p_2, due to the higher rate of conditional value decline, the conditional value of k' falls below the conditional value of k. Beyond this *preference reversal point*, a buyer might choose to adopt the more distant substitute - an SLR - conditional on the prior adoption of a smartphone, even though the standalone value of a compact camera exceeds the standalone value of an SLR.

At threshold p_2, compact camera utility equals smartphone utility *for situations where convenience matters most.* As with threshold p_1 for the SLR, the compact camera remains superior in terms of photo quality, but this advantage is matched by superior smartphone performance in terms of convenience. Beyond threshold p_2 both camera types are equally

[4] Where $x_{k''} = X_{1k} + X_{2k}$ and $\frac{X_{1k''}}{X_{2k''}} = \frac{\beta_{12i}}{\beta_{11i}} = \frac{\beta_{21i}}{\beta_{22i}}$, the rate of utility increase for k'' is $\partial/\partial x = (\sqrt{0.9} + \sqrt{0.1})/2\sqrt{x}$. Of that rate of increase, $(0.1\sqrt{0.9} + 0.9\sqrt{0.1})/2\sqrt{x}$ comes from Situation 1 (k'' area of weakness), and $(0.9\sqrt{0.9} + 0.1\sqrt{0.1})/2\sqrt{x}$ from Situation 2 (k'' area of strength). The values of k and k' *fall* by at same rate until k'' reaches performance threshold p_1. Beyond this point, the rate of declining value slows to $-(0.1\sqrt{0.9} + 0.9\sqrt{0.1})/2\sqrt{x}$ for k (falling at the rate of utility increase for k'' in its area of weakness, Situation 1). Beyond p_2 the rate of declining value for k' falls to the same level. The absolute rate of decline is slowing for both because of the diminishing marginal utility parameter α, for the improving k''.

affected by any improvement in smartphone performance for situations where photo quality matters most. At the point where the conditional value of k' falls to zero, it continues to offer superior performance for situations where photo quality matters most, but this incremental utility is offset by the cost of adopting the compact camera.

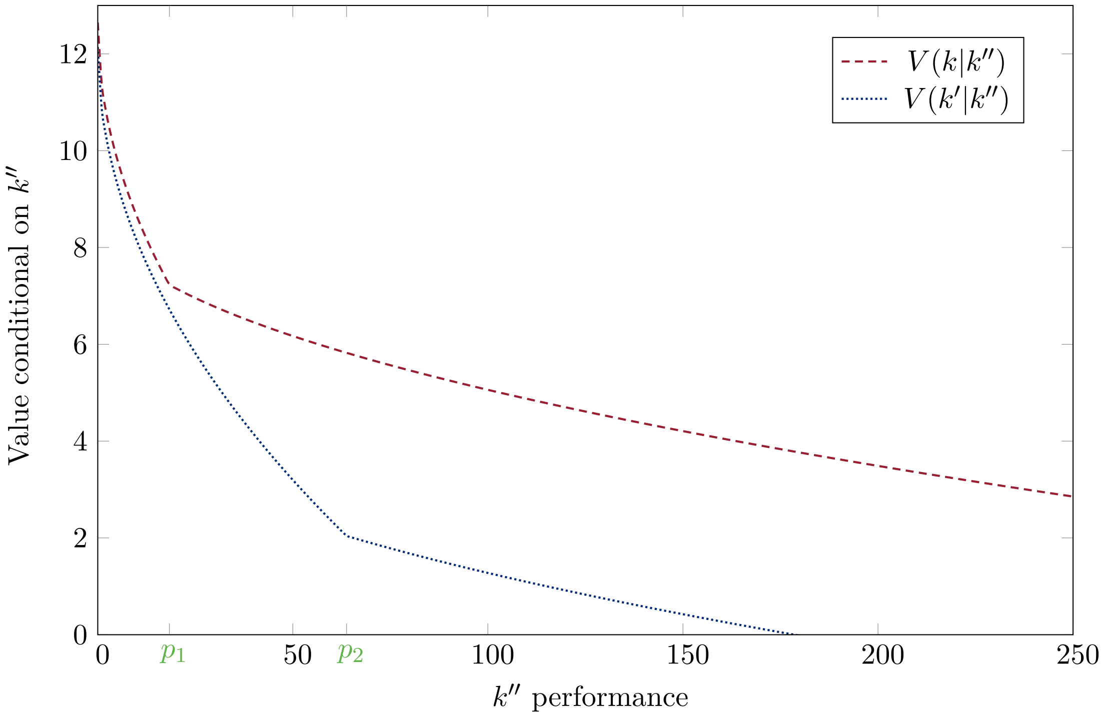

Figure 2: Offering k always preferred. $c_k = 0$.

While $V(k') > V(k)$ independent of k'' performance, beyond the crossover point $V(k|k'') > V(k'|k'')$. As long as $V(k|k'')$ remains positive, discrete adoption preferences for this buyer reverse beyond this crossover. Prior to the crossover, the buyer would adopt the compact camera. After the crossover, the buyer would adopt the SLR. The crossover in adoption preference, observed in Figure 1 between performance thresholds p_1 and p_2, requires three conditions. If $V(k') > V(k)$ was not true, as shown in Figure 2, offering k would always be preferred. If $V(k|k'') > V(k'|k'')$ was not true, as shown prior to the preference reversal in Figure 1 and in Figure 3 offering k' remains the preferred choice. Finally, if conditional value falls to zero for all partial substitutes, no adoption will occur.

These dynamics highlight an important implication of this model. While the adoption of

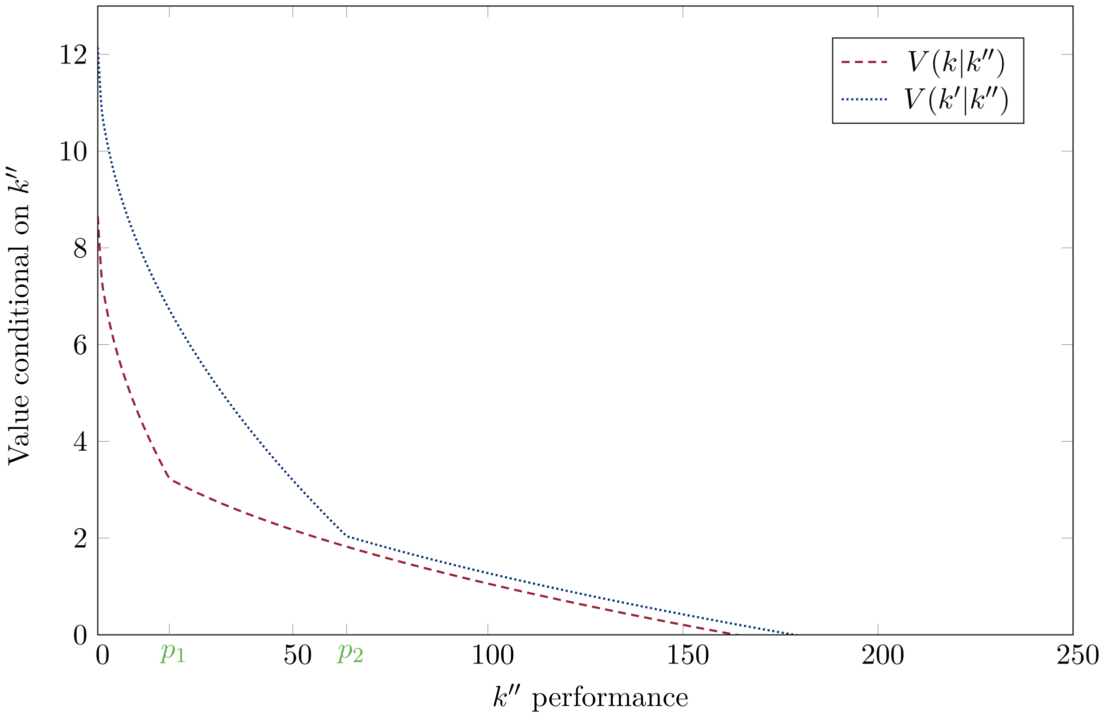

Figure 3: Offering k' always preferred. $c_k = 4$.

a new technology will not always induce preference reversal, when it does it will increase adoption of technologies for which it is a more distant substitute relative to technologies for which it is a more proximate substitute. In the context of the digital camera industry, assuming that a smartphone is a more proximate substitute for compact cameras than it is for interchangeable lens cameras (SLR or mirrorless), the probability of SLR/mirrorless camera adoption should increase after the adoption of a smartphone.

Hypothesis 1: The adoption of a technology which is a more distant substitute for some offerings than others will be associated with an increased rate of adoption for the distant relative to the proximate.

3.1.1. Indirect complementarity in prior research

The mechanisms described here are very close to the concepts of indirect or compensated complementarity previously used to describe the relationship between commodities. Indirect complementarity exists when the presence of a third offering affects the rate of substitutability between two offerings (Ogaki, 1990). Compensated complementarity is the realized rate of substitutability, taking into account all direct and indirect effects (Samuelson, 1974). Direct complementarity captures the rate of substitutability between two technologies considered in the absence of any other complements or substitutes, which in practice may be an entirely theoretical exercise.[5] The measure of indirect complementarity is the difference between direct complementarity and compensated complementarity.

While the descriptions of direct complementarity, indirect complementarity, and compensated complementarity describe relationships in terms of price and continuously variable quantities, this research is focused on value creation based on willingness to pay and cost, and discrete adoption choice. While the analyses cannot be directly carried over, indirect complementarity as characterized here can be seen where the adoption of a smartphone, which is a partial substitute for an SLR camera, increases the added value of the SLR camera (or decreases its value disadvantage) in the presence of a compact camera. This could happen without altering the discrete choice of a buyer, as seen in Figures 2 and 3, or prior to crossover in Figure 1, but could also lead to adoption choice reversal, as seen in the regime beyond the crossover point in Figure 1. The analyses here focus on preference reversal based on these changes in conditional willingness to pay, and where this is observed it will be characterized as indirect complementarity or substitutability, depending on the focal technology.

3.2. Preference variance, adoption, and co-use

While a buyer might adopt one technology over another, such as an SLR camera over a compact camera, conditional on a third, such a smartphone, this behavior depends not only on the nature of the technologies, but also the preferences of the individual. Returning

[5]Samuelson (1974) uses tea and coffee as example commodities, where the rate of substitutability depends on the price of lemon and cream. It is not so easy to imagine a direct rate of substitutability between an SLR camera without a lens and a compact camera, as the former is useless without at least one lens. In the example perhaps most relevant to this context, Samuelson (1974, p. 1255) describes enjoying cream as a complement to both coffee and tea. However, if much more cream is used with tea than coffee, a falling price for coffee can reduce cream consumption, despite dyadic complementarity - “an odd thing to happen between so-called complements.”

attention to Equation 2.4 and Equation 3.1, the value of co-adoption depends on individual-level situational variance - the presence of multiple situations where a technology might be used, but where the dimensions of performance which drive utility vary across situations. The effect of situational preference variance is illustrated in Figure 4. The x-axis in this figure captures situational variance as the ratio of relative preferences across Situations 1 and 2. Where $\frac{\beta_{11i}}{\beta_{12i}} / \frac{\beta_{21i}}{\beta_{22i}} = 81$, $\beta_{11i} = \beta_{22i} = 0.9$ and $\beta_{12i} = \beta_{21i} = 0.1$. [6] Across the x-axis Situation 2 is held constant until $\frac{\beta_{11i}}{\beta_{12i}} / \frac{\beta_{21i}}{\beta_{22i}} = 1$, where $\beta_{12i} = \beta_{22i} = 0.9$ and $\beta_{11i} = \beta_{21i} = 0.1$. Offering k is characterized by $\frac{X_{1k}}{\beta_{11i}} / \frac{X_{2k}}{\beta_{12i}} = 1$, so that offering k is aligned with Situation 1.

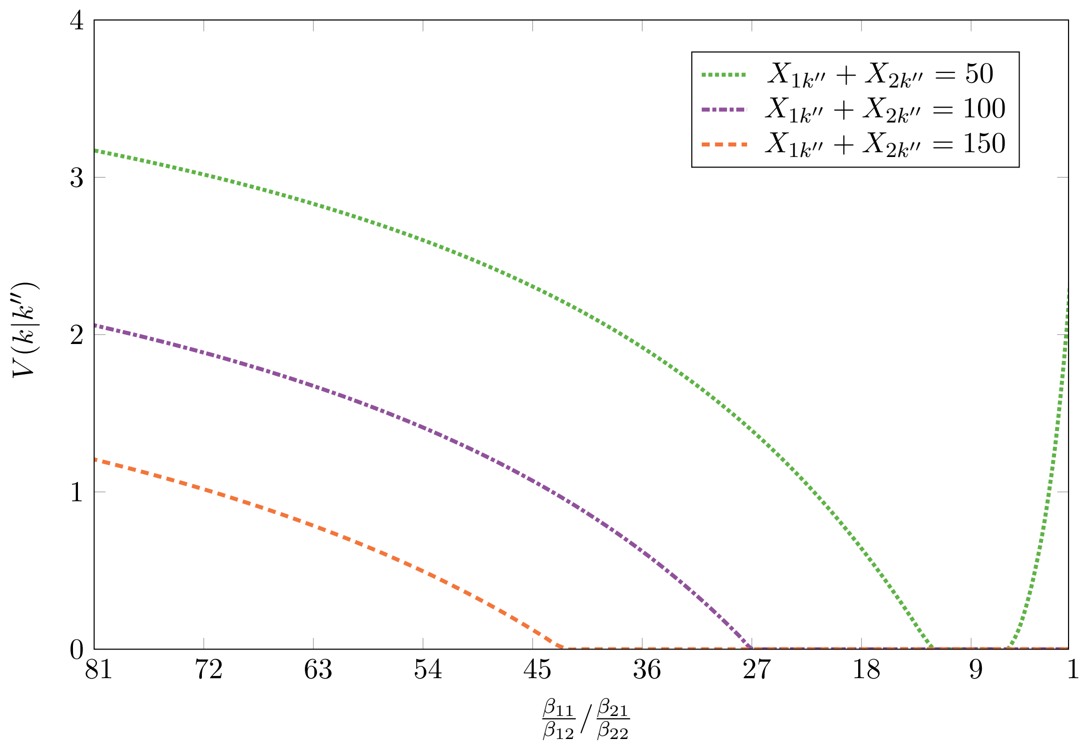

Figure 4: Individual-level preference variance and $V(k|k'')$, at varying performance levels for k'', with $\frac{X_{1k}}{\beta_{11i}} / \frac{X_{2k}}{\beta_{12i}} = 1$. Where the x-axis equals 81, situational variance is high, with utility 90% determined by X_1 for Situation 1, and 90% determined by X_2 for Situation 2. Where the x-axis equals 1, preferences are identical across situations, with utility 90% determined by X_2 for both Situations 1 and 2.

As shown in Figure 4, higher levels of situational variance are required to create value

[6] Reminder: β subscripts are for situation (s), dimension (1... n), and individual (i).

conditional on the prior adoption of a partial substitute. As preference trajectories, and associated technological trajectories diverge, incremental utility increases.[7] Because value is only created when incremental value exceeds the cost of adopting a second technology, situational variance because increasingly important as performance of the partial substitute increases, as seen in the figure where higher levels of k'' performance increase the minimum threshold in situational variance necessary for for the co-adoption of k.

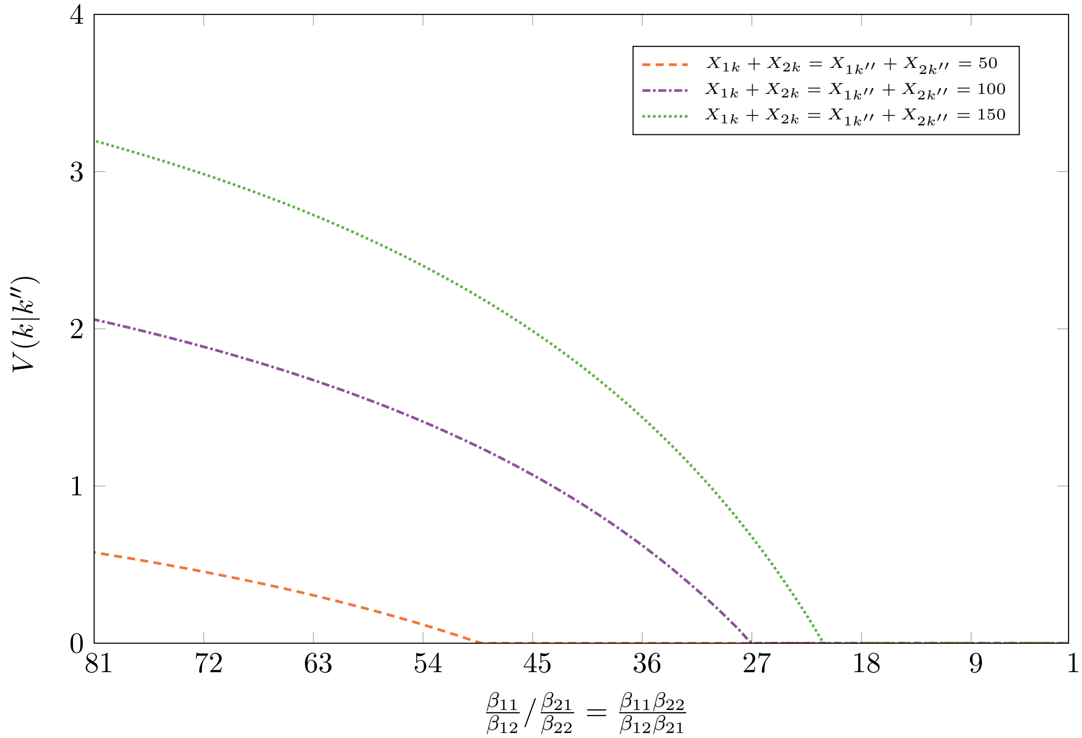

Figure 5: Varying performance levels for both k and k''.

Figure 6: Individual-level preference variance and $V(k|k'')$, at varying performance levels for k'', with $\frac{X_{1k}}{\beta_{11i}} / \frac{X_{2k}}{\beta_{12i}} = 1$. Where the x-axis equals 81, situational variance is high, with utility 90% determined by X_1 for Situation 1, and 90% determined by X_2 for Situation 2. Where the x-axis equals 1, preferences are identical across situations, with utility 90% determined by X_2 for both Situations 1 and 2.

The challenge of creating sufficient incremental value to justify the added cost of co-adopting is illustrated in Figure 4, with increasing situational variance necessary to create any value

[7] The exception to this is where the performance of k'' is very low relative to the performance of k, and where there is essentially no situational variance. In this case the higher performance of k, targeted for Situation 1, makes it superior for both situations. This is what creates the spike in the dotted line on the far right side of Figure 4.

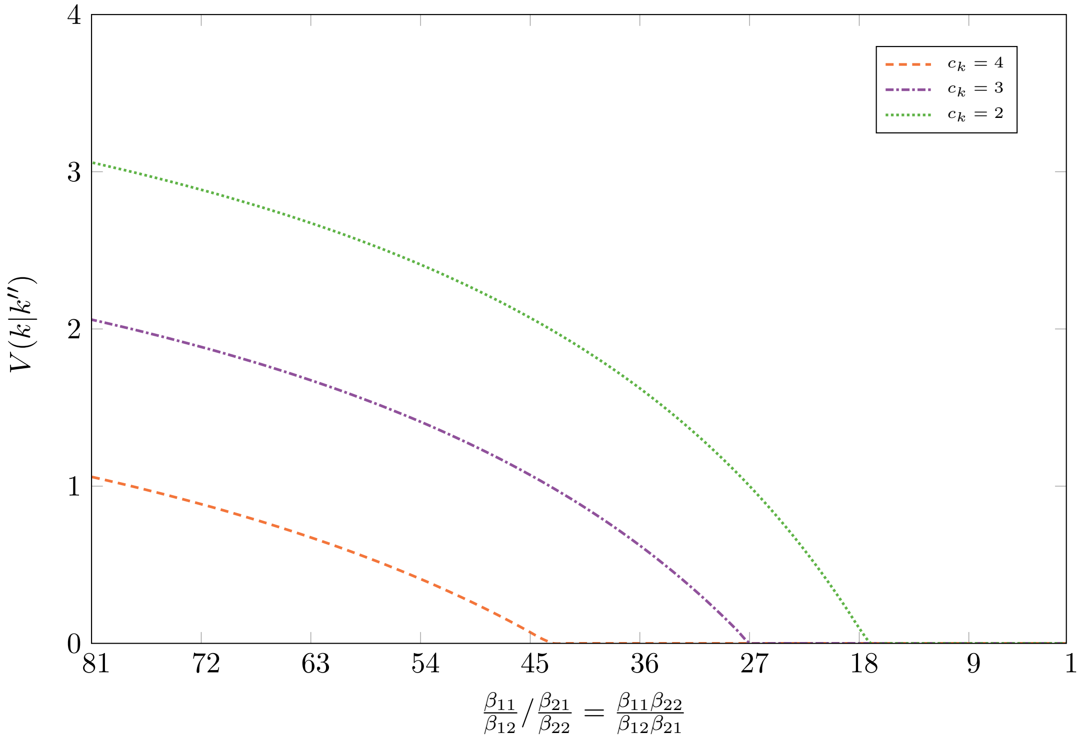

Figure 7: Varying cost for k.

Figure 8: Individual-level preference variance and $V(k|k'')$, at varying performance levels for k'', with $\frac{X_{1k}}{\beta_{11i}} / \frac{X_{2k}}{\beta_{12i}} = 1$. Where the x-axis equals 81, situational variance is high, with utility 90% determined by X_1 for Situation 1, and 90% determined by X_2 for Situation 2. Where the x-axis equals 1, preferences are identical across situations, with utility 90% determined by X_2 for both Situations 1 and 2.

as the performance of the partial substitute increases, but trade-off is also affected by the absolute level of performance for each technology, as shown in Figure 5, or the direct cost of the supplemental technology, as shown in Figure 7. If the performance of both the focal technology and its partial substitute are low, very high situational variance is necessary to create any value. As technologies progress along different technological trajectories, their differences in absolute performance along each performance dimension increases. This absolute difference is what creates sufficient incremental value to justify the added cost of co-adoption. Changes in the cost of a technology can act in a similar way. If the cost of co-adoption falls, less situational variance is required to justify co-adoption. If each camera costs $10,000, it would be very difficult to justify the purchase of multiple cameras, no matter how distinct each particular situation was. If the cost of each fell to $10, justification becomes easier, holding situational variance constant.

While the incremental utility to cost trade-off can be achieved in several ways, importance of situational preference variance remains clear as an important driver of potential co-adoption. However, it may also play a role in single-adoption choice. Some technologies are inherently more flexible than others. Sometimes this appears simply as a higher level of maximum performance, as with processing speed in a computer, where maximum processing power is used for processes which require it, but the processor can also operate at lower speeds for processes that require less power. Other times, however, technologies may allow for both lower lows and higher highs on a particular performance dimension, in ways that matter. This is the case for digital photography, which is the context being studied. An SLR camera will offer shutter speeds that are both faster than those offered on a compact camera or smartphone (for example, keeping the sensor exposed for 1/1000th of a second) and slower (for example, keeping the sensor exposed for a full second or more). As a baseline, consistent both with the model presented and prior theory, it might be expected that situational variance will drive adoption of technologies which are more flexible - in this case, interchangeable lens cameras (SLR or mirrorless).

Hypothesis 2: A higher level of situational variance will be associated with the adoption of a technology which is more flexible.

While prior theory and this model can predict the adoption of a single technology, this model offers additional explanatory power with respect to co-adoption as a solution to situational variance. This becomes particularly relevant for situations where trade-offs between performance dimensions are binding, such as computer processing speed and power consumption. In the context of digital cameras, this trade-off appears in terms of technical performance and convenience and portability. Prior theory can only suggest adoption of a technology which balances these needs (which may suggest a compact camera over an interchangeable lens camera for some), the model presented here offers an alternative -

co-adoption of partially substituting technologies for a range of needs. As shown in the figures above, the value of adopting a supplemental technology increases with the situational variance of the buyer.

Hypothesis 3: A higher level of situational variance will be associated with the co-adoption and use of multiple technologies.

CHAPTER 4 : EMPIRICAL APPROACH AND ANALYSES

4.1. Empirical Approach

The previous chapter developed several empirical predications. First, the adoption of a technology which is a more distant substitute for some offerings than others will be associated with an increased rate of adoption for the former relative to the latter. Second, and also consistent with prior models, higher levels of situational variance will be associated with the adoption of more flexible technologies. Third, higher levels of situational preference variance will be associated with the co-adoption and use of multiple technologies.

Context

The digital camera industry provides an opportunity to test these ideas empirically, based on the nature of the products within it. Within this industry, there are several broad categories of cameras. Interchangeable lens cameras, most commonly single lens reflex (SLR) and mirrorless cameras, provide a high level of technical performance, but at the cost of larger size and greater weight, together reducing convenience and portability.[1] Compact (also "pocket" or "point and shoot") cameras offer lower technical capabilities, but are also smaller and weigh less, increasing the convenience of carrying it around. Cameras embedded in smart-phones offer even less performance, but are even more convenient to carry around, to the point that they are nearly always available to buyers as part of a device that is widely adopted for many other reasons. These devices reflect trade-offs that are inherent to photography generally. The light captured by the sensor is a function of focal length (length between lens and sensor), aperture (size of the shutter opening through which light passes), shutter speed (how long the shutter is open), and sensor sensitivity (with larger sensors being more sensitive). Each of these requires a larger size in order to maximize the range of capabilities, and the ability to swap lenses further increases the range of possibilities.

[1] SLR cameras reflect light through the lens to a viewfinder, using a mirror (shutter), which is flipped out of the way to expose the sensor when taking a photo. Mirrorless cameras allow light to pass directly through the lens to the sensor, with images typically previewed on a digital screen or through a separate viewfinder.

An aspect of the industry that is particularly useful for testing this theory is that these categories of devices are not mutually exclusive. Many buyers own cameras in multiple form factors, using each where it offers the greatest combination performance and convenience for their particular needs. While several of the constructs described above are fairly abstract, the availability of data within this context provides several unique ways to test whether the model presented can provide insight into how the world works. Broadly, this theory is consistent with the idea that the rise of smartphones should be associated with an increase in market share for interchangeable lens cameras, relative to compact cameras, as smartphones are a proximate substitute for the latter.

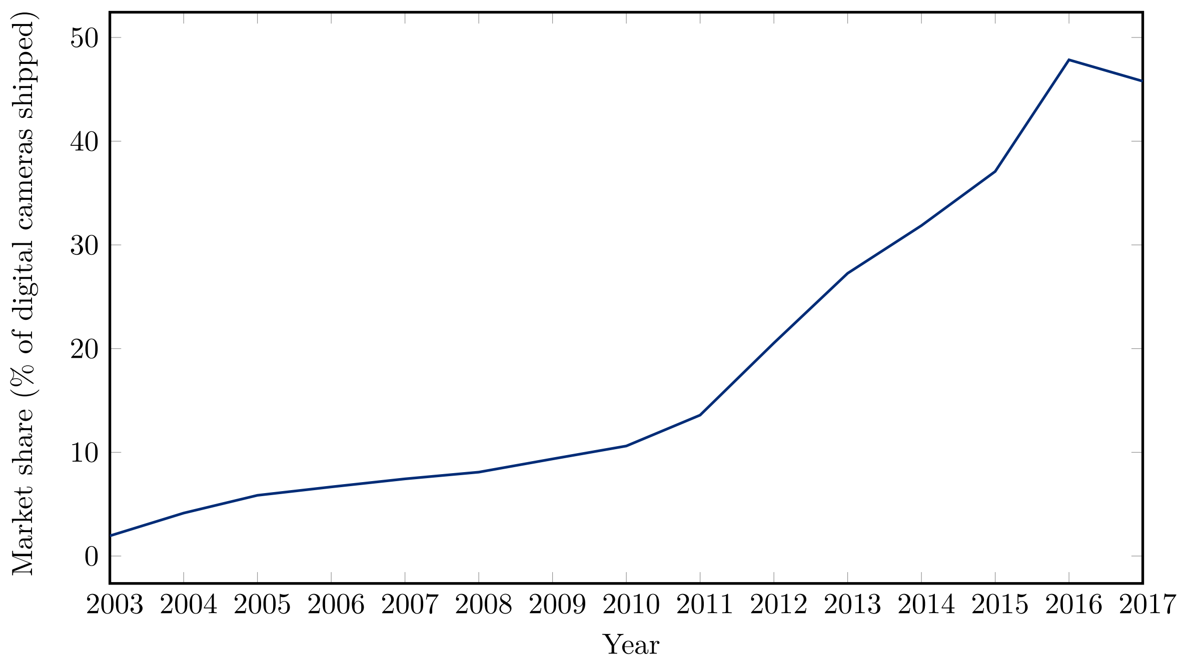

Figure 9: Interchangable lens camera share (North America, by unit)
Source: Data from Camera & Imaging Products Association

Data

The analyses rely on data derived from the metadata for a set of 100,000,000 photos uploaded to Flickr, sampled by Yahoo Labs for the purposes of training image classification machine learning models (Thomee et al., 2016). The core dataset is composed of identifying information for the photo and the user who uploaded it.[2] Two additional "expansion packs," or supplementary datasets provided by Yahoo Labs for the same 100 million photos, were used to create the datasets for the analyses. The first expansion pack contains the Exif metadata embedded in photos. This typically includes the time a photo was taken, the camera make and model that was used, and specific attributes of the photo, including size (resolution), ISO (a measure of sensor sensitivity), f-stop (a measure of the aperture), exposure time, and focal length.[3] The second expansion pack identifies "autotags" generated by Yahoo Labs to categorize each photo/video based on content, along with weights of how certain their algorithm is about the subject. The unit of analysis for the combined set is an individual photo, but transformations of the data aggregated data at the unit of analysis required for each hypothesis (e.g., user-year or adoption).

The analyses take place from 2000 through mid-2014 for adoption models, and from 2000 through 2013 for co-use models, which are measured at the person-year level. This period is particularly interesting as it captures the rise of smartphones. Concurrent with this, sales (shipments) of compact cameras collapsed, as shown in Figure 10. The distribution of person-year observations within the sample can be found in Figure 11. This reflects both the growth of digital photography, as well as the decline in photography using standalone cameras. With this decline, use began to shift from sites like Flickr to social media like Instagram (introduced in 2010 for the iPhone, and 2012 for Android phones) and Facebook (which saw the importance of mobile photography at around the same time, acquiring Instagram in 2012). The sharp drop in 2014 reflects data availability for the first part of the year only. Analyses that require aggregation of use across the year do not include 2014.

[2]This data is sufficient to spot check photos online, to confirm the accuracy of the underlying metadata. For example, there were some extreme outliers for exposure time, but each of those photos were examined and determined to be long-exposure photos taken in low light conditions.

[3]The f-stop is actually somewhat complicated, but is generally used to describe the denominator of a ratio, where the denominator is the aperture, or width of the shutter opening (diaphragm). The area through which light can pass can be approximated by $\pi(aperture/2)^2$, though the actual opening is an equilateral polygon with n sides, where n is the number of blades that make up the diaphragm (more expensive lenses have more blades, and better approximate a circle, which affects the shape of out of focus elements of a photo). The full ratio is comprised of the focal length divided by the aperture, written as f/1.4, though most would refer to this f-stop as 1.4, and that is also how it is captured in the metadata.

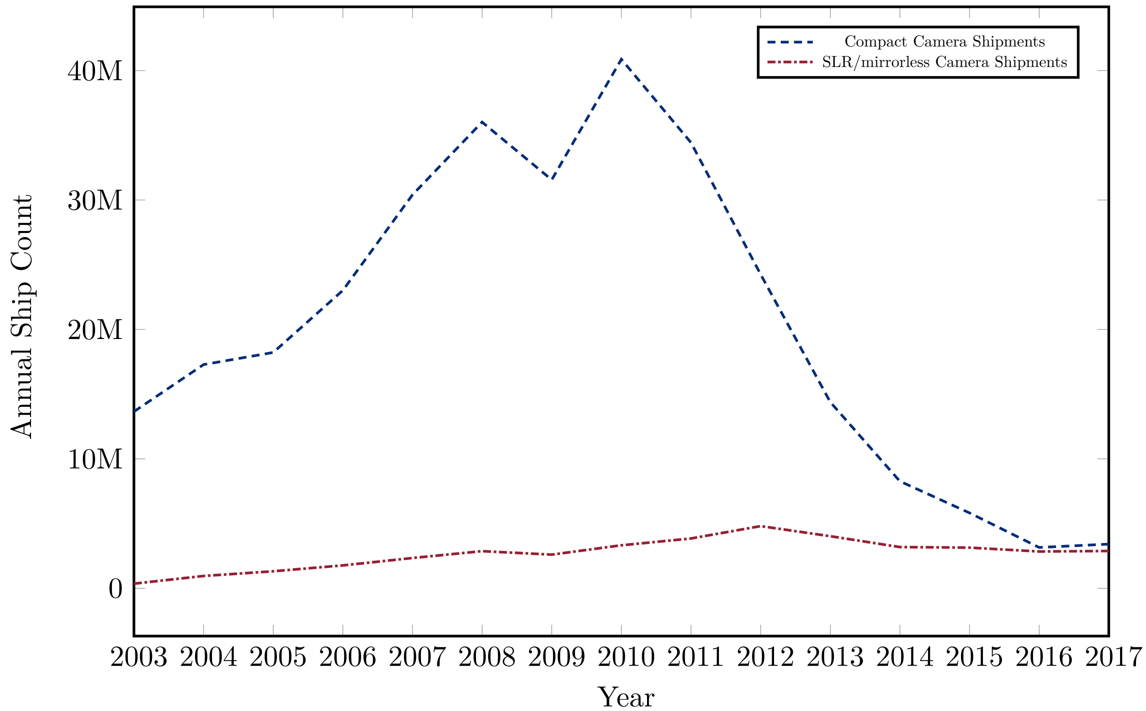

Figure 10: Cameras Shipped by Year in North America
Source: Data from Camera & Imaging Products Association

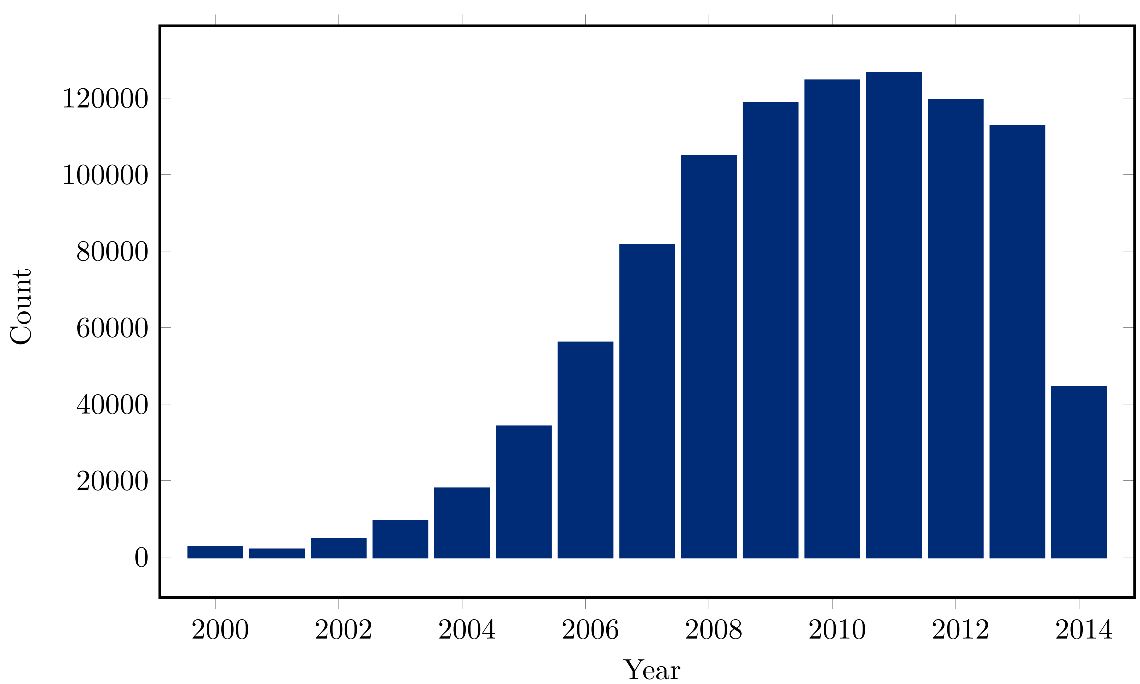

Figure 11: Person-year observations by year

4.1.1. Dependent variables: Adoption and co-use

Hypotheses 1 and 2 predict adoption decisions. Hypothesis 3 predicts co-adoption (co-use) of multiple technologies. For the model predictions related to adoption, the dependent variable is whether the adopted device was an SLR/mirrorless camera (1) or, alternatively, a compact camera (0). The initial use of a smartphone is omitted, given the focus on within-industry competitive dynamics. Thus, the analysis describe the relationship between predictors and the dependent variable *conditional on adoption.* At any given moment, each user can be imagined as facing a set of decisions. First, whether to buy a new device. If that decision is yes, what type of device to buy. These analyses are taking place at the level of the second decision.

Loosely defined, "co-use" within a year could be defined as using multiple cameras within a year. However, this definition would also capture replacement purchases, where Camera A is used for half the year, and Camera B for the other half. To measure camera co-use at the person-year level, I created a list of cameras used by each person during the year, sorted by the date and time each photo was taken (photo metadata being the source of camera usage information). Taking the last camera used in the year, going back to the first time that camera was used within the year, I created a co-use measure which indicates whether another camera was used during that time. If somebody used Camera A for half the year, and Camera B for the other half, no co-use would be recorded (a value of 0). If Camera A was used, then Camera B, then Camera A, co-use would be recorded (taking a value of 1). Note that this is based on the date the photo was taken, and not the date uploaded, which would provide a biased picture of co-usage. If two cameras were used during the year, but the photos from one were only uploaded at the end of the year (or even in a later year), this co-use would still be detected by the measure.

Several relevant patterns can be observed in the sample data. First, if sales data is used as the only measure of whether a technology has been displaced, displacement can be vastly overstated, given use rates that exceed adoption rates for all time periods. Use of purchases

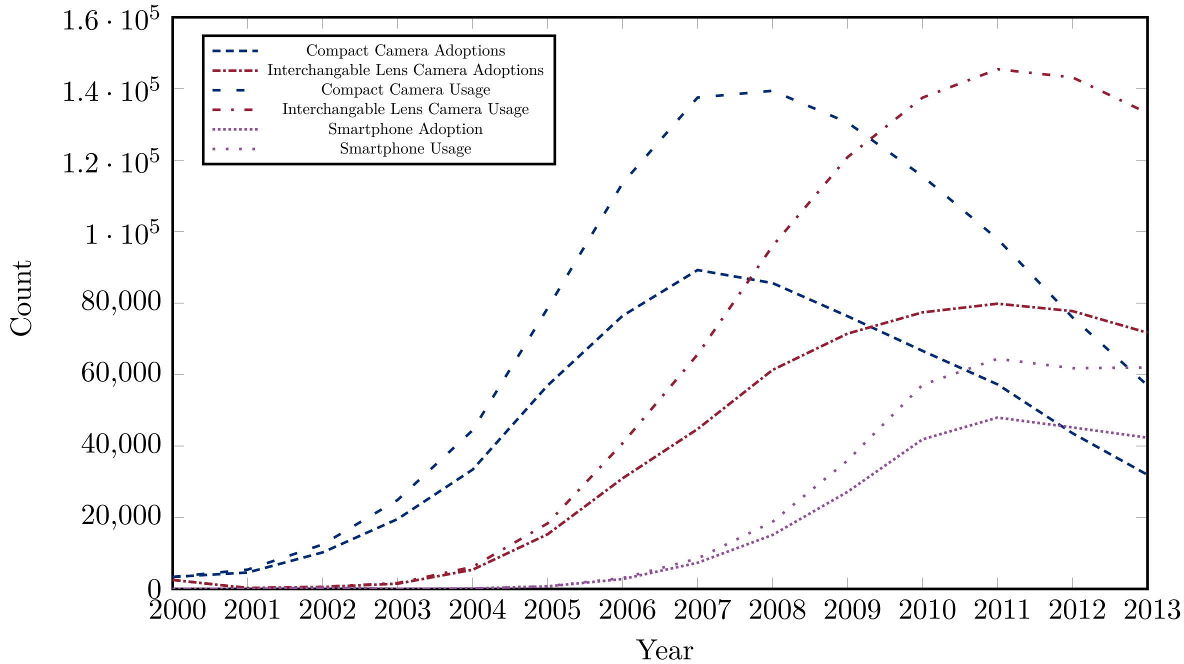

Figure 12: Cameras Used or Adopted by Year
Source: Data from Dissertation Sample

as a proxy for use also risks systematic bias, as measures of use and adoption diverge early in the technology cycle, and converge later in the cycle. Figure 12 also highlights several limitations of this sample. Smartphone usage is clearly underrepresented in an absolute sense (unit sales vastly exceed camera unit sales in the later periods), but likely also in terms of the use of smartphones as cameras. This is not cause for huge concern, given the focus on competitive dynamics within the digital camera industry - users that never used a standalone camera are outside the scope of consideration. A larger concern is that the sample of Flickr users is not necessarily representative of the population more broadly. Flickr users are likely to be particularly enthusiastic photographers, with preferences that diverge from the broader population. This can be seen in the differences in peaks for compact and interchangeable lens cameras between Figure 12, of the sample for this study, and Figure 10, for North America in total. This is also not a major concern, with the focus of this research on the existence of a mechanism - indirect complementarity, which can be demonstrated independently of whether the sample is representative. Care should be taken, however, in attempting to extrapolate any effect sizes from this study to the population more broadly.

4.1.2. Independent variables: Prior smartphone adoption

The first implication of the model indicates a relationship between adoption of a technology (smartphone) and the subsequent adoption of technologies for which a smartphone represents a more proximate or distant substitute. This measure takes the value of an indicator variable for whether an individual has *ever* previously used a smartphone to upload a photo to Flickr (1), or not (0). The basis for this indicator is the assumption that the first upload of this type indicates the *continued* ownership of a smartphone - assuming that the user has not since gone back to using a feature phone (flip or candy-bar form-factor phones, generally). In addition to being a plausible assumption, this takes into account that users may use other sites (such as Instagram or Facebook) with later phones, such that they may not appear to be used on Flickr even if the user continues to use a dedicated camera for uploading to Flickr.

As a placebo test, an indicator is also created for users that have previously adopted *only* a feature phones is calculated. As a very weak substitute even for compact cameras any effect should be very small, if not indistinguishable from zero.

4.1.3. Independent variables: Situational preference variance

An association with situational variance is predicted both for individual adoptions and co-adoption and use. While only the latter takes place at the person-year level, the calculation of situational variance takes place at that level for all analyses. This is because consistent measurement requires use of a consistent amount of time. At the limit, measurement at the individual photo level would indicate a complete absence of situational variance. Situational variance can be conceived of in two ways - with a greater number of situations, or more variance in the needs between situations.

Situations (S)

First, a larger number of situations (S), indicates greater variance in the subject matter being photographed. A user that only photographs flowers can be characterized as having "fewer situations" relative to somebody who photographs flowers, architecture, and people. While this may weakly predict greater situational variance (βs), in that not every subject matter will call for a different mix of technical attributes, it is also something that photographers may be more consciously aware of. In fact, it is common for buyers to seek advice on a camera "for weddings" or "for portraits," even if the device is likely to be used for both.

This measure captures variation in *subject matter* of photos by an individual. Each photo in this dataset has been tagged by Yahoo Labs, using a machine learning algorithm to assign subject tags and confidence weights to each photo. For example, a photo might have the tags bridge, architecture, boat, and outdoors, with weights 0.9, 0.6, 0.2, and 0.8, respectively. That photo will likely be outdoors and contain a bridge (a type of architecture) and a boat, but the autotags are attempting to identify the *subject* of the photo, and not just the contents - so the algorithm, in this case, would be predicting that the subject is more likely the bridge than the boat, even if it contains both (perhaps because the bridge is more prominent in the photo, or in sharper focus). Each photo is placed in n-dimensional space based on these tags and weights.[4]

User-year variance is calculated by *summing the eigenvalues of the set of photos in that conceptual (tag-based) n-dimensional space*, with the set defined at the person-year level. Because each photo represents a single point, at least two photos are required at the person-year level for a value to be calculated. The less overlap there is in photo subjects, the greater the variance for the person-year observation. This characterization of variance is most analogous to the situations (S) in the sub-utility function model. More photos in different areas of the conceptual space are analogous to a greater number of situations. Results are

[4]There are approximately 1500 tags, but no individual photo has anywhere near this number of tags.

presented using the raw measure, the measure winsorized (at the 99th percentile), and the measure logged (of the summed eigenvalues plus one). The logged measure best corrects for skew, but all are reported because this decision was not made ex ante. When effect sizes are expressed in terms of standard deviations, effect sizes are quite similar (smaller coefficients for the more skewed measure, but one standard deviation is much larger).

One advantage of this measure is that it can capture, to some degree, the importance of convenience. A user with pictures of many different things may want to carry a camera at all times, so that it is available when the mood strikes. This is not captured by any technical measure of a particular photo. Another advantage is that it does not require any particular technology to be revealed. While an individual who enjoys photographing flowers may benefit from a macro lens, any device can be used.

Situational variance (βs)

Alternatively, variance can be conceived as in terms of the technical variance between photos. Photos may have a very short exposure, with a longer focal length, the reverse, or a long exposure with a shorter focal length. Variance in these measures necessarily call for differences in technology to address each challenge, whether a single technology which flexibly covers the range, or a mix of technologies, where each has a designated purpose.

This measure attempts to quantify variance in the underlying needs by placing each photo in a point in "technical space." Four technical parameters were gathered for each photo, using the Flickr Exif dataset from Yahoo Labs: ISO, f-stop, focal length, and exposure time. Because variance is being measured in n-dimensional space, it is important to standardize these dimensions so that no one dimension dominates the variance[5] For example, ISO values do not typically follow a linear scale (e.g., 100, 200, 300), but instead increase through doubling (e.g., 100, 200, 400, 800). By contrast, focal length is continuously variable (depending on choice of lens, a particular SLR camera might use any focal length between 16

[5] Subject matter tags are already standardized to a 0 to 1 scale based on confidence.

and 400 mm, with additional options for fixed focal lengths above or below that range), and exposure time is linear but highly skewed (most exposure times are a tiny fraction of a second, but there are very long exposures of subjects like the night sky). For my primary analysis, ISO, f-stop, and exposure time are logged.[6] Then all four are standardized to a mean of zero and standard deviation of one. Observations where any of these variables are missing are dropped.[7]

With all photos within the level of analysis plotted in technical space, summed eigenvalues are calculated for each person-year observation. Because an eigenvalue requires at least two points, person-year observations with fewer than two photos are coded as missing. This measure, like the measure of conceptual variance, is highly skewed. Higher values indicate greater variance in those attributes. Results are presented using the raw measure, the measure winsorized (at the 99th percentile), and the measure logged (of the summed eigenvalues plus one). The logged measure best corrects for skew, but all are reported because this decision was not made ex ante. When effect sizes are expressed in terms of standard deviations, effect sizes are quite similar (smaller coefficients for the more skewed measure, but one standard deviation is much larger).

4.1.4. Statistical approach

All models use linear probability models and are, because some individuals are captured multiple times for both adoption and person-year analyses, clustered at the individual level.

There are many factors that go into the decision to adopt one or more cameras, as well as when somebody might adopt a smartphone. No demographic information is available at the user level, and the license for the data prohibits attempts to infer demographic data or match users to external sources based on the data provided. Instead, user fixed effects are applied to *all* models.

[6] Results are robust to every variation of transformations I tried.

[7] The most frequently omitted measure is ISO. I performed the same analysis based only on the other three dimensions, and results did not differ. For some photos, all these details are missing. This could happen for photos that are scanned and uploaded, or if photos extensively modified in some photo editing suites, for example.

In addition to user fixed effects, models are also tested with and without year fixed effects. This attempts to correct for general trends in adoption decisions. These models are not necessarily appropriate where the general trends are themselves affected by the independent variable. A central premise of this paper is that the broader trend in camera adoptions, with a massive relative shift towards SLR/mirrorless cameras, is driven in large part by increased adoption of smartphones. The implications for estimated effects are discussed where appropriate in the results.

4.2. Empirical Results and Analyses

Before turning to specific results, I will briefly discuss the summary statistics describing the measures used in these analyses, which can be found in Table 2. This sample starts with 1,853,295 person-year observations. Within this sample, there are 1,213,857 standalone camera adoption decisions. There could be multiple within a year, or a user could use the same camera for several years. Of these adoption decisions, about 45.76% are for SLR or mirrorless digital cameras (collectively, interchangeable lens cameras), with the remainder being compact cameras. This is reduced to a sample of 890,524 adoptions for which some prior adoption history is available within the data (this omits all "initial adoptions" that are the first appearance of a user in the data). Of these, 28.64% adoptions are subsequent to the prior adoption of a smartphone, and 3.77% are subsequent the prior adoption of a *only* feature phone (if a user has used both, they are counted as smartphone adopters). Returning to the person-year unit of analysis, there are 1,682,376 person-year observations with enough data to measure co-use and preference variance in conceptual space (which requires multiple photos within the observation-unit with camera identifying information). Of these person-year observations, 33.92% of person-year observations include the co-use of multiple device (at least once cycle from one device to another, and then back to the first). In terms of preference variance in conceptual space, as noted earlier, the raw measure and winsorized measures are highly skewed, with means of about 4.6, over a range from 0 to 28.3565 and 11.7348, respectively. When the raw measure (plus one) is logged, the mean is

1.6572, over a range from 0 to 3.3795. The person-year sample that includes measures of preference variance in technical space falls to 1,421,568, as photos with missing Exif data reduce the sample. Again, measures of variance in technical space are highly skewed. For the raw and winsorized measures, with means of about 2.2, values range from 0 to 124.5471 and 10.631, respectively. With the raw measure (plus one) logged, the mean is 1.0176, and values range from 0 to 4.8327.

Table 2: Summary Statistics

Variable	*Observations*	*Mean*	*Std.Dev.*	*Min*	*Max*
Year	1853295	2009.272	2.8126	2000	2014
Adopt Mirrorless/SLR	1213857	0.4576	0.4982	0	1
Prior Adopt Smartphone	890524	0.2864	0.4521	0	1
Prior Adopt Feature Phone	890524	0.0377	0.1905	0	1
Co-use	1682376	0.3392	0.4734	0	1
Conceptual Σ Eigval	1682376	4.644	2.1884	0	28.3565
Conceptual Σ Eigval Winsorized 99%	1682376	4.6295	2.1279	0	11.7348
Conceptual Log(Σ Eival + 1)	1682376	1.6572	0.3906	0	3.3795
Technical Σ Eigval	1421568	2.2221	2.2744	0	124.5471
Technical Σ Eigval Winsorized 99%	1421568	2.1693	1.8706	0	10.631
Technical Log(Σ Eival + 1)	1421568	1.0176	0.5257	0	4.8327

A correlation table can be found in Table 3. As discussed above, all models are linear probability models, with user fixed effects, errors clustered at the user level, and year fixed effects where noted.

4.2.1. Substitute proximity and indirect complementarity

The first hypothesis based on the model above is that the adoption of a technology which is a more distant substitute for some offerings than others will be associated with an increased rate of adoption for the former relative to the latter. In this context, this argues that smartphone adoption will be associated with an increased probability of SLR/mirrorless camera adoption, relative to compact camera adoption. Results are shown in (Table 4), for smartphones (models 1 and 3), and the feature phone (e.g., flip phone) placebo treatment (models 2 and 4), without (models 1 and 2) and with (models 3 and 4) year fixed effects. All models include individual fixed effects, with errors clustered at the individual level.

Table 3: Cross-correlation table

Variables	Year	Adopt Mirrorless/SLR	Prior Adopt Smartphone	Prior Adopt Feature Phone	Co-use	Conceptual Σ Eigval	Conceptual Σ Eigval Winsorized 99%	Conceptual Log(Σ Eival + 1)	Technical Σ Eigval	Technical Σ Eigval Winsorized 99%
Adopt Mirrorless/SLR	0.265									
Prior Adopt Smartphone	0.324	0.024								
Prior Adopt Feature Phone	−0.041	−0.036	−0.103							
Co-use	0.013	−0.048	0.108	0.027						
Conceptual Σ Eigval	0.273	0.081	0.055	−0.024	−0.054					
Conceptual Σ Eigval Winsorized 99%	0.275	0.080	0.057	−0.024	−0.051	0.997				
Conceptual Log(Σ Eival + 1)	0.253	0.066	0.070	−0.017	−0.021	0.964	0.969			
Technical Σ Eigval	0.125	0.217	0.023	−0.017	0.033	0.218	0.219	0.218		
Technical Σ Eigval Winsorized 99%	0.147	0.247	0.035	−0.018	0.050	0.245	0.247	0.248	0.928	
Technical Log(Σ Eival + 1)	0.178	0.263	0.070	−0.013	0.100	0.253	0.256	0.268	0.878	0.948

Table 4: Smartphone adoption and SLR/Mirrorless camera adoption

	(1) SLR/Mirrorless	(2) SLR/Mirrorless	(3) SLR/Mirrorless	(4) SLR/Mirrorless
Prior Smartphone Adopt	0.1507***		0.0127***	
	(0.0028)		(0.0033)	
Prior Feature Phone Adopt		0.0342***		−0.0033
		(0.0068)		(0.0064)
Observations	651863	651863	651863	651863
R^2	0.468	0.462	0.481	0.481
Adjusted R^2	0.209	0.200	0.228	0.228
Year FE	*No*	*No*	*Yes*	*Yes*
User FE	*Yes*	*Yes*	*Yes*	*Yes*

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Linear probability model. Standard errors clustered at user level.

Results are consistent with the model, in that the prior adoption of a smartphone is associated with an increased conditional probability of adopting an SLR/mirrorless camera. Models using the placebo treatment - prior adoption of a feature phone - find much smaller or insignificant effects. The significant coefficient on model 2, however, may indicate the presence of omitted variable bias.[8] Particularly likely is bias introduced based on technological factors that change over time. This calls for year fixed effects. The challenge with interpreting the models with year fixed effects is that they control for a general trend which is arguably driven in large part by the treatment variable.[9] Because the relationship between the variable of interest and the proxy is positive, the true effect size should be somewhere between the effects estimated with and without the proxy control. Comparing the effects shown in Models 1 and 3 in Table 4, this range is quite large. These are linear probability models, so the effect sizes are additive changes in the conditional probability of adopting an interchangeable lens camera. For reference, within this sample the baseline (average) probability is 0.4576, so the prior adoption of a smartphone is associated with an increased conditional probability of adopting an interchangeable lens camera by 3% to 33%. As noted above, care should be made in any attempt to extrapolate these effect sizes

[8] It would be shocking if there were not.

[9] Angrist and Pischke (2008) would call this a "bad control," through a proxy variable , while Dell et al. (2014) would describe this as "over-controlling."

to the general population, but this introduces additional concern about the magnitude of any relationship.

Because all models incorporate user fixed effects, these results indicate that users are more likely to adopt an SLR/mirrorless camera after they have adopted a smartphone than before. This analysis requires a change in behavior, so this coefficient specifically captures switching from a compact camera to an SLR or mirrorless camera after the adoption of a smartphone. Given the interest in the *existence* of this pattern, rather than its universality, the model does provide an explanation for the observed behavior.[10]

4.2.2. Situational variance, adoption, and co-use

The second and third hypotheses based on the model argued for a positive relationship between situational variance and the adoption of more flexible technologies and the co-adoption and use of multiple technologies.

Adoption of more flexible technologies

The second hypothesis based on the model is that increased situational variance will be associated with the adoption of more flexible technologies. This is consistent both with prior theory and the new model. The question is whether the new model adds additional insight. First, however, the results of the test of this hypothesis are provided in Table 5. While results are positive for models that omit year fixed effects, these effects vanish with the inclusion of year fixed effects. While models without year fixed effects are reported in the interest of consistency, the bias described above for models using smartphone adoption as a predictor is not a concern here. These results do not provide support for the idea that subject-matter situational variance drives the adoption of more flexible devices. This could

[10]This use of language is intentional. While the data allow for the observation of behavior that is consistent with the model, this is not a true test. If the theorized behavior were not observed, it could just as easily be argued that the underlying conditions were more like those plotted in Figure 2 or 3. In fact, Figure 3 likely characterizes the majority of camera users, seen in the decrease in compact camera adoptions that is substantially larger than any increase in SLR/mirrorless camera adoptions, which always represented a smaller market by units sold.

indicate that this type of situational variance is not associated with variance in underlying needs, or that this type of variance calls for a flexibility not present in the most technical flexible technologies (e.g., subject-matter variance may equally call for convenience in a camera that is always available).

Table 5: Situations (S) and SLR/Mirrorless camera adoption

	(1) SLR/Mirrorless	(2) SLR/Mirrorless	(3) SLR/Mirrorless	(4) SLR/Mirrorless	(5) SLR/Mirrorless	(6) SLR/Mirrorless
Σ S Eigval	0.0158^{***}			-0.0005		
	(0.0006)			(0.0006)		
Σ S Eigval (Winsorized 99%)		0.0169^{***}			-0.0004	
		(0.0006)			(0.0006)	
Log(Σ S Eigval + 1)			0.0925^{***}			-0.0048
			(0.0030)			(0.0031)
Observations	1061505	1061505	1061505	1061505	1061505	1061505
R^2	0.500	0.500	0.500	0.521	0.521	0.521
Adjusted R^2	0.216	0.216	0.216	0.249	0.249	0.249
Year FE	*No*	*No*	*No*	*Yes*	*Yes*	*Yes*
User FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Linear probability model. Standard errors clustered at user level.

This hypothesis is also tested with an alternative measure of situational variance which better captures variance in underlying need. This construct for situational variance (βs) is measured using the technical aspects underlying each photo. Results are reported in Table 5. These results align much more closely with the behavior predicted by the model and prior theory. In Model 5, a 1 SD increase in variance is associated with an increase in the conditional probability of interchangable lens camera adoption of 0.0752, for an increase of 16.4%. In Model 6, a 1 SD increase in variance is associated with an increase in the conditional probability of interchangable lens camera adoption of 0.0839, for an increase of 18.3%. This model does provide support for the idea that underlying preferences, including the need for technical flexibility, to shape adoption behavior.

In the next model, situational variance (S) is combined with the indicator of prior smartphone adoption, to provide some insight into the robustness of both results. Note that the reintroduction of this smartphone indicator brings in the concerns about bias introduced by the year fixed effects, so that true effect sizes should be between those shown. These results, shown in Table 7, indicate little change in effect size for prior smartphone adoption.

Table 6: Situational variance βs and Mirrorless/SLR camera adoption

	(1) SLR/Mirrorless	(2) SLR/Mirrorless	(3) SLR/Mirrorless	(4) SLR/Mirrorless	(5) SLR/Mirrorless	(6) SLR/Mirrorless
Σ βs Eigval	0.0359***			0.0277***		
	(0.0011)			(0.0009)		
Σ βs Eigval (Winsorized 99%)		0.0522***			0.0402***	
		(0.0007)			(0.0006)	
Log(Σ βs Eigval + 1)			0.2116***			0.1596***
			(0.0023)			(0.0022)
Observations	930975	930975	930975	930975	930975	930975
R^2	0.507	0.510	0.513	0.520	0.522	0.523
Adjusted R^2	0.223	0.228	0.233	0.244	0.247	0.248
Year FE	No	No	No	Yes	Yes	Yes
User FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Linear probability model. Standard errors clustered at user level.

This measure of situational variance does become positive and significant in models 1 and 3, indicating that there may be some predictive power in this construct when combined with a measure of prior adoption of partial substitutes (which would not be predicted as a necessary control by prior models). The effect size of situational variance is no interpretable in models 2 and 4, as the placebo should not be provide any meaningful variance.

Table 7: Situations (S), smartphone adoption, and SLR/Mirrorless camera adoption

	(1) SLR/Mirrorless	(2) SLR/Mirrorless	(3) SLR/Mirrorless	(4) SLR/Mirrorless
Prior Smartphone Adopt	0.1434***		0.0129***	
	(0.0029)		(0.0033)	
Prior Feature Phone Adopt		0.0357***		−0.0034
		(0.0067)		(0.0064)
Log(Σ S Eigval + 1)	0.0537***	0.0932***	0.0144***	−0.0141***
	(0.0040)	(0.0040)	(0.0041)	(0.0041)
Observations	651863	651863	651863	651863
R^2	0.469	0.463	0.481	0.481
Adjusted R^2	0.209	0.202	0.228	0.228
Year FE	No	No	Yes	Yes
User FE	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Linear probability model. Standard errors clustered at user level.

Finally, situational variance (βs) is combined with prior smartphone adoption, as shown in Table 8 The estimated coefficients for smartphone adoption do fall somewhat, relative to prior estimates. But, again, results are consistent with the predictions of the model, that path dependence and situational variance predict adoption choice.

Table 8: Situational variance βs, smartphone adoption, and Mirrorless/SLR camera adoption

	(1) SLR/Mirrorless	(2) SLR/Mirrorless	(3) SLR/Mirrorless	(4) SLR/Mirrorless
Prior Smartphone Adopt	0.1087***		0.0081**	
	(0.0030)		(0.0035)	
Prior Feature Phone Adopt		0.0076		−0.0071
		(0.0070)		(0.0068)
Log(Σ βs Eigval + 1)	0.1908***	0.2040***	0.1610***	0.1611***
	(0.0028)	(0.0028)	(0.0027)	(0.0027)
Observations	590102	590102	590102	590102
R^2	0.481	0.478	0.488	0.488
Adjusted R^2	0.222	0.217	0.232	0.232
Year FE	*No*	*No*	*Yes*	*Yes*
User FE	*Yes*	*Yes*	*Yes*	*Yes*

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Linear probability model. Standard errors clustered at user level.

Situational variance and co-adoption/use

The third hypothesis argued for a positive relationship between situational variance the co-adoption and use of multiple technologies. As above, this variance can be conceptualized as more situations (S) or greater situational variance (βs). Results for situations (S) are reported first, in Table 9. Again, there is no reason to believe year fixed effects would bias the results, so the models with year fixed effects are likely to be more reliable. Given a base rate probability of co-use of 0.3392, a 1 SD increase in situations (S) associated with a 25% increased probability of co-use (Model 6). This result is sensitive to the skew of the underlying measure (a 1 SD increase in the winsorized measure is associated with only a 2.7% increase in co-use probability).

Shifting, again, to situational variance (βs) as measured by underlying technical variance, results are shown in Table 10. As with adoption choice, results are much stronger when using situational variance (βs) instead of situations (S). Model 5 indicates that a 1 SD increase in variance is associated with an increase in the probability of co-use of 0.0421, or

Table 9: Situations (S) and device co-use

	(1) Co-use	(2) Co-use	(3) Co-use	(4) Co-use	(5) Co-use	(6) Co-use
Σ S Eigval	0.0063***			0.0010***		
	(0.0004)			(0.0004)		
Σ S Eigval (Winsorized 99%)		0.0076***			0.0020***	
		(0.0004)			(0.0004)	
Log(Σ S Eigval + 1)			0.0857***			0.0522***
			(0.0021)			(0.0021)
Observations	1682376	1682376	1682376	1682376	1682376	1682376
R^2	0.480	0.480	0.481	0.502	0.502	0.503
Adjusted R^2	0.305	0.305	0.307	0.335	0.335	0.336
Year FE	*No*	*No*	*No*	*Yes*	*Yes*	*Yes*
User FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Linear probability model.

a 12.4% increase, while Model 6 indicates an increase of 0.0651, or a 19.2% increase.

Table 10: Technical space variance and device co-use

	(1) Co-use	(2) Co-use	(3) Co-use	(4) Co-use	(5) Co-use	(6) Co-use
Σ Eigval	0.0182***			0.0137***		
	(0.0005)			(0.0005)		
Σ Eigval (Winsorized 99%)		0.0294***			0.0225***	
		(0.0005)			(0.0005)	
Log(Σ Eigval + 1)			0.1545***			0.1238***
			(0.0018)			(0.0018)
Observations	1421568	1421568	1421568	1421568	1421568	1421568
R^2	0.513	0.515	0.521	0.527	0.528	0.532
Adjusted R^2	0.343	0.346	0.354	0.362	0.364	0.369
Year FE	*No*	*No*	*No*	*Yes*	*Yes*	*Yes*
User FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Linear probability model. Standard errors clustered at user level.

CHAPTER 5 : DISCUSSION AND CONCLUSION

The central premise of this research is that buyers may adopt partial substitutes, which are not necessarily mutually exclusive, and that this can drive competitive dynamics that might be missed using existing models of competition. Competition between two technologies depends not only on demand for the relative performance attributes of each offering, but on the existence of partial substitutes which may differentially affect demand for the focal technologies. More specifically, the introduction of a new technology may induce buyers to shift future adoption decisions away from closer substitutes, to more distant substitutes, due to indirect complementarity. Individual-level situational preference heterogeneity also plays an important role, both in the adoption of individual devices or the decision to co-adopt partial substitutes, as individual adoption behavior is shaped by their range of needs.

Evidence for the usefulness of this theory was found in the digital camera industry, where a unique dataset allowed for the observation of individual adoption and use over time. In this context, individuals are more likely to adopt an SLR or mirrorless camera after they have adopted a smartphone. This behavior is also shaped by situational variance, as users who are exposed to more situations, and particularly users whose needs indicate greater variance in technical needs across situations, are more likely to adopt technologies with greater technical flexibility, as predicted by this and prior models. Critically, this model also explains why these users are also more likely to adopt multiple technologies, given their situational variance.

This research opens up a new avenue for understanding substitute technology competition beyond a binary choice between offerings, but as a domain where managers can also pursue strategies that allow for buyer adoption *even if* a competing offering has already been selected. Beyond highlighting the fact that substitutes do not need to be conceived only as mutually exclusive offerings, this research highlights one mechanism that drives the possibility of co-adoption - a range of needs which can be met either by a single offering, or a combination of offerings. These dynamics also point to opportunities for competitive positions that may exist only because of partial substitutes. One example of this might be tablet computers, which can be designed for a very narrow set of needs in part because most buyers own multiple computing devices to cover their range of other needs.

While this analysis focused on the technology level, and how the rise of a substitute can create position-specific opportunities or threats, there are also clear implications for firms in considering the horizontal scope of their offerings, where thinking must expand beyond segmentation and complements, to consider partial substitutes that might offer particularly attractive combinations for meeting a range of needs. These dynamics also open paths for prolonging survival in the face of increasingly dominant technologies, pointing to positions that are not only defensible in the face of the substitute, but may even increase in value relative to intermediate positions.

The recognition that substitutes are not necessarily mutually exclusive, depending on prior adoption history and within-buyer preferences, is critical for strategists competing in technologically dynamic industries, and highlights many avenues for future research to improve our understanding of the dynamics of substitute competition.

5.1. Limitations and Future Directions

While this dissertation has covered a range of parameters that affect competition between and co-adoption of partial substitutes, it has also abstracted away from many important dimensions. While this limits the completeness of the current picture of this type of competition, it also points to many interesting projects to come.

A central question in strategy is why some firms perform better than others. This model and empirical test focuses entirely on the technology level, while abstracting away from firm-level competition. This is important for several reason. For example, a firm may want to design their portfolio of offerings to maximize the chance of co-adoption within their own offerings. This can be seen in Apple's one-time strategy of limiting the maximize size of an iPhone and the minimum size of an iPad, in the hopes that many of their customers would buy both. There are also important supply-side considerations that play a role in any kind of technology competition. Even if buyer preferences can be perfectly measured and targeted, the capabilities and resources of a firm might limit what they can profitably offer, in terms of both offering position and range.

In addition to abstracting away from the firm, this dissertation uses value-based modeling, which takes into account willingness to pay and cost, but not price. This omission takes focus away from several key opportunities. The first relates to the previous limitation. Because this research relates to partial substitutes, the value of adopting multiple offerings is less than the sum of the value of adopting each. The approach to pricing optimized for one may need to differ when optimizing for the other. In some cases, it may make sense to bundle offerings, with a bundle price, but this may only be possible if the same seller is offering both. Another research opportunity related to pricing could take into account that there is heterogeneity between buyers (the focus of much of the previous work in this area), while this dissertation focuses on the heterogeneity within buyers. In the absence of perfect price discrimination, creating the most value does not always mean the buyer will purchase the offering, if profits are maximized by setting the price above willingness-to-pay for some buyers.

A third omission of this dissertation, and potential avenue for future research, is the socio-cognitive element of adoption behavior. Buyers may not be able to perfectly understand their own preferences, instead using heuristics to shape their choice. Beyond this, not every offering in the marketplace can be considered for every purchase, because of bounded rationality. This means that a decision set must be created, and then an offering selected from that set. How these processes occur have been considered in other domains, but may present uniquely interesting wrinkles in the context of partial substitutes.

Finally, this study takes the adoption of a particular technology as given, without considering the elements that shape smartphone adoption. The smartphone incorporates many functions beyond a camera, and it is the combination of these that determine not only whether to buy a smartphone, but which device to buy. For example, if a user plans to use the smartphone in place of their compact camera, they may spend more on a phone with a better camera. This would not invalidate the model, but would shift the focus of valuation from conditional value (of a camera conditional on smartphone adoption) to joint value (where the buyer considers the value of buying both in choosing which smartphone to buy). It is also possible that the phone is chosen for many other reasons, such as having the fastest data speeds and largest screen for watching movies, but the phone with those also happens to have a better camera, making the decision to buy a camera, or not, more of the conditional value question. The extent to which buyers approach these decisions sequentially, simultaneously, or even with the expectation of future improvements all are important for firms to understand how best to position themselves.

Together, these limitations point the way to an expansive stream of future research, which will paint a more complete picture of how firms can compete with and against partial substitutes.

APPENDIX

A.1. "Choose single best" positioning

Laptop vs. Desktop: A Lifestyle Choice

Tags: Desktops Tech Tips & Tricks Laptops More

Until recently, if you were in the market for a new computer and had to decide between a laptop and a desktop, the choice was simple. The laptop versus desktop dilemma was usually decided by whether mobility or performance was more important to you. Oftentimes, students and remote workers chose laptops, while gamers and designers went for desktops.

Fortunately, computer technology has come a long way since the days of laptops with limited battery life and desktops with cumbersome hard drives and tangles of wires. Nowadays, when you choose a new computer, you really can take *your* needs into account.

Laptop vs. Desktop: More Choice Than Ever Before

If you enjoy the wireless mobility and touchscreen capabilities of a laptop to stay connected and quickly navigate your favorite sites, all while sipping coffee at your neighborhood café, then the Intel-inspired Ultrabook™ might be the new breed of computer that fits your life on-the-go.

For those who enjoy a near theatre-quality experience while viewing their favorite HD movies, the new all-in-one PC is a stylish alternative to the traditional home computer. It's a popular choice for families who love getting together in their leisure time for online gaming and listening to music.

Laptop or Ultrabook™

Advances in Intel® Core™ processors, battery life, and visual displays have vastly improved the performance possibilities of laptops. Multitasking—like staying connected to your social network while preparing a report for school or work—is faster and more efficient than ever.[1]

For the exciting combination of a laptop with the capabilities of a tablet, including touchscreen technology and a range of screen displays from sliding to double-sided, check out the Ultrabook™ convertible.[2]

Laptops and Ultrabook™ with Intel® Core™ processors include:

- Intel® Smart Connect Technology to constantly keep you updated on email and social networks
- Intel® Rapid Start Technology[3] to get you from standby to up-and-running in under seven seconds
- Intel® Anti-Theft Technology (Intel® AT)[4] to disable your laptop or Ultrabook™ if lost or stolen
- Intel® Identity Protection Technology (Intel® IPT)[5] to protect your identity while social networking and using the Internet

Desktop or All-in-One PC

A redesign of the desktop is moving the PC from the home office to the living room. Wireless capability and the option of a 27-inch wall-mountable monitor make the all-in-one PC a popular choice with families who want less clutter and simple elegance. The result is more performance.

Everyone, from serious gamers to parents who enjoy streaming their favorite family-friendly programs, will appreciate the improved performance of Intel® Core™ processors in desktops and all-in-one PCs.

Choose What Fits

Today, the laptop versus desktop choice is more than a product comparison—it's a question of knowing your lifestyle. So take a moment and consider all the work, entertainment, and social networking activities you use a computer for and you'll be well prepared to find a device that fits your life.

The Intel Product Finder can help you decide between laptop, desktop, Ultrabook™, or tablet.

Source: `https://web.archive.org/web/20160605081526/http://www.intel.com/content/www/us/en/tech-tips-and-tricks/laptop-vs-desktop-which-is-right-for-you.html`

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